Comparative of Desktop-based and Mixed Reality-based Cognitive Test using EEG Analysis

Chean Khim Toa, *Member, IAENG,* Kok Swee Sim, *Member, IAENG,* Shing Chiang Tan

***Abstract*— This study performs an assessment of the use of Mixed Reality (MR) technology in the cognitive field. Previously, most of the studies commonly used desktop-based for cognitive testing. However, this approach is limited to screen projection in two dimensions and requires adequate physical space and a table for performing testing. This incurs the concern of the immersive during the test. The study found that MR, as an immersive tool, could address those concerns. Thus, the experiment in this paper performs the comparison between desktop-based and MR-based environments. This study aims to propose a testing framework that can provide analytical analysis based on the EEG data to demonstrate participant engagement, concentration, and immersion level in different environments. Fifteen students participated in the study, with their EEG data collected during tests in Mixed Reality Visual Colour (MRVC) and Desktop Visual Colour (DVC). Subsequently, the collected EEG data was analyzed using the Cognitive Signal Domain (CSD) method. Analysis of collected data revealed that participants in the MRVC showed higher levels of engagement, concentration, and immersion. This study implies that MR-based testing can be an effective method for eliciting cognitive responses in participants.**

***Index Terms*— Cognitive Test, Desktop-based, Electroencephalogram, Mixed Reality-based**

I. Introduction

COGNITIVE is a process that impacts various aspects of life, from school to work. This process encompasses problem-solving, memory retention, critical thinking, and judgment [1]. Historically, numerous research studies have employed desktop-based cognitive tasks to assess human cognitive capabilities. For instance, Tamura et al. [2] developed a modified trail-making task using a personal computer and touch panel to evaluate the cognitive mental state for detecting mild cognitive impairment in the elderly. Hendrawan et al. [3] similarly designed a desktop-based test to assess students' working memory. In addition, Yazdani et al. [4] created a desktop-based Selective Visual Attention Test (SeVAT) to evaluate the selective attention of first-grade school children.

While desktop-based cognitive tasks have been widely employed, this approach reveals two significant research gaps. Firstly, the cognitive test was presented on the screen, which exhibits a two-dimensional (2D) representations to the user. This will result in a lack of immersive visual engagement for participants. Furthermore, interaction though the mouse or keyboard was presented with limited engagement, which may lead to reduce motivation and potentially affect their performance. Secondly, to have an optimal test visualization, there is a need to have a well physical space to set up the desktop. Those setups will result in cumbersome in data collection because there is a need to be careful consideration on the space allocation and the equipment arrangement. Thirdly, the setup which needs to be fixed on specific location will limit the participant's mobility, reducing the flexibility to conduct the test in diverse setting and accommodating individual with mobility challenges.

In order to address these gaps, the study investigates the potential of Mixed Reality (MR) technology to create more immersive and interactive cognitive tasks. MR is an emerging holographic technology that merges virtual and real environments to create a novel immersive environment where users can interact with virtual objects in the real world. The application of MR was applicable for a wide range of fields [5]. For instance, Yusoff et al. [6] conducted assessment of user perception and acceptance of MR in education, finding that students having a strong interest and willingness to use MR. This results in having potential to enhance academic performance. Weng et al. [7] discussed the integration of MR in education, demonstrating its value as a learning supplement that can improve students' learning outcomes. Flavián et al. [8] highlighted the impact of MR on the customer experience in marketing, illustrating the way MR technology can provide customers with highly immersive experiences.

In this paper, Mixed Reality (MR) technology will be applied to develop cognitive testing frameworks specifically designed to measure cognitive functions related to visual attention. We introduce the Mixed Reality Visual Colour (MRVC) test as a novel MR-based cognitive assessment. Additionally, to compare with different environmental contexts, the Desktop-based Visual Colour (DVC) test was designed. After that, an Electroencephalogram (EEG) headset was adopted to record brain signals. The use of non-

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invasive electrophysiological monitoring method can provide us a much deeper insight into participants' cognitive state through the brain activity [9]. The EEG data can be categorized into five frequency sub-bands: alpha (8-12 Hz), beta (13-30 Hz), gamma (31-50 Hz), theta (4-7 Hz), and delta (0.5-3 Hz). These EEG data will be analyzed using the Cognitive Signal Domain (CSD) method, which includes power spectrum analysis, Event-Related Spectral Perturbation (ERSP), Engagement Index (EI), and Concentration Index (CI) values. The result obtained from CSD method will provide a comprehensive evaluation that allows us to assess the participants' levels of engagement, concentration, and immersion during cognitive tasks.

The objectives of this study can be summarized as following:

1. To design cognitive testing framework in both desktop-based and MR-based environments for assessing participants' cognitive function.
2. To conduct a comparative analysis of the EEG data collected from DVC and MRVC tests using the Cognitive Signal Domain (CSD) method.

The following sections of this paper are divided into Materials and Methods, Desktop-Based and Mixed Reality-Based Cognitive Tests, Electroencephalogram Signal Processing, Results and Discussions, and Conclusion.

II. MATERIAL AND METHODS

A. *Mixed Reality Headsets*

In this research, we utilized the Microsoft HoloLens 2, a wearable mixed reality (MR) headset developed by Microsoft [10]. It is a pair of MR smart glasses that provides an immersive MR experience by seamlessly merging the real and virtual worlds. It enables physical and virtual objects to coexist and interact in real time. This standalone headset projects virtual objects onto a near-eye screen, creating holographic displays within the real world. Equipped with built-in sensors. The device tracks the user's movements in physical space, adjusting the virtual object's location accordingly [11].

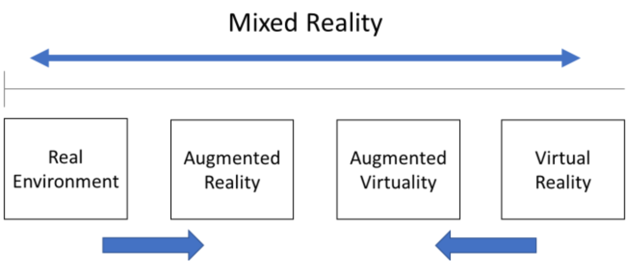


Fig.1: Reality-virtuality continuum (redrawing based on [12])

For clarity, MR encompasses specific elements of both augmented reality (AR) and virtual reality (VR) [12], [13]. AR involves overlaying digital objects onto the real world [14], while VR generates an entirely digital virtual environment with the controller to interact with digital objects [15]. According to the reality-virtuality continuum as shown in Figure 1, it is a scale that spans from the real-world environment to the virtual environment [12]. The zone between complete reality and complete virtuality is defined as MR. The key distinction among AR, VR, and MR lies in user interaction. AR permits users to view digital elements in the real-world environment without direct interaction. Conversely, VR immerses users in a fully virtual environment, requiring isolation from the physical world and obstruction-free spaces to prevent unforeseen incidents while wearing a VR headset. It interacts with the virtual object through the usage of a controller.

It is worth noting that AR and VR have found applications in various fields, such as cognitive training and educational learning [16], [17], [18]. However, the utilization of MR in these contexts is still in its early stages, and its full potential is yet to be explored. MR, as an intermediate technology, blends the capabilities of AR and VR, enabling users to interact with digital elements within their real-world surroundings. This fusion of realistic renderings and interactions creates an MR experience that closely resembles real-life scenarios [19], [20].

B. *Emotiv Insight Headsets*

The Emotiv Insight is a consumer-grade EEG headset that can be used in research application and personal use. There are several reasons Emotiv Insight was chosen over other consumer-based EEG headsets. First, it is cost-effectiveness. Although other EEG headsets with more channels provide extensive data acquisition capabilities, Emotiv Insight's 5-channel configuration provides a good balance between functionality and affordability. Second, it meets specific requirements of our research. The 5-channel setup matches our study's objectives by covering the frontal (AF3, AF4), parietal (Pz), and temporal (T7, T8) regions associated with attention-related cognitive functions. Third, it is user-friendly, with a straightforward electrode setup and the calibration process only takes about 2 minutes [21].

C. *Participants*

Fifteen healthy students, including of 10 males and 5 females, aged between 21 and 26 years, voluntarily participated in this experiment. Participation was limited to individuals with normal or corrected-to-normal vision. Those with specific eye conditions, such as color blindness, low vision, cataracts, or any other conditions that might affect visual perception, were not eligible to participate. Each participant provided informed consent taking part in the tasks. Throughout the signal acquisition process, they wore an EEG device. Later, the EEG datasets collected from all participants were used for analysis. During the experiment, participants performed the same task in two distinct environments: a desktop-based environment and an MR environment. Participants were informed of their right to discontinue their participation at any point if they felt unwell.

III. DESKTOP-BASED AND MIXED REALITY-BASED COGNITIVE TESTS

The study primarily focused on designing a visual color search test in both desktop-based and MR-based environments. Visual search is a perceptual task that

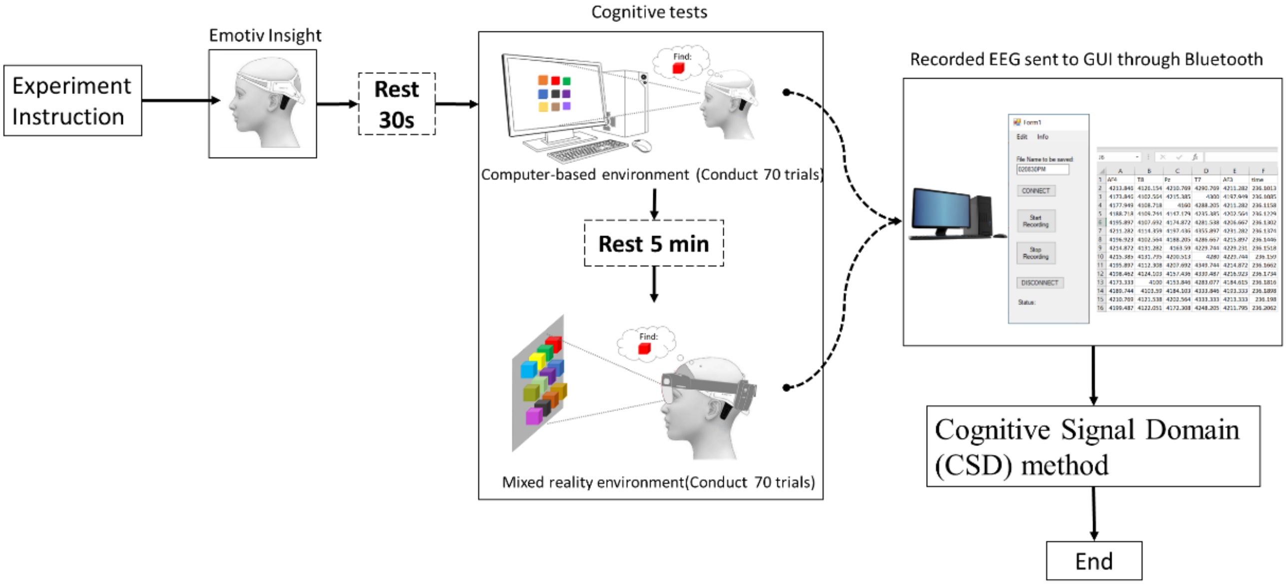


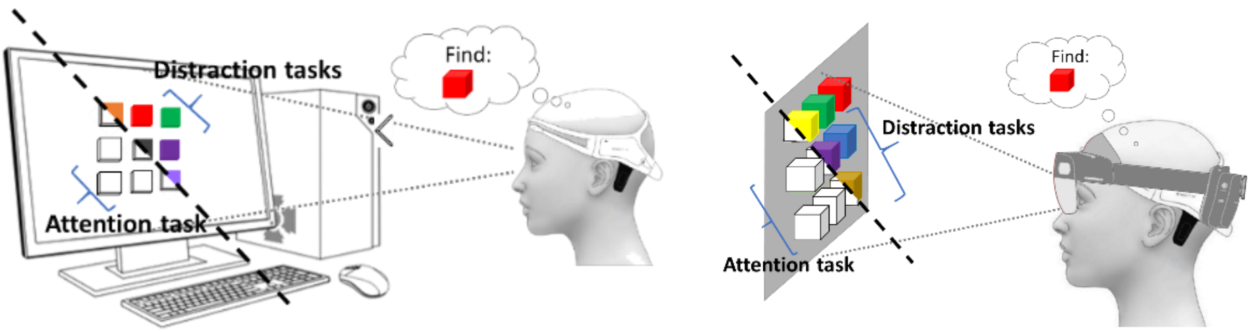
Fig.2. The flow diagram of proposed cognitive testing frameworks

involves actively scanning the visual environment to locate specific information [22], [23]. It has previously been utilised in platforms such as PsyToolkit, [24], and CogniFit [25], [26] for studying cognitive functions. Figure 2 provides a block diagram illustrating the process of the Visual Colour test in both desktop-based and MR-based environments, utilizing EEG for analysis. A comparative analysis of EEG signals between these two environments will be conducted using the CSD method to determine which environments provide greater participant engagement, concentration, and immersion levels during the tasks.

The visual color test consists of two components, which are an attention task and a distraction task. Both tasks will need the participants to locate a target stimulus. In the attention task, participants tasked to identify a specific color target stimulus among a group of stimuli, with all uniformly white. The distraction task also requires participants to identify the color target stimulus. But this task having a group of stimuli with variety colors that are either slightly similar or different from the target stimulus. Both tasks are presented randomly during the test and are performed without any induce any audio distractions.

The reason having both tasks performed in a single test was to measure participant concentration, immersion, and engagement, making it possible to have a comparison on their performance across different environments. A sample display of the Desktop Visual Colour (DVC) and Mixed Reality Visual Colour (MRVC) tests is provided in Figure 3, with a dotted line indicating that both tasks are presented randomly within a single test.

Figure 4 displays the flowchart used for both the Desktop Visual Colour (DVC) test and the Mixed Reality Visual Colour (MRVC) test. This flowchart served as a guide for designing a logic flow graph for the virtual elements of the visual color test within the Unreal Editor. The total task duration is set at 70 seconds, consisting of 70 trials, each lasting 1 second. This time limit was determined based on a prior experiment conducted in CogniFit [26]. However, the initial and final 5 seconds (equivalent to 5 trials) of EEG recording are excluded from analysis due to concerns about potential poor EEG signal quality at the beginning and end of the recording. Consequently, only 60 seconds of recorded EEG signals will be subjected to analyse.



(a) (b)

Fig.3. Sample Display of (a) Desktop-Based Visual Colour (DVC) Test and (b) MR-Based Visual Colour (MRVC) Test

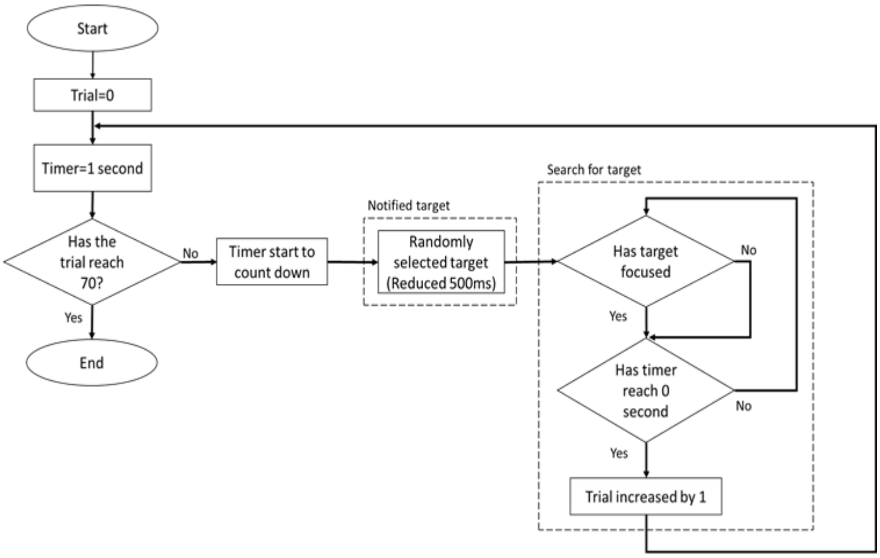


Fig.4. Flow chart of Visual Colour Test for Desktop-based Environment and Mixed Reality (MR)-Based Environment

IV. ELECTROENCEPHALOGRAM SIGNAL PROCESSING

A. Environmental Noise Filtering

When recording brainwaves with the Emotiv Insight headset, the Electroencephalogram (EEG) signal is often contaminated by environmental noise that is generated in the environment with electrical wiring, either 50 Hz or 60 Hz. To filter out the noise, the headset has built-in filters, namely a digital dual notch filter and a 5th-order Sinc filter. The digital dual Notch filter is used to attenuate raw EEG signals in the stopband frequency range and pass the signals below and above the stopband. This filter is particularly effective at eliminating electrical line noise present in the signals. Equation 1 shows the formulation of the Notch filter.

$$N(z) = \frac{1 - 2\cos\omega_0 \, z^{-1} + z^{-2}}{1 - 2\cos\omega_0 \, r z^{-1} + r^2 z^{-2}}, \quad (1)$$

where z is the signals frequency content, ω_0 is the stopband center frequency, and r is the notch bandwidth, ranging from 0 to 1. The Sinc filter is a low-pass filter that cuts off the high frequencies, without affecting lower frequencies. Equation 2 shows the formulation of the Sinc filter, S(n)

$$S(t) = 2f_c sinc(2f_c \, t), \quad (2)$$

where f_c is the cutoff frequency and t is the frequency content of the signals.

B. Cognitive Signal Domain (CSD) on EEG Analysis

The Cognitive Signal Domain (CSD) method was introduced to perform analytic calculation of the EEG data collected from both environments for comparative analysis. The CSD method analyzes EEG data based on the parameters includes power spectrum, Event-Related Spectral Perturbation (ERSP), Engagement Index (EI), and Concentration Index (CI) values. These parameters provided the evaluation metric to calculate participants' levels of engagement, concentration, and immersion within their respective environments

The power spectrum was applied to calculate the distribution of signal power across different frequencies. It represents the coefficients of each frequency band, measured through the Fast Fourier Transform (FFT), in the form of a power value plot. In this study, our objective is to analyze participants' states of engagement, concentration, and immersion. Consequently, we focus solely on the theta (4-7 Hz), alpha (8-12 Hz), and beta (13-30 Hz) frequency bands. The FFT transforms the time-domain function into a frequency-domain representation, as depicted in Equation 3.

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi f t} dt, \quad (3)$$

where $x(t)$ is the time-domain signal, f is the frequency to analyze, and $X(f)$ is the frequency domain Fourier transform. An example of an EEG signal decomposed into a Fast Fourier Transform (FFT) is shown in Figure 5.

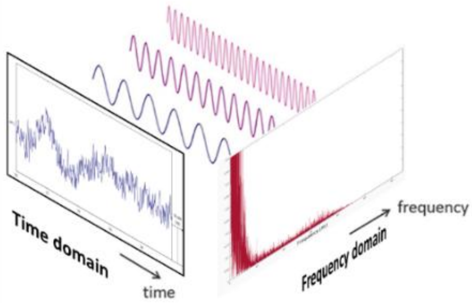


Fig.5. Visualization of electroencephalogram (EEG) signals in the time-domain decomposed into FFT in the frequency domain.

Later, the Fourier transform is inserted into the power spectrum formulation as shown in Equation 4 to calculate the harmonic power in the signals.

$$\boldsymbol{PS(f) = \lim_{T\to\infty} \frac{1}{T} |X(f)|^2}, \quad (4)$$

where PS(f) is the power spectrum of frequency bands, X(f) is the Fourier transform, and T is the arbitrary period. Using the computed power spectrum, a 2-dimensional topographical interpolation plot is constructed by defining grid points based on the 10/20 system as shown in Figure 6.

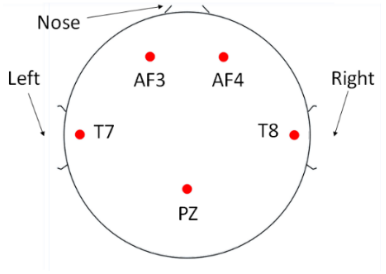


Fig.6. Grid point on the 2-dimensional head plot

The colour intensity is used to indicate the strength of the power spectrum in the DVC and MRVC. The colour radius in the topographic is computed using Equation 5.

$$R_n = \frac{max\left(\tilde{x_c}(f)\right)}{max\left(\forall \tilde{x_c}(f)\right)} * r_s, \qquad (5)$$

where R_n is the size of the radius for maximum intensity, r_s is the maximum radius size of each grid, $max\left(\tilde{x_c}(f)\right)$ is the power spectral density maximum value for channels, and c is the channel labels where $c \in (1,2,3,4,5)$. Later, colour interpolation is used between the intersection grids to smooth the topographic map [27], [28].

Next, to detect the event-related changes in the power spectrum, a time-frequency technique named Event-Related Spectral Perturbation (ERSP) was used. It measures changes in EEG frequency spectrum amplitude as a function of time relative to the trials. Figure 7 provides a visualisation of ERSP, where the circle with a blue arrow (inside a red rectangular prism) represents the decomposition of the time-frequency points for each trial. These points were averaged across the trials and converted into an event-related spectrum using Equation 6.

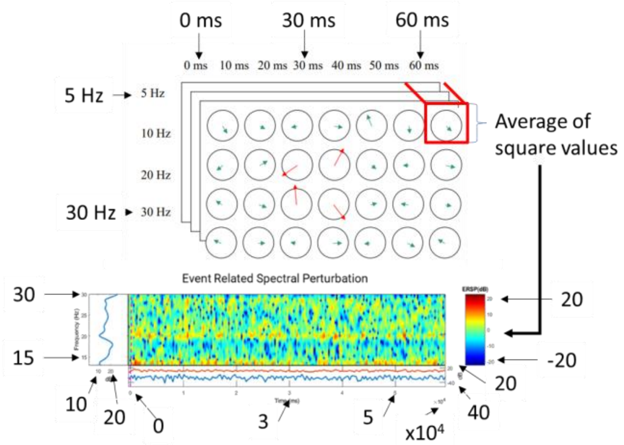


Fig.7. Event-Related Spectral Perturbation (ERPS) technique

$$ERSP\ (f,t) = 10\,log_{10}\frac{1}{n}\textstyle\sum_{k=1}^{n}|F_k(f,t)|^2, \qquad (6)$$

where $F_k(f,t)$ is a complex number in vector with f as frequency and t as time, k as the trial number, and n is the length of a vector. The value of ERSP will be scaled to decibels (dB) to have an easier visualization of frequencies with different amplitudes.

Afterward, to calculate the sense of engagement and concentration, the power spectra of theta, alpha, and beta bands were averaged and applied to the Engagement Index (EI) and Concentration Index (CI) using Equation 8 and Equation 10.

$$ABR = \frac{\alpha_{channel}}{\beta_{channel}} \qquad (7)$$

$$EI = \frac{1}{ABR} \qquad (8)$$

$$TBR = \frac{\theta_{channel}}{\beta_{channel}} \qquad (9)$$

$$CI = \frac{1}{TBR} \qquad (10)$$

where $\alpha_{channel}$, $\beta_{channel}$, and $\theta_{channel}$ is the alpha, beta, and theta for each channel, ABR is the alpha-to-beta ratio, and TBR is the theta-to-beta ratio. Previous studies have shown that a lower ABR indicates higher engagement in cognitive processes during decision-making, and a lower TBR reflects stronger concentration ability [29].

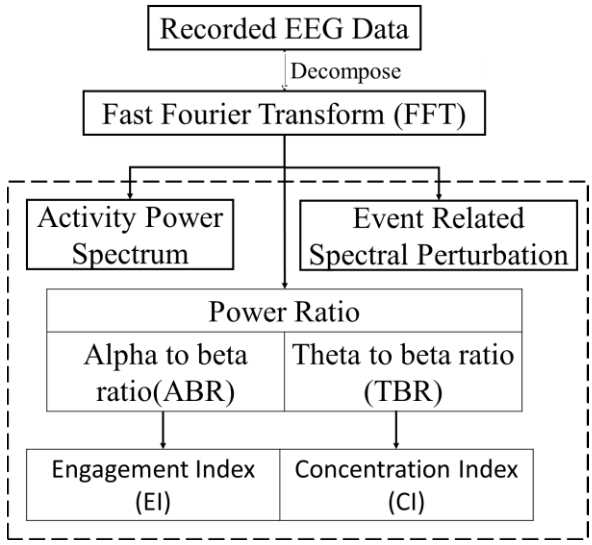


Fig.8. Overall flow of the Cognitive Signal Domain (CSD) method

Figure 8 shows the block diagram of the CSD method used to analyze participants' engagement, concentration, and immersion in both environments. The process was initially decomposing the EEG data into Fast Fourier Transform (FFT) to calculate the average power spectrum of the signal across five electrodes (AF3, AF4, Pz, T7, and T8). Following that, topographical maps of these electrodes were generated to identify which brain lobes having increased or decreased brain activity during cognitive tasks. Subsequently, the β power values collected from the test were calculated using three evaluation metrics. First is evaluating concentration through activity power spectrum. Second is evaluating immersion through Event-Related Spectral Perturbation (ERPS). Third is evaluating engagement and concentration through the Engagement Index (EI) and Concentration Index (CI).

V. RESULTS AND DISCUSSIONS

A. Participant Feedback on Desktop-Based and Mixed Reality-Based Environments

After participant completed the Visual Colour test in both Desktop-based and MR-based environments, their feedback was collected. This feedback provides valuable insight into the comparative effectiveness of both environments for cognitive testing. Table 1 summaries their feedback on each environment. To keep participants' confidentiality, all feedback is anonymized, and any identifiable information that has been excluded from this section.

TABLE 1.
Presentation of Participants' Feedback

Desktop-Based Environment	
Positive Experiences :	Participant: *"The Desktop-based task offers a familiar setting and it was relatively easy to operate. Maybe because of the common use of the computer."*
Challenges Faced:	Participant: *"While the DVC task was manageable, it was monotonous which affected our motivation to perform at our best."*
Mixed Reality-Based Environment	
Positive Experiences :	Participant: *"The MR-based environment made the tasks feel more engaging and immersing. The interactive nature of MRVC tasks enhanced my focus on it. It was fascinating to see the virtual objects integrated into the real environment."*
Challenges Faced:	Participant: *"While MRVC was immersive, it put some weight on our head. After prolonged usage, maybe for a few hours, it began to become warm and our forehead and back of head tend to sweat."*

To have a comparative analysis of participants' cognitive states during the DVC and MRVC tests, the CSD method was applied and the result was presented in the following section with the discussion of the finding.

B. Application and Trial Sequences of Visual Colour Tests

In this study, to gather EEG data from participants in various environments, we designed the application and trial sequences for both the Desktop-based Visual Colour (DVC) test and the MR-based Visual Colour (MRVC) test, as illustrated in. Figure 9.

In the desktop-based environment, the test was displayed on a 2D screen placed on a table, and participants were required to sit at a distance from the screen for viewing. In contrast, in the MR-based environment, participants simply wore the HoloLens 2 headset to see the test seamlessly integrated into the real environment.

Both the DVC and MRVC tests encompassed two distinct target-searching conditions. The first task involved participants searching for a specific color target stimulus within a group of stimuli, all uniformly white. The second task required them to identify the same color target stimulus, but this time among stimuli with various colors. These tasks were integrated into a single test and presented randomly, allowing us to measure participant engagement, concentration, and immersion across different environments.

Regarding participant mobility during the experiment, using the HoloLens 2 headset offered greater flexibility compared to a desktop screen. In the desktop computer setup (as shown in Figure 9a), a suitable and stable viewing location is needed to be provided. However, this constraint was alleviated in the MR-based environment, where participants could wear the headset to visualize the test projected seamlessly into the real environment (as shown in Figure 9c)

C. Average Power Spectrum

The activity power spectrum technique involves the calculation of power values within the β frequency range (13 Hz-30 Hz) in both the frontal lobe (AF3 and AF4) and the parietal lobe (Pz). The β activity was selected because it serves as an indicator of the participant's arousal during the execution of visual cognitive tasks. Higher β activity is associated with increased engagement, concentration, and immersion. To determine which environments elicited higher β activity, we computed, averaged, and visualized the power values of 15 participants while they performed the DVC and MRVC tests. These visualizations were generated using EEGLAB [30].

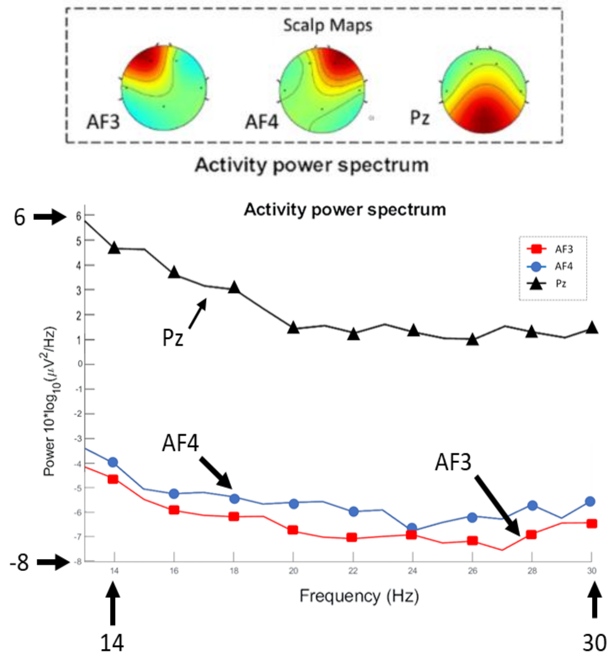


Fig.10. Desktop-Based Visual Colour (DVC) Test: Scalp Maps and Activity Power Spectrum from 13 Hz –30 Hz

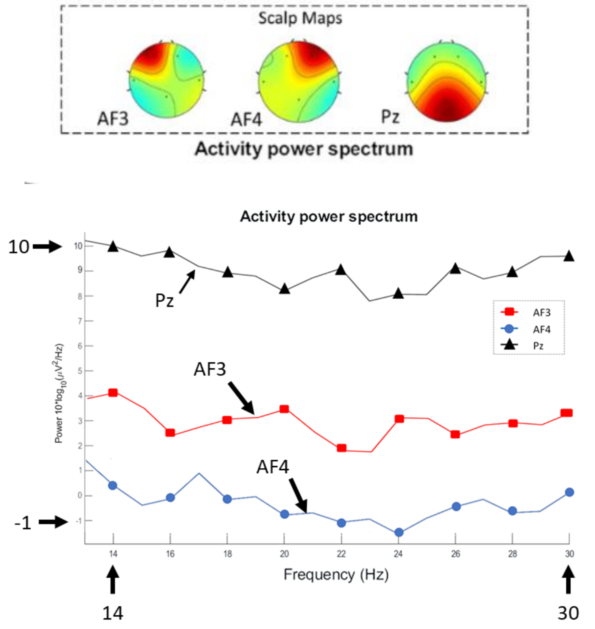


Fig. 11. MR-Based Visual Colour (MRVC) Test: Scalp Maps and Activity Power Spectrum from 13 Hz –30 Hz

Scalp maps as shown in Figure 10 and Figure 11 indicate that both environments exhibit high EEG variation in AF3, AF4, and Pz locations. The activity power spectrum line graph for each location shows significant distinct patterns for DVC and MRVC tests. During the DVC test, an exponential decrease in β power values was found at AF3 (from -4 dB/Hz to -7.5 dB/Hz), AF4 (from -3.5 dB/Hz to -6.5 dB/Hz), and Pz (from 6 dB/Hz to 1 dB/Hz). For MRVC test, the β power values remained within the range at AF3 from 1.75 dB/Hz to 4 dB/Hz, AF4 ranged -1.2 dB/Hz to 1.2 dB/Hz, and Pz from 8 dB/Hz to 10.1 dB/Hz. It shows that the average β power values remained relatively constant across the frequency range. This indicates that participants maintained their concentration levels throughout the MRVC test. As the average β power values of the DVC test having exponentially decrease, this suggests that there is a sign of decline of concentration levels. Additionally, there is a noticeable higher value of overall β power for the MRVC test as compared to DVC test.

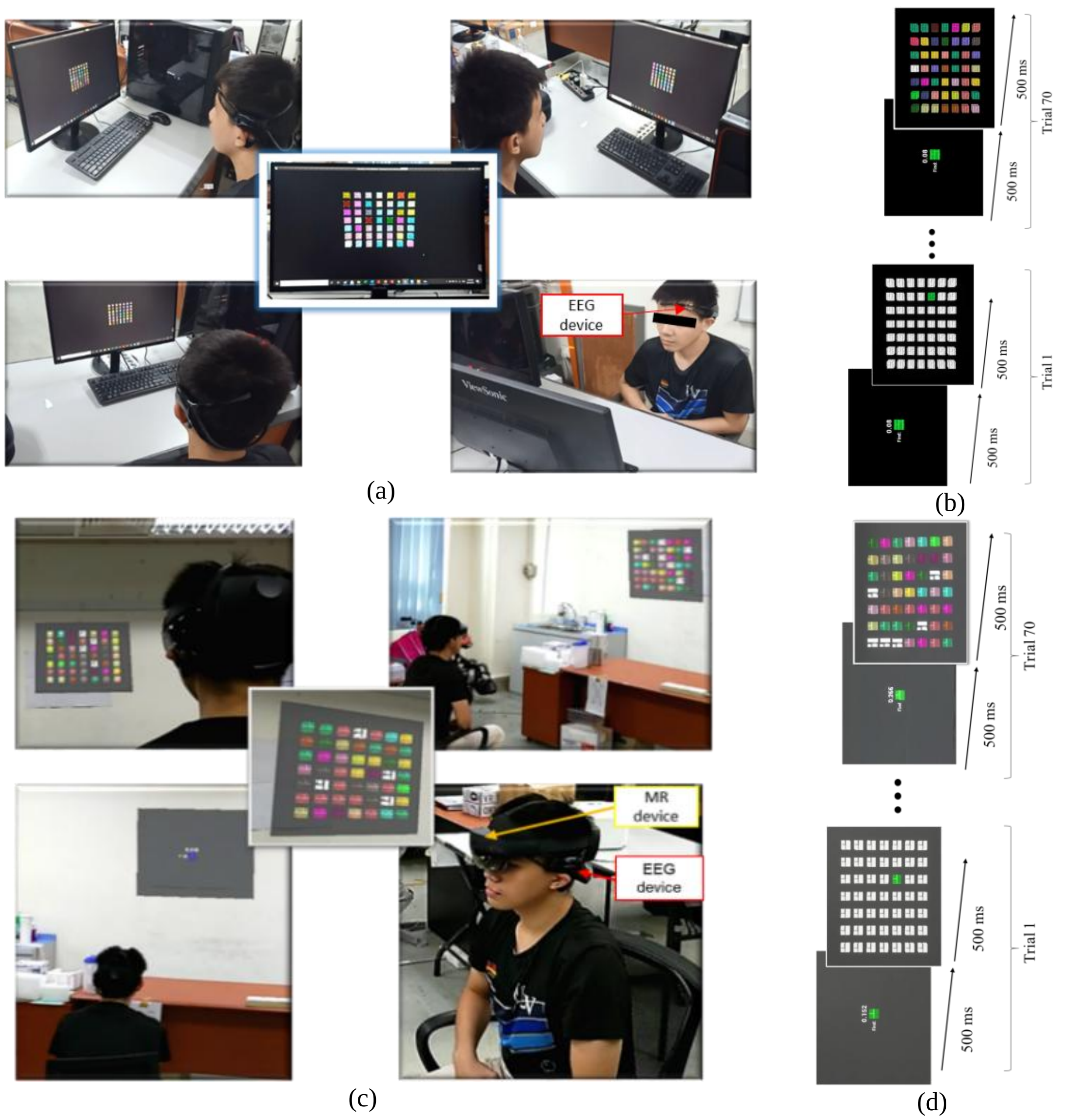
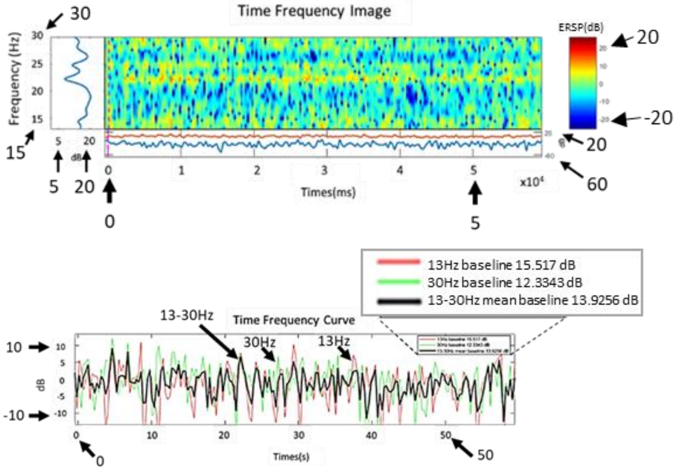


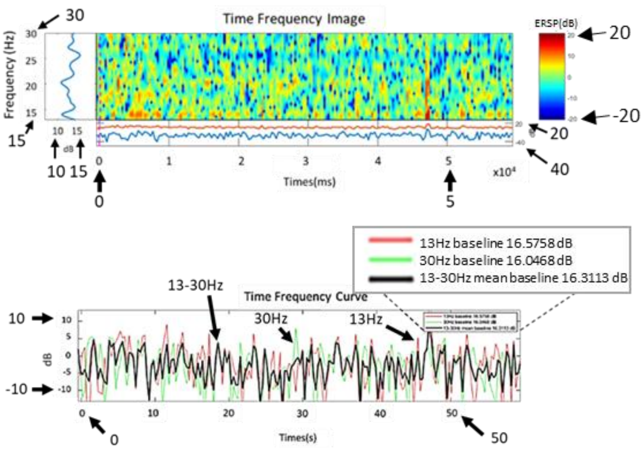
Fig.9. Desktop-Based Visual Colour (DVC) Test and MR-Based Visual Colour (MRVC) Test: (a) & (c) Application and (b) & (d) Trial Sequences

D. Event Related Spectral Perturbation (ERSP)

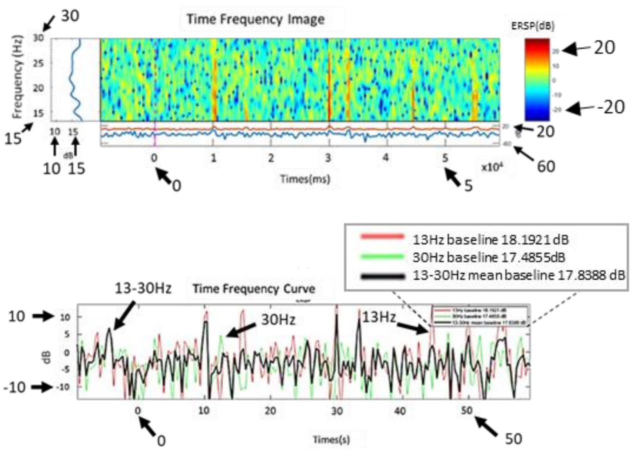
The Event-Related Spectral Perturbation (ERSP) method was employed to identify mean event-related changes in the β power spectrum across a period of time ranging from 0 to 60 seconds. The EEGLab was applied to perform the calculation. The results were then presented in the form of time-frequency images and curves, as shown in Figure 12 and Figure 13.



(a) AF3

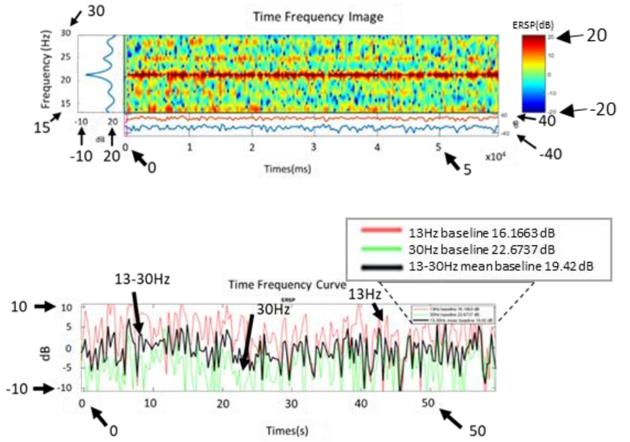


(b) AF4

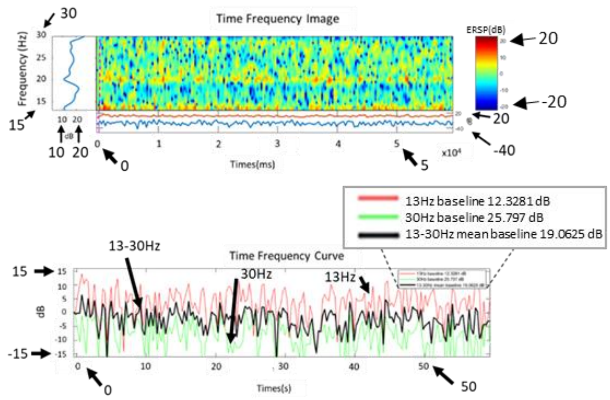


(c) Pz

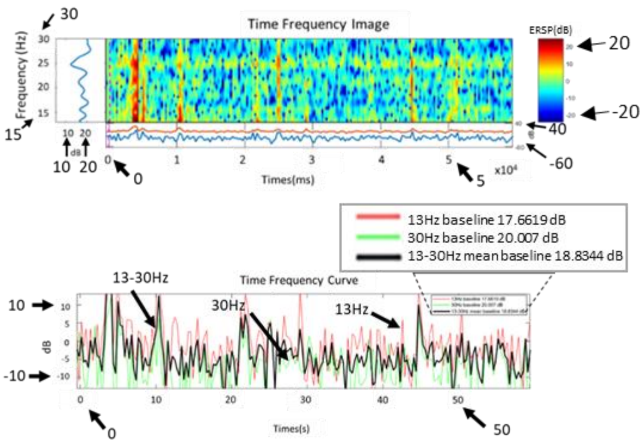
Fig.12. Time-Frequency Images and Curves of Desktop-Based Test at AF3, AF4, and Pz Channels



(a) AF3



(b) AF4



(c) Pz

Fig.13. Time-Frequency Images and Curves of Mixed Reality (MR) Test at AF3, AF4, And Pz Channels

These figures show a variation of ERSP values over time within the 13 Hz to 30 Hz frequency range. The red color is corresponding to the highest activity and the blue color corresponding to lowest activity presented. If the ERSP values remain relatively stable within this specific frequency band, it suggests that the ongoing test has a minimal impact on participants' cognitive processes. Conversely, any observed variation in ERSP values indicates a significant influence of the test on participants' cognitive processes.

According to the time-frequency images, distinct variations in ERSP values between 20 Hz to 25 Hz were observed at the AF3 location during both the DVC and

MRVC tests. In the DVC test, ERSP values ranged from 5 dB to 20 dB, while the MRVC test exhibited a wider range, varying between -10 dB to 20 dB. Notably, the time-frequency image revealed a significant observation: the MRVC test displayed a more prominent red region compared to the DVC test. This suggests that participants were more focused on the task in the MR-based environment. However, for the remaining frequencies analysed in both tests, the ERSP values consistently fell within the range of 18 dB to 20 dB.

There was less variation in ERSP values at the AF4 location across 13 Hz to 30 Hz frequency range for both tests, indicating that similar cognitive processes were conducted. Still, the MRVC test having wider range compared to DVC test. At the Pz location, the ERSP values of the DVC test remained relatively stable from 13 Hz to 30 Hz, hovering around 15 dB. In contrast, the MRVC test showed changes in ERSP values at 25 Hz, ranging between 10 dB and 20 dB. This may indicate that participant's brain activities were engaged differently on both tests.

As for the time-frequency curves at AF3, AF4, and Pz locations, it was observed that there have significant differences in ERSP values between both tests. For instance, the mean baseline ERSP values of the MRVC test were found to be 5.49 dB, 2.75 dB, and 0.99 dB higher than those of the DVC test at AF3, AF4, and Pz locations, respectively. This suggest that the participants more engaged during the MRVC test.

Based on the above findings, it suggested that the MRVC test significantly influenced participants' cognitive processes, as evidenced by the substantial changes in ERSP values compared to the DVC test. This also implies a higher level of immersion in the MR-based environment.

E. Engagement Index (EI) and Concentration Index (CI)

The power ration technique was applied to assess the engagement and concentration levels in both test by calculating the ratio of power within the alpha-to-beta and theta-to-beta frequency bands. In the experiment, each of the participant's EEG power values were aggregated, and the average power ratios were calculated, as shown in the bar chart in Figure 14 and Figure 15.

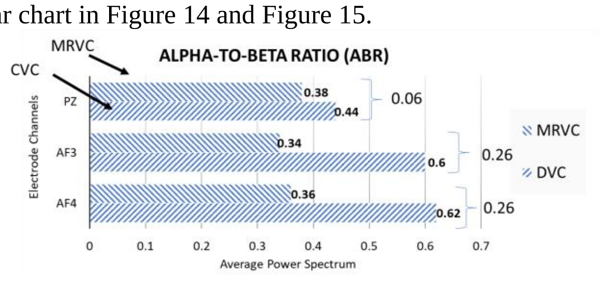


Fig.14. Alpha-to-Beta Ratio (ABR)

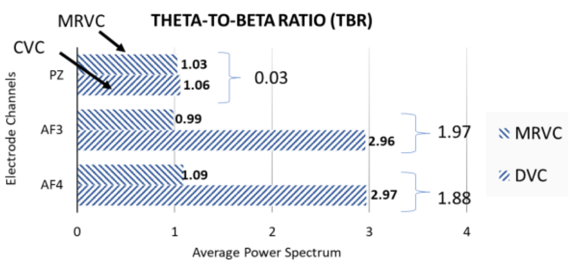


Fig.15. Theta-to-Beta Ratio (TBR)

The chart shows that the overall ABR values in MRVC test were 0.06 and 0.26 lower than those in the DVC test. This suggests a higher percentage of beta activity and a lower percentage of alpha activity in the MRVC test. Similarly, the overall TBR values in the MRVC test were 0.03, 1.88, and 1.97 lower than those in the DVC test, indicating a higher percentage of beta activity and a lower percentage of theta activity in the MRVC test.

Later, these ratio values will be used as the inputs to calculate the Engagement Index (EI) and Concentration Index (CI), as presented in Table 2. The results revealed that the EI in the MRVC test were higher than DVC test, with difference value from 0.36 to 1.32. Similarly, the CI in the MRVC test were higher than that DVC test, with difference from 0.03 to 0.67. These findings suggest that participants exhibited higher levels of engagement and concentration in the MRVC test compared to the DVC test.

TABLE 2.
Engagement and Concentration Indexes for Visual Colour Test

	Engagement Index (EI)			Concentration Index (CI)		
Electrode Channels	DVC	MRVC	**Differences**	DVC	MRVC	**Differences**
AF4	1.62	2.77	**1.15**	0.34	0.92	**0.58**
AF3	1.66	2.98	**1.32**	0.34	1.01	**0.67**
Pz	2.26	2.62	**0.36**	0.94	0.97	**0.03**

Based on the overall result, it suggests that MRVC test can provide participants with a significantly higher level of engagement, concentration, and immersion as compared to the DVC test. This was proved with the experimental result from activity power spectrum, ERSP values, and the EI and CI values. This outcome presents that MR-based environment can enhance the participant's cognitive test experience.

VI. CONCLUSION

This study performs an analytical comparison of desktop-based and MR-based cognitive testing. The analysis was done by utilizing the consumer-based EEG device to record participant's brain activities while performing the DVC and MRVC tests. The recorded EEG data from each test were analyzed using the CSD method and three parts of the result were obtained. Firstly is the activity power spectrum. The participants showed higher engagement during the MRVC test than during the DVC test. The increased engagement is because of a high beta activity power spectrum were observed. Secondly is the ERSP value. It seems that highest values were obtained in the MRVC, indicating a greater sense of immersion. Thirdly, there are the EI and CI scores. It seems highest scores were recorded during MRVC test, indicating that participants were more engaged and concentrated in the MR environment.

Overall, participants can demonstrate a stronger sense of engagement, concentration, and immersion in MR environment as compared to desktop-based environment. This highlights the potential of MR as an immersive technology for measuring cognitive function in various domains. Further work could be conducted by collecting diverse sample size to validate the observed differences in engagement, concentration, and immersion between desktop-based and MR environments. Additionally, a variety of cognitive tests can be designed for both environments to further explore and gain deeper insight into how it can affect the cognitive state.

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