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Effect of audiovisual stimulation on adult memory performance based electroencephalography wavelet analysis

Syarifah Noor Syakiylla Sayed Daud, Rubita Sudirman *

School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

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ABSTRACT

Human memory stores various information and events that can be retrieved when needed. Many factors can influence memory performance which either provide positive or negative feedback. This research investigates the effect of audiovisual stimulation on adult memory based on electroencephalography (EEG) analysis. Sixty college students are participating in this experimental study. They must memorize visual assessment at two different levels in Mozart's Sonata music and white noise stimulation. During memorizing duration, the EEG machine records brain electrical activity based on 10–20 electrode placement. The collected raw brain signals are processed using the wavelet-based method. The stationary wavelet transform (SWT) is used for artifact elimination, whereas discrete wavelet transform (DWT) is applied to obtain alpha, beta, theta, and gamma rhythms. The time–frequency domain features are collected from the EEG signals to discover the influence of audiovisual stimulation. The findings showed a different increasing and decreasing trend of mean, standard deviation, and peak-to-peak EEG signal amplitude before and after audiovisual stimulation exposure. The theta and alpha rhythms showed the most influence with the highest relative power. Suppression of relative gamma and beta power is vital for improving visual information processing and attention level. Memorizing in audio stimulation has suppressed the relative alpha, beta, theta, and gamma power, leading to better visual memorizing ability. The white noise stimulation provides more influence on adult visual memory.

1. Introduction

Numerous studies on memory have identified the primary factors that influence its performance [1–6]. However, the neurobiology of memory has not been fully elucidated and discovered, necessitating additional research. Atkinson and Shiffrin classify memory according to its storage capacity and duration [7]. Each memory is uniquely capable of storing, retaining, and recalling the information it receives. The human memory system is comprised of three primary storage areas: sensory memory, short-term memory, and long-term memory. Sensory memory, alternatively referred to as the sensory register. It is a temporary storage location for information received via the human senses [8–10]. The success of encoded information is retained in short-term memory; however, if interference occurs, the information may be permanently lost from consciousness. Sensory memory is a prelude to short-term memory, allowing the individual to process and recall the sensations. The sensory memory is critical for scientific understanding of consciousness, individual differences, and memory control. Short-term memory, also called active or primary memory, is a type of memory in which a small amount of information is stored in the mind for a brief period of approximately 20 to 30 s (<1 s) [8–10]. If the information is not subjected to rehearsal or active maintenance, it can be retained in a matter of seconds and decays over time.

Previously, psychologist George Miller suggested that people retain between five and nine items in short memory [11]. However, recent research indicates that humans can hold approximately four chunks of information in short-term memory [7]. As a result, additional research should be conducted to determine the precise storage capacity of short-term memory. Long-term memory is the storage of information for an extended period of time. This type of memory is relatively stable and can last for an extended period of time, frequently years. According to the Atkinson-Shiffrin or multi-modal model, all short-term memories are automatically retained in long-term memory after a period of time [12–14]. However, interference, time, and environmental conditions can all have an effect on the encoded information in memory. The simplest analogy for memory operation is that of a computer. Human senses first pick up on the information and store it in sensory memory. The information is then encoded into short-term memory, and some of it is transferred to long-term memory. The flow of information acquired by

* Corresponding author.
E-mail address: rubita@utm.my (R. Sudirman).

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Nomenclature

A	approximation
AgCl	silver chloride
ASCII	American Standard Code for Information Interchange
αp	absolute power of alpha rhythm
βp	absolute power of beta rhythm
D	detail
dB	decibel
db	daubechies
Hz	hertz
n	total number of observations
μ_m	mean of the dataset
n r	total number of observations
μ_{sd}	mean of the dataset
PD	absolute rhythms power
Max	maximum or the highest value in the dataset
Min	minimum or the lowest value in the dataset
ms	milliseconds
μ_{pp}	mean of the dataset
x	observe value
$\overline{X}$	mean value
x_{sd}	dataset value
γp	absolute power of gamma rhythm
σ_m	standard deviation of the dataset
θp	absolute power of theta rhythm
DWT	discrete wavelet transform
EEG	electroencephalography
SWT	stationary wavelet transform
MSE	mean square error

the human senses until it is stored in specific memory is depicted in Fig. 1.

To scientifically deduce the factors and influences affecting memory, a quantitative approach using brain imaging tools is preferred. Electroencephalography (EEG) is a non-invasive brain imaging technique that is widely used in research and clinical settings to study and diagnose brain diseases and functions. The EEG is non-harmful and painless for the patient, has a short acquisition time, excellent temporal resolution, and is inexpensive, but has a high noise level and poor spatial resolution [15–20]. Thus, a method for removing artifacts and enhancing the quality of EEG signals is required. The EEG signal can be processed in a variety of ways. A wavelet-based method is an extremely effective technique for processing non-stationary signals such as EEG.

Wavelet method is a time–frequency analysis technique that is based on the Wigner-Ville distribution and linear transformation, which decomposes the input signal into low-frequency and high-frequency domains [21–25]. Therefore, it is advantageous to separate the required brain rhythms from the input signal. Brain rhythms must be extracted from recorded EEG signals in order to ascertains individuals' responses to provided stimulation. Additionally, to investigate the brain's behaviour and activities. Alpha rhythm (8–13 Hz), beta rhythm (13–30 Hz), delta rhythm (0.5–4 Hz), theta rhythm (4–8 Hz), and gamma rhythm (0.5–2 Hz) are the five major types of brain rhythms [26–28]. Typically, the delta rhythm is omitted from analysis because it is constantly confused with a low-frequency artifact that results in eye blinking and movement. The delta rhythm is, however, still used in research involving sleep patterns and eye movement activities [29–31]. The following Table 1 details the brain rhythms.

The audiovisual stimulation is selected as a factor to explore the brain activities based on EEG analysis. In this research, the Mozart's Sonata music and pure white noise have been chosen as audio stimulation. Several research on the influence of Mozart's music on cognitive performance have revealed improvements in spatial reasoning abilities

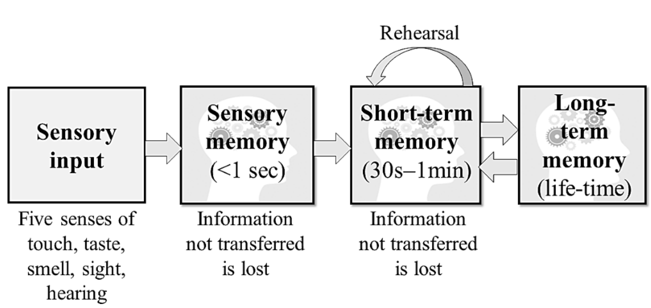

Fig. 1. The flow of information in the human memory.

[34], spatial–temporal performance [35], oddball visual task [36], visuospatial rotation task [37], trigonometry task [38], and science test [39]. For instance, Jausovec et al., [37] examined the effect of Mozart's Sonata music and Brahms Hungarian music on adult visuospatial performance. The researchers discovered that listening to Mozart's Sonata music enhanced gamma, theta, and alpha activity. The activation of these rhythms was found to increase visuospatial skills. The subject performed better under Mozart's music circumstances than under Brahms's Hungarian and quite conditions. Additionally, Taylor and Rowe [38] discovered that listening to Mozart's music improved subjects' performance on a mathematics test when compared to quite circumstance. Similar findings are reported by Perlovsky et al. [39] who found that adolescents were more adept at answering science questions when listening to Mozart's music than Koto Music. There is, however, evidence that Mozart's music impairs cognitive performance [40,41]. They assert that there were no significant variations in student groups' scores on Raven's Progressive Matrices – Advanced Form and paper folding and cutting tests prior to and following exposure to Mozart's music. Motivated by this distinction in Mozart's music's effect on cognitive function, this latest experiment examined the influence on visual memory, determining if it has a beneficial or detrimental effect.

White noise is another type of audio that has been shown to boost cognitive performance in specific studies, where it was found to improve visuospatial working memory [42,43] and verbal memory tests [44,45]. Soderlund et al., [42] examined the effect of white noise on children with normal and attention deficit hyperactivity disorder (ADHD) doing a visuospatial working memory test. When ADHD children were exposed to white noise versus silence, a beneficial effect on visuospatial performance was observed. However, the normal children that exposed to white noise, they demonstrated less effect on task performance than the ADHD groups. Additionally, Helps et al., [44] established the effect of white noise on three distinct child groups: the sub-attentive, the normal, and the super-attentive. The findings indicated that when exposed to white noise, sub-attentive children performed better on delayed recognition and verbal episodic recall tests than when exposed to silence. However, white noise has little effect on the performance of typical children. The majority of past research has examined the effect of Mozart's music and white noise on visuospatial skills. Thus, this study employs visual memory assessments of varying degrees of difficulty as a form of visual stimulation or cognitive testing. Apart from visuospatial memory, having an excellent visual memory is equally critical, as the majority of daily activities require this sort of memory. Visual memory is described as a person's capacity to recall or recollect information or events captured in the past. Additionally, these stimuli were chosen because few studies have examined the effectiveness of Mozart's Sonata music against white noise stimulation on cognitive assessments based on

Table 1
Classification of EEG brainwaves with their properties [32,33].

Brain rhythms	Amplitude (μV)	Frequency (Hz)	Brain states
Delta 	100 – 200	0.5 – 4	Deep sleep or awake state
Theta 	5 – 10	4 –8	Drowsiness, the initial stage of sleep, access to unconscious material, creative inspiration, and deep meditation
Alpha 	20 – 80	8 – 13	Relaxed awareness without attention and concentration
Beta 	1 – 5	13 – 30	Active thinking, a high level of arousal, alertness, and attention
Gamma 	0.5 – 2	> 30	Mental activity at a higher level, including awareness and consciousness, is associated with movement and sensory processing.

visual memory.

The majority of studies chose to conduct their research using one of these. The remaining challenge is which of them is the most useful for visual memory improvement? Do Mozart's Sonata music and white noise have identical effects on visual memory performance, or does one have a more positive effect? To the best of author's knowledge, the only study that compared the effectiveness of both of these audios is Bottiroli et al., [46]. The purpose of this study was to determine the effect of Mozart's music, white noise, Mahler's music, and no-audio on older people' declarative memory and processing speed. It had been discovered that when Mozart's music was played, the processing speed task performed better than under other situations. Additionally, music circumstances resulted in a considerable performance advantage over no-audio and white noise conditions which had a similar effect on declarative memory tests. According to Bottiroli et al., [46], Mozart's music performed better than white noise and other conditions for older individuals' declarative memory based on score performance. However, in Bottiroli et al., [46] the influence of audios on subjects was established only on task score performance, without regard for brain activity. Therefore, in this current research, brain analysis and task score performance are used as the researched factors in order to determine their relationship to auditory stimulation. The primary explanation is that the activation and inhibition of specific brain activity may have an effect on adults' visual memory abilities. This comparison study enables the determination of the trend and pattern of brain activity in response to the stimulations with the greatest and least influence.

2. Materials and methods

This section details the data acquisition equipment and procedure used in this study, as well as the presented stimulation, denoising process, and feature extraction methods. As seen in Fig. 2, there are four major stages of data processing involved in achieving research objectives.

2.1. Experimental setup and data acquisition

This study enrolled a total of 60 healthy volunteers (40 females and 20 males, mean age: 23 years). All participants signed informed permission forms prior to the experiment's procedures beginning. The Malaysian National Medical Research Register (21–02365-GVD) authorised all techniques used in this study. Each participant attended one data collecting session lasting approximately 50 min and was seated comfortably 90 cm away from the screen displaying the visual presentation and external speaker exposing them to the audio. The participant is urged to maintain a relaxed demeanour with little movement in order to avoid unnecessary changes in the wave patterns caused by bodily activity.

The EEG equipment (Nihon Kohden, Neurofax 9200) was utilised to acquire EEG data using a 10–20 electrode placement scheme. The participant's scalp is covered with the EEG cap. Electrodes were placed at Fp1 [47,48], Fz [49], Pz [50,51], T3 [52], and T4 [52]. These five electrodes were chosen because they are associated with human memory and the auditory region of the brain [53]. The reference electrode was placed over the left mastoid, and the ground electrode was attached over the right mastoid. The Ag-AgCl gel binds the electrode to the

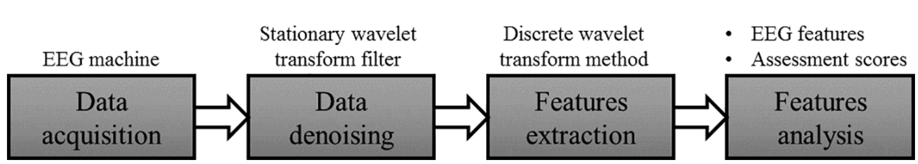

Fig. 2. Stage of data processing in this research.

patient's skin and distributes electrical stimulation efficiently to the target area. The EEG cap connector is then connected to the EEG machine's electrode board adapter. The EEG system is controlled by setting the data acquisition sensitivity to 10 μV, the time constant to 0.3 s, the high pass filter to 70 Hz, the EEG pattern and reference to an average level, and the signal sampled to 500 Hz. The captured EEG signal was imported into ASCII format to assist data processing. Fig. 3 depicts the experimental procedure used in this study.

The participants were randomly assigned into two groups named Group A and Group B. Each group consisted of 30 participants were 20 females and 10 males. They must listen to the audio while observing the visual presentation. The order of audio stimulation was reversed to rebalance the participant's response to audio. In comparison to the audio stimulation setting, the quiet environment is used as a control condition. The participants were given 2 min to perform and 30 s to rest between the 1st and 2nd levels of assessment. They are asked to rest for 1 min during audio changes. The EEG datasets were collected while participants observed the visual presentation and listened to audio stimulation.

2.2. Audiovisual stimulation

Each participant was instructed to listen to Mozart's Sonata 2 pianos in D Major, K448, and pure white noise, as well as see the visual presentation during EEG data collection. The audios were played at a volume of 40 – 55 dB, as assessed by decibel meter software, to minimize the detrimental influence on participants' hearing perceptions. The visual presentation consists of object images and numbers that the participant must memorize. The visual assessments were presented in black, grey, and white to reduce the effect of color on participant performance. Two levels of visual assessments were chosen: 1st level and 2nd level. The 1st level consists of an image with two-digits, whereas the 2nd level contains a picture with four-digits. The audiovisual stimulation programme was created using CapCut software to standardize the time of the experiment for each participant. Fig. 4 depicts the visual assessment that was used.

2.3. Elimination of artifacts from EEG datasets

Denoising of the raw EEG datasets (time-point: 60 000, sampling interval: 2 ms) from the Fp1, Fz, Pz, T3, and Pz channels was performed using the stationary wavelet transform (SWT) in Matlab version R2021b, which used the db3 mother wavelet and five levels of decomposition. Through the convolution procedure, the imported EEG signal was broken into low-pass and high-pass filters with impulse responses dependent on selected wavelet criteria. Low-pass filters generate approximation coefficient, whereas high-pass filters yield detail coefficients. Since the input EEG signal was 500 Hz, thus the frequency of signal was divided in half for each filter. Therefore, the low-pass and high-pass filters will have a frequency of 250 Hz. However, the EEG signal's final output has an initial frequency sampling of 500 Hz. Similar frequency sampling is achieved for the initial and final EEG signals by upsampling the signal by two as it goes through the sample.

The SWT is a powerful method for EEG processing because its properties are time-invariant and provide improved time resolution for artifacts identification, pattern recognition, change detection, and feature extraction [54,55]. The main reason for utilizing SWT filter to remove artifacts from EEG datasets is that it may retain the signal's original frequency sampling, which contains the actual information. Additionally, the SWT can preserve the signal's time-invariance properties, which are critical for localizing and identifying the changes or transient properties in the EEG signal [56–58]. Furthermore, the db3 mother wavelet has spiky characteristics, making it well-suited for removing muscle movements and eye movements/blinks artifacts [59–61]. The flow chart in Fig. 5 illustrates the filtering procedure for removing artifacts from an EEG signal using the SWT approach.

Selection of the mother wavelet and decomposition level is critical because to their effect on denoising performance. The wrong choice of mother wavelet and decomposition level resulted in the failure to remove artifacts and loss of desirable features. According to Sarkela et al., 2007 [62], any Daubechies (db) type higher than three is undesirable for EEG denoising due to its sinusoidal shape and more stretch in time-axis. The best decomposition level 5 was determined based on the lowest mean square error (MSE) value. The decomposition level of the SWT filter was chosen from levels 2 to 8. Level 1 decomposition was omitted because to its inadequacy for EEG denoising. Table 2 shows the result of MSE for denoising of selected EEG channels.

According to Table 2, the MSE value decreased as the level of decomposition increased. However, when decomposition level 6 was used, the MSE value increased almost half and continued to rise until

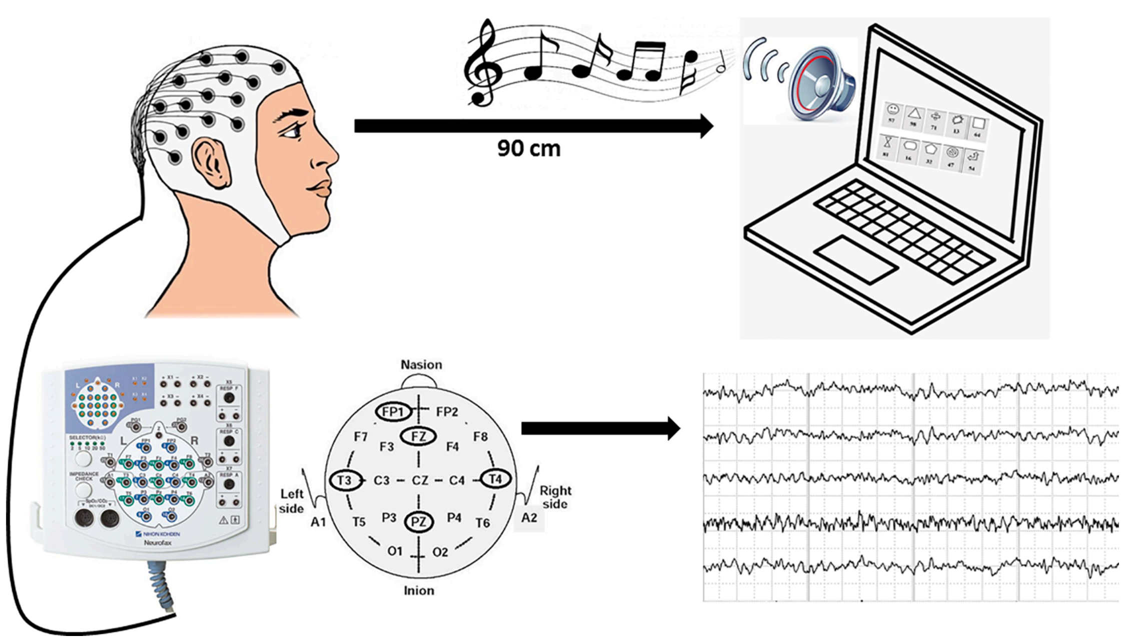

Fig. 3. Illustration of the data acquisition process.

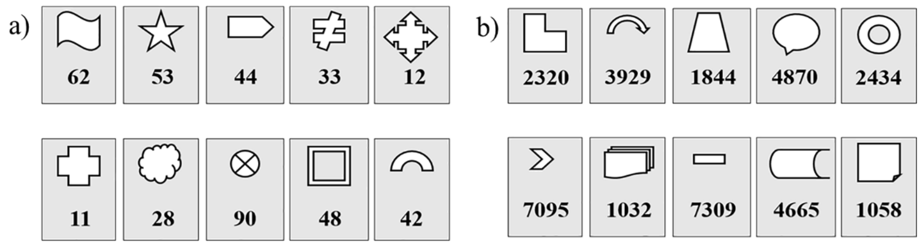

Fig. 4. Visual assessment at various levels: a) First level and b) Second level.

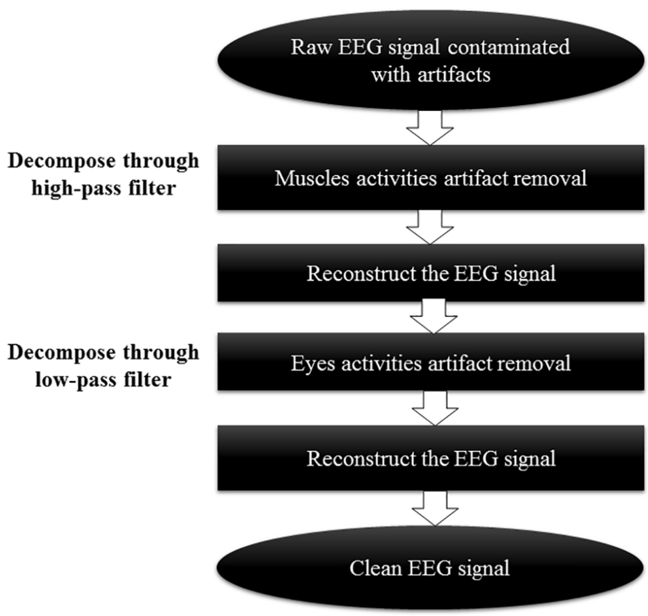

Fig. 5. Artifacts elimination process from EEG signal using a stationary wavelet transform filter.

level 8. A small MSE score indicates that a significant amount of noise has been eliminated from the raw signal through filtering. The lowest MSE of 2.189 was found from decomposition level 5. Therefore, the SWT filter with a db3 mother wavelet and a decomposition level of 5 was utilized in this study to filter out artifacts in the EEG signal.

2.4. Decomposition of brain rhythms

After filtration process, the brain rhythms are decomposed from EEG signal using the DWT method. The DWT decomposition process was chosen as the rhythmic extractor since it is more computationally efficient than other transformations because of its superior localization properties, which resulted in a higher extraction accuracy. Several earlier research have proven the efficiency of DWT for feature extraction, including Jothimani et al., [17], Choudhry et al., [63], Balamareeswaran et al., [64] and Li et al., [65]. Five distinct brain rhythms are obtained: alpha, beta, theta, and gamma. The mother wavelet's Daubechies order 4 (db4) and seven levels of decomposition of DWT was chosen. This mother wavelet was selected because it is well-suited for detecting changes in EEG signals and provides a better accuracy than other wavelets.

The DWT method has a similar execution process as SWT, but the input signal of DWT will be downsampled by two each time passes through the low-pass and high-pass filters. Low-pass filtering generates approximation (A) coefficients with low-frequency components. Additionally, the high-pass filter produces the detail (D) coefficients, which contain components with a high-frequency components. Therefore, the DWT is an appropriate method for obtaining brain rhythms with different frequency components. Since, the 500 Hz sampling rate of the EEG input employed in this study, seven decomposition levels are necessary to decompose the desired brain rhythms. Fig. 6 illustrates the DWT tree structures used to decompose an EEG signal with a frequency sample of 500 Hz. It can be seen that decomposition level 4 (D4) has a frequency of 31–63 Hz, which corresponds to the gamma rhythm. Meanwhile, D5 (16–31 Hz), D6 (8–16 Hz), and D7 (4–8 Hz) correspond to the beta, alpha, and theta rhythms, respectively.

2.5. Features extraction and analysis of EEG dataset

This section discusses the features and analysis method used in this research. Two primary parameters are used as benchmark features based on EEG datasets and score evaluation. The *t*-test and sign test analysis are used to determine the significant relationship between the variables under investigation.

2.5.1. EEG dataset features

This research extracts four major features from EEG signals in order to ascertain the influence of audiovisual stimulation on adult memory. The features are the mean of EEG signal amplitude, the standard deviation of the EEG signal amplitude, the peak-to-peak of EEG signal amplitude, and absolute rhythms. Each of the features is normalized to standardize the final results. The specified features are denoted by the following Eqs. (1)–(6):

$$\text{Mean} = \frac{\sum x}{n} \tag{1}$$

Table 2
Mean square error of decomposition level for Fp1, Fz, T3, T4, and Pz using stationary wavelet transform filter of db3 mother wavelet.

Decomposition	Mean square error (MSE)					Average MSE
	Channel Fp1	Channel Fz	Channel T3	Channel T4	Channel Pz	
Level 2	2.551	2.550	2.149	2.412	2.459	2.424
Level 3	2.634	2.562	1.720	2.351	2.412	2.336
Level 4	2.593	2.511	1.981	2.154	2.303	2.308
Level 5	2.500	2.390	1.883	2.022	2.149	2.189
Level 6	2.414	2.310	1.942	1.920	14.500	4.617
Level 7	2.462	2.347	1.894	1.881	14.555	4.628
Level 8	2.490	15.031	1.895	1.857	14.590	7.173

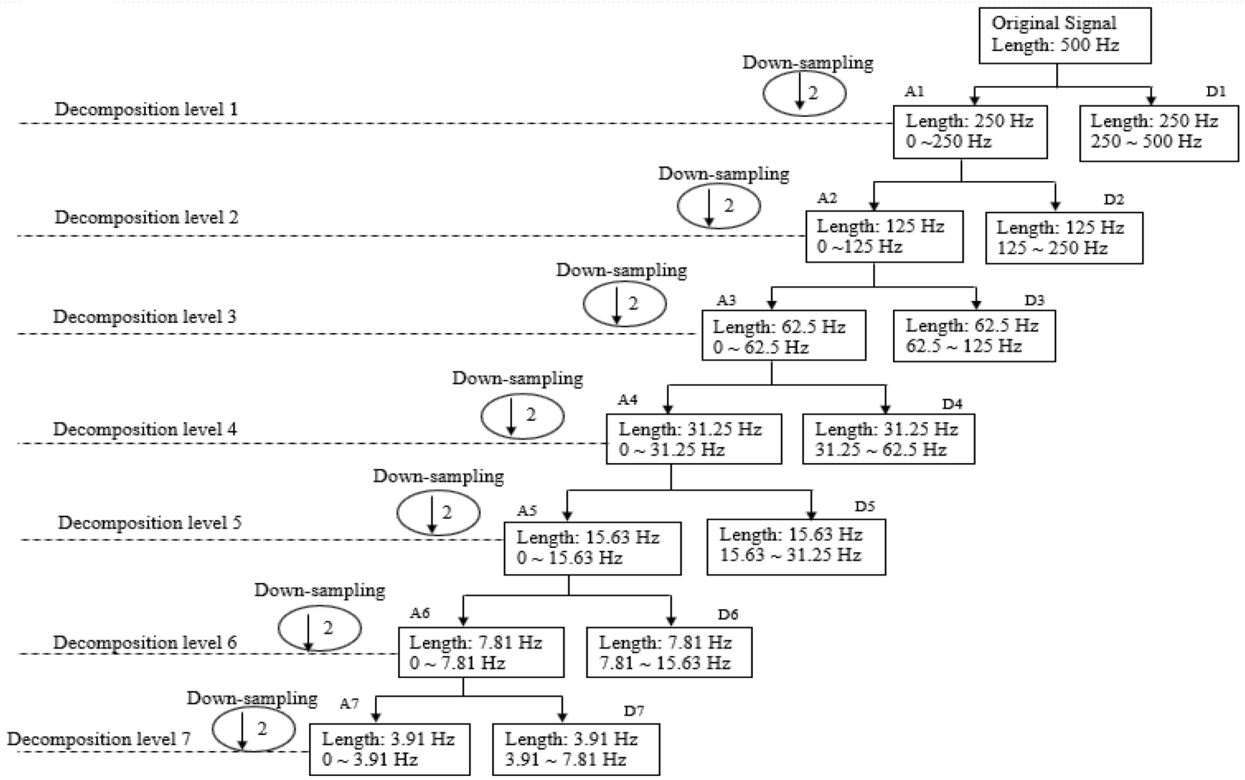

Fig. 6. Decomposition of brain rhythms using the discrete wavelet transform method for an EEG signal with a sampling rate of 500 Hz.

$$\text{Normalize mean} = \frac{x_m - \mu_m}{\sigma_m} \tag{2}$$

where x refers to observe value, n refers to the total number of observations, x_m refers to the dataset value, μ_m refers to the mean of the dataset, and σ_m refers to the standard deviation of the dataset.

$$\text{Standard deviation} = \sqrt{\frac{\sum (Xi - \overline{X})^2}{n}} \tag{3}$$

$$\text{Normalize coefficient of variation} = \frac{x_{sd} - \mu_{sd}}{\sigma_{sd}} \tag{4}$$

where Xi refers to observe value, $\overline{X}$ refers to mean value, n refers to the total number of observations, x_{sd} refers to dataset value, μ_{sd} refers to mean of the dataset, and σ_{pp} refers to standard deviation of dataset.

$$\text{Peak} - \text{to} - \text{peak amplitude} = Max - - Min \tag{5}$$

$$\text{Normalize peak} - \text{to} - \text{peak amplitude} = \frac{x_{pp} - \mu_{pp}}{\sigma_{pp}} \tag{6}$$

where Max refers to the maximum or the highest value in the dataset, Min refers to the minimum or the lowest value in the dataset, x_{pp} refers to dataset value, μ_{pp} refers to mean of the dataset, and σ_{pp} refers to standard deviation of dataset.

The absolute rhythms power is obtained to determine the energy produced by the signal in a given amount of time. The absolute rhythms power can be estimated as represented in (7):

$$PD_i = \sum_{j=1}^{N} \frac{|D_{ij}|^2}{N} \quad i = 4, 5, 6, 7 \tag{7}$$

where, $\sum_{j=1}^{N} |D_{ij}|^2$ represents the energy value to the number of detail coefficient (N) at each decomposition level. Eqs. (8)–(11) represent the normalized rhythms power or relative rhythms power that was obtained from Park et al., (2011) study [66].

$$\text{Normalize alpha power} = \text{Relative alpha power} = \frac{\alpha_P}{\alpha_P + \beta_P + \gamma_P + \theta_P} \tag{8}$$

$$\text{Normalize beta power} = \text{Relative beta power} = \frac{\beta_P}{\alpha_P + \beta_P + \gamma_P + \theta_P} \tag{9}$$

$$\text{Normalize gamma power} = \text{Relative gamma power} = \frac{\gamma_P}{\alpha_P + \beta_P + \gamma_P + \theta_P} \tag{10}$$

$$\text{Normalize theta power} = \text{Relative theta power} = \frac{\theta_P}{\alpha_P + \beta_P + \gamma_P + \theta_P} \tag{11}$$

where α_p refers to the absolute power of alpha rhythm, β_p refers to the absolute power of beta rhythm, γ_p refers to the absolute power of gamma rhythm, and θ_p refers to the absolute power of theta rhythm.

2.5.2. Score evaluation

The second measurement is the score evaluation, which is used to test the subject's memory following audiovisual stimulation. The subject's ability to accurately recall the material is assessed. To begin, subjects must memorize the object and its corresponding number within the allotted time period. Then, as illustrated in Fig. 7, the answer sheet was distributed. Following that, they must finish each object's missing number. It will be considered correct when the object is paired with its corresponding number. The accurate pairing of object-number elements earns the student a point. If subjects could memorise everything, the total valid score was ten. The sign test is utilized to investigate the significance of score differences between conditions. This score evaluation was used to assess respondents' memory performance. The higher visual assessment score indicates that the subjects were capable of memorizing the items. This measurement is critical for determining the relationship between the scores and brain activities. This relationship reveals the pattern of EEG properties associated with excellent and poor visual

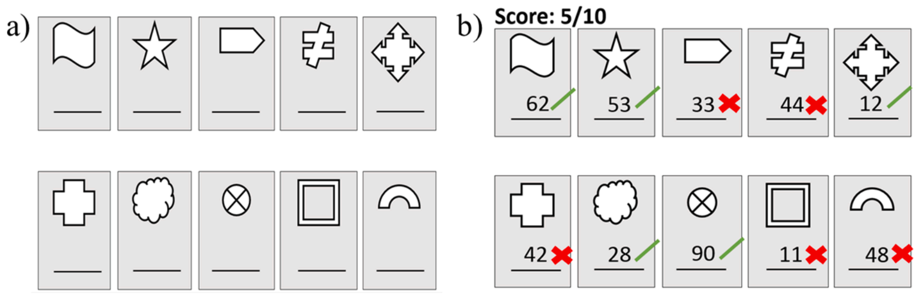

Fig. 7. Example of visual assessment: a) answer sheet and b) score evaluation.

assessment scores.

3. Results

This section summarised the research findings. The effect of audio-visual stimulation on EEG features for selected EEG channels of normalizing mean, normalizing standard deviation, normalizing peak-to-peak amplitude, and relative rhythms power is described comprehensively. Additionally, the score evaluation result was presented to substantiate these conclusions.

3.1. Normalized mean, normalized standard deviation, and normalized peak-to-peak amplitude of EEG voltages

Table 3 shows the normalized mean value of EEG voltage for 1st and 2nd level visual assessment under audio stimulation. In general, voltage is the quantitative measure of the charge potential difference between 2-points in an electrical field [67–69]. The voltage is classified into direct and alternating. EEG voltage represents the ionic current flowing through the brain's neurons and is categorized as alternating voltage. The greater EEG voltage shows a larger flow of ionic current from activated neurons. The control condition's result is utilised to compare to the auditory stimulation condition.

As can be seen, the Fp1 channel had the highest normalized mean for 1st level visual assessment when Mozart's Sonata music and white noise conditions were used. Meanwhile, the greatest normalized mean for the 2nd level of visual assessment was observed in the T4 channel for Mozart's Sonata music and the Fp1 channel for white noise. The lowest normalized mean value for 2nd level of visual assessment was found in the Fz channel for Mozart's Sonata music and the T4 channel for white noise. In comparison to the silence condition, Mozart's Sonata music of 1st level visual assessment exhibited a higher normalized mean in the Fp1, Fz, T4, and Pz channels. In contrast, the T3 and Pz channels showed the highest normalized mean for white noise. For the T4 channel that correlated with emotional memory, the white noise condition resulted in the lowest normalized mean for both visual assessment levels. According to the normalized mean of EEG voltage, particular channels are suppressed and attenuated when the subject is exposed to audiovisual stimulation in comparison to the control condition.

The standard deviation is used to measure the dispersion of a dataset relative to its mean [70]. It indicates the degree to which the data deviates from the mean value. The larger standard deviation indicates that the dataset is more dispersed relative to the mean. Meanwhile, the lowest standard deviation suggests that the dataset has the least fluctuation. According to Table 1, the Fp1 channel had the highest normalized standard deviation across all tested audiovisual stimulations. Therefore, it implies that the Fp1 channel dataset has a greater dispersion relative to the mean. The lowest normalized standard deviation was found in the T4 channel for white noise stimulation for both assessments associated with emotional memory. The lowest standard deviation was seen for Mozart's Sonata music in the Pz channel for the 1st level of visual assessment and in the Fz channel for the 2nd level of visual assessment. This suggests that listening to Mozart's Sonata music resulted in little variation in the Pz and Fz channels relative to the mean of the dataset.

The term "peak-to-peak amplitude" refers to the difference between the maximum and minimum values of the datasets. The normalized peak-to-peak amplitudes for the highest and lowest difference in EEG voltage for various audiovisual stimulations were determined in this study. The outcome of normalizing the peak-to-peak amplitude is shown in Table 4. As can be observed, the highest amplitude difference was discovered in the Fz channel for 1st level visual assessment and the Fp1 channel for 2nd level visual assessment when Mozart's Sonata music was used. Meanwhile, the white noise EEG dataset demostrated the highest amplitude difference in the Fp1 channel for 1st visual assessment and the Pz channel for 2nd visual assessment.

The analysis of EEG voltage features such as normalized mean, normalized standard deviation, and normalized peak-to-peak amplitude shows that the audiovisual stimulation has a dinstinct effects on these features, as previously mentioned. However, these features showed only the highest and the lowest trends of dataset, which is insufficient to assess and explain the influence of audiovisual stimulation on adult memory. As a result, this research yields conclusions based on brain rhythms, which can help explain the effects of stimulation on memory.

Table 3
Normalize mean ± standard deviation of EEG voltage under various audiovisual stimulation.

	1st level visual assessment			2nd level visual assessment		
Channels	Control	Mozart's Sonata music	White noise	Control	Mozart's Sonata music	White noise
Fp1	39.6 ± 38	42.9 ± 23	38.3 ± 38	32.8 ± 44	20.0 ± 25	32.7 ± 38
Fz	30.0 ± 18	37.0 ± 21	28.6 ± 19	35.7 ± 22	18.6 ± 19	28.0 ± 20
T3	36.3 ± 25	35.9 ± 21	37.9 ± 30	29.3 ± 31	19.3 ± 22	28.9 ± 29
T4	32.9 ± 22	36.1 ± 22	10.8 ± 16	23.8 ± 16	26.2 ± 23	13.2 ± 15
Pz	34.7 ± 25	40.1 ± 20	37.8 ± 29	35.7 ± 29	19.2 ± 23	30.8 ± 25

Table 4
Normalize peak-to-peak amplitude of EEG voltage under various audiovisual stimulation.

	1st level visual assessment			2nd level visual assessment		
Channels	Control	Mozart's Sonata music	White noise	Control	Mozart's Sonata music	White noise
Fp1	25.8	32.7	41.0	35.9	25.3	35.3
Fz	31.6	35.6	26.3	28.9	24.3	31.6
T3	22.1	28.9	40.0	28.5	25.0	23.1
T4	26.4	30.3	25.9	29.8	27.3	26.1
Pz	26.7	27.3	38.5	29.4	27.8	39.4

3.2. The relative power of EEG rhythms

Brain rhythms are distinct patterns of aggregated neuronal activity associated with particular actions, sleep states, and arousal levels [26,71]. The overall relative power for each rhythm at various audio-visual stimulus levels is shown in Table 5.

The gamma rhythm is associated with sensory processing, movement, and activities requiring a high level of cognition [71,72]. The Figs. 8 and 9 show the relative gamma power in response to various audiovisual stimulation. As expected, white noise stimulation exhibited the highest relative gamma power at both visual assessment levels. The white noise facilitates the processing of sensory input information better than other situations. In this case, the visual item can be encoded and registered more successfully in the memory when listening to white noise. The high activation of gamma rhythm is vital for activities related to memory since it reflects the human sense's greater ability to keep up with provided information. In comparison to the control condition, both audio stimulations resulted in a significant increase in relative gamma power in nearly all selected channels. However, the Fp1 and T3 channels of Mozart's Sonata music stimulation achieved the lowest relative gamma power for 1st level of visual assessment. For 2nd visual evaluation level, the lowest relative gamma power was found in Fp1 and T4 channels. The Fp1 channel is associated with people's attention state, whereas T3 and T4 are related to verbal memory/remembering what we see and emotional memory. The main reason that led to the attenuation at specific channels in Mozart's Sonata music is caused by disruption of subject attention and emotion, which reduces sensory processing. Based on summation from the selected channel, it can be seen that the relative gamma power of Mozart's Sonata music stimulation for the 1st level was higher than the 2nd level of visual assessment. The reduction of relative gamma power for the 2nd level may disrupt sensory processing to register/encode an increased number of items that must be memorized when listening to Mozart's Sonata music. Meanwhile, the relative gamma power for white noise stimulation increased from the 1st to 2nd level of visual assessment. It can be stated that the sensory processing of the subject was raised when more items needed to be memorized under white noise stimulation.

Beta rhythm is related to active thinking, high wakefulness, alertness, and focus [73,74]. The high relative beta power represents the high alertness and focused level toward provided visual assessment in this study. From the total relative beta power in Table 5, it can be observed that for 1st level visual assessment, the value is approached each other for the three tested conditions. The difference was 3.12% for Mozart's Sonata music and 2.33% for white noise relative to the control condition. Therefore, it can be stated that the alertness and focus level of the subject in audio stimulation is almost similar with no audio. This may happen because the fewer items in 1st level visual assessment need to remember, which does not require a high attention level. Therefore the audio does not have a significant influence on relative beta power. Based on the percentage difference, Mozart's Sonata music had a higher distinction than white noise because the subject needs to give great attention to tasks when listening to Mozart's music. This may be caused by a different audio tone, frequency, and rhythm arrangement. Mozart's Sonata music and white noise showed higher relative beta power in Fp1, Fz, T3, and Pz channels except for the T4 channel compared to control condition for 1st level visual assessment (Figs. 10 and 11). The white noise stimulation showed the highest relative beta power in all selected channels for the 2nd level of visual assessment compared to Mozart's Sonata music and control condition. However, Mozart's Sonata music had different attenuation and suppression trends than the control condition for the 2nd level of visual assessment, where the relative power beta in Fp1, Fz, T3, and Pz channels were attenuated, and T4 was suppressed.

Table 5
Relative power of brain rhythms in response to various audiovisual stimulation.

Brain rhythms	1st level visual assessment: Control	Mozart's Sonata music	White noise	2nd level visual assessment: Control	Mozart's Sonata music	White noise
Gamma	29.13	30.11	31.98	28.06	29.96	32.13
Beta	53.66	55.33	54.91	53.67	53.89	57.32
Alpha	83.59	84.83	84.87	86.20	86.29	83.68
Theta	114.24	114.35	115.38	114.48	115.58	116.72

Alpha rhythm is a neural oscillation of 8–12 Hz frequency. The positive influences of boosting the alpha rhythm include reducing anxiety, lowering stress, decreasing depression, and improving creative thinking [36,73,75]. Figs. 12 and 13 show that performing 1st level of visual assessment under audio stimulation had increased the relative alpha power. Mozart's Sonata music and white noise stimulations achieved the highest value for all selected channels relative to the control condition. The highest total relative alpha power for 1st visual assessment was found in white noise stimulation (Table 5). Therefore, it indicates that the subjects feel enjoy and less stressed when listening to audio stimulation while memorizing 1st level of visual assessment. However, different influences were found for 2nd level of visual evaluation. The white noise stimulation obtained the lowest value based on the total relative alpha power. This may happen because the subject feels disrupted and a bit stressed while performing the 2nd level visual assessment. However, when Mozart's Sonata music was played, the relative alpha power was improved than control and white noise conditions. This showed that the subjects enjoyed and felt less stress in Mozart's Sonata music. The highest relative alpha power was found in the Fp1 channel, followed by the Fz channel for tested audiovisual stimulation. These two channels are associated with attention and the working memory process. These findings parallel the other studies where the alpha rhythm is always activated at the frontal brain region when involved with the attentional assessment [36,73,75]. Based on relative alpha power, it can be concluded that listening to Mozart's Sonata music and white noise stimulation while memorizing fewer visual items able to help subjects more relaxed and calm. However, the selected audio stimulation gave different influences when the number of visual items to remember increased.

Theta rhythms are usually strong during meditation, internal focus, prayer, spiritual awareness, learning, and memory retrieval [36,69,75]. The experts believe that the theta waves are essential for processing information and making memories. Figs. 14 and 15 show the relative theta power for selected channels at different audiovisual stimulation. It can be seen that the Fp1 channel showed the highest relative theta power, which indicates that this rhythm is related to people's internal focus. The maximum relative theta power was found in white noise stimulation for both levels of visual assessment. Therefore, it recommended that the subject's internal focus on visual assessment was higher when listening to white noise than Mozart's Sonata and control condition. The Fz channel associated with working memory function showed that white noise stimulation improved relative theta power relative to control condition in 1st level visual stimulation. However, for 2nd level visual assessment, reduction of relative theta power was found for white noise stimulation compared to the control condition. Listening to white noise in 1st level can improve visual information processing, but the performance was reduced for 2nd level, which may cause by interruption of audio with stimuli which causes a bit relative theta power reduction. The relative theta power for T3, T4, and Pz, the trend of increasing and decreasing, was different for each stimulation. Based on total relative theta power, the highest value was obtained from white noise stimulation for both levels of visual assessment (Table 5). Besides, Mozart's Sonata music also had better relative theta power than the control condition. Therefore, it revealed that the audios gave better internal focus and information processing than the control condition.

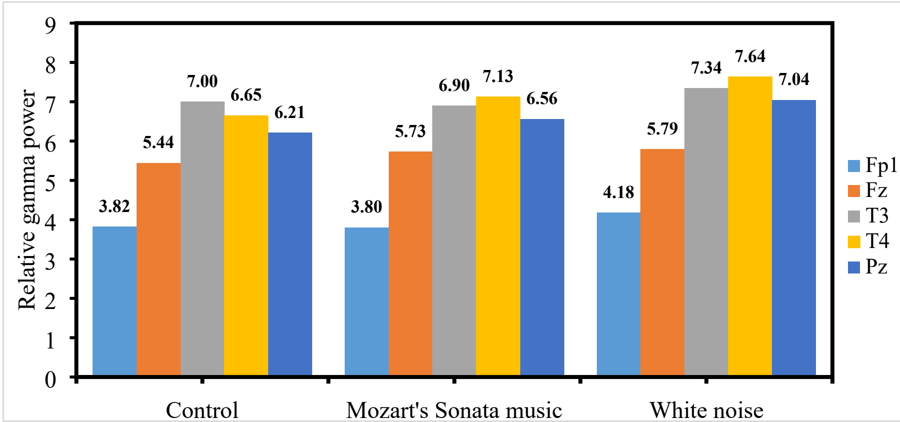

Fig. 8. Relative gamma power for 1st level visual assessment at different audio stimulation.

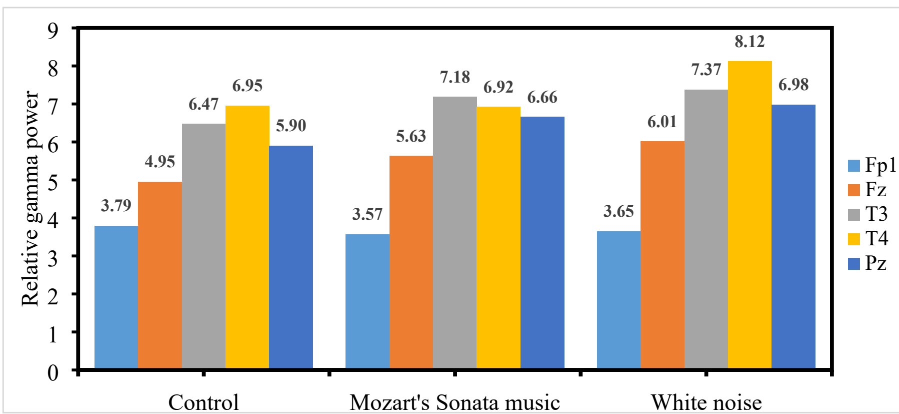

Fig. 9. Relative gamma power for 2nd level visual assessment at different audio stimulation.

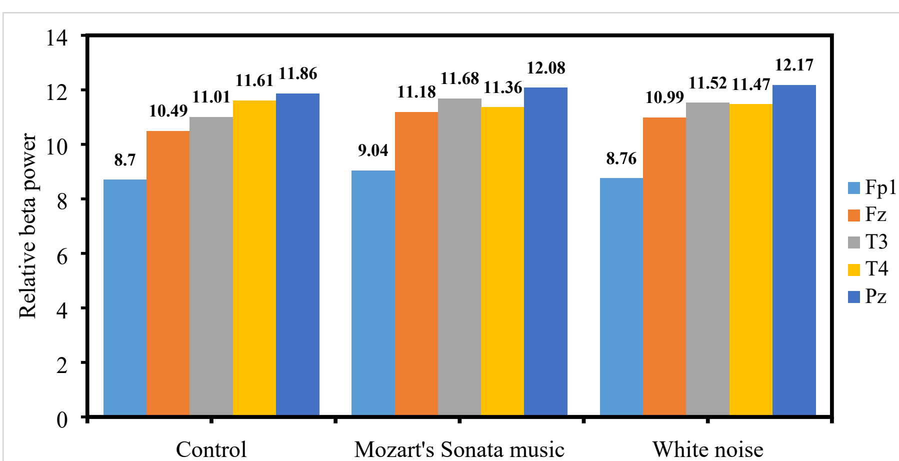

Fig. 10. Relative beta power for 1st level visual assessment at different audio stimulation.

3.3. Score evaluation

To discover the relation between relative rhythm power activation with visual memory performance, the score evaluation result was included (Figs. 16 and 17). The sign test analysis was performed to determine the significant difference in visual assessment performance in tested audiovisual stimulation. A *p*-value lower than 0.05 is considered the audio stimulation significantly influences score performance relative to the control condition. The highest percentage score was found from white noise stimulation for both levels of visual assessment (1st level: 36% and 2nd level: 39%). Meanwhile, Mozart's Sonata music score performance was 34% for the 1st level and 34% for the 2nd level. The scores showed that subjects' performance was better in audio stimulation than the control condition (1st level: 30% and 2nd level: 27%) for both groups of visual assessment. Based on sign test analysis, the scores of white noise stimulation showed a significant difference with a *p*-value of 0.009 for the 1st level and 0.001 for the 2nd level visual assessment relative to the control condition. However, no significant influence was

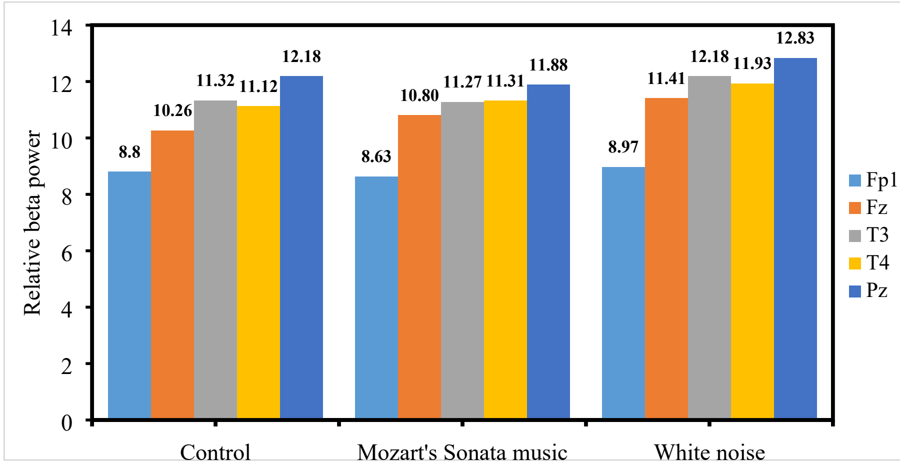

Fig. 11. Relative beta power for 2nd level visual assessment at different audio stimulation.

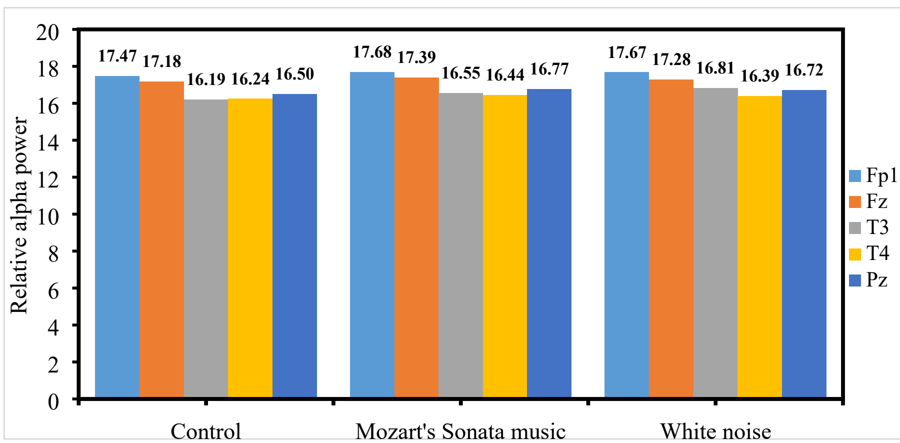

Fig. 12. Relative alpha power for 1st level visual assessment at different audio stimulation.

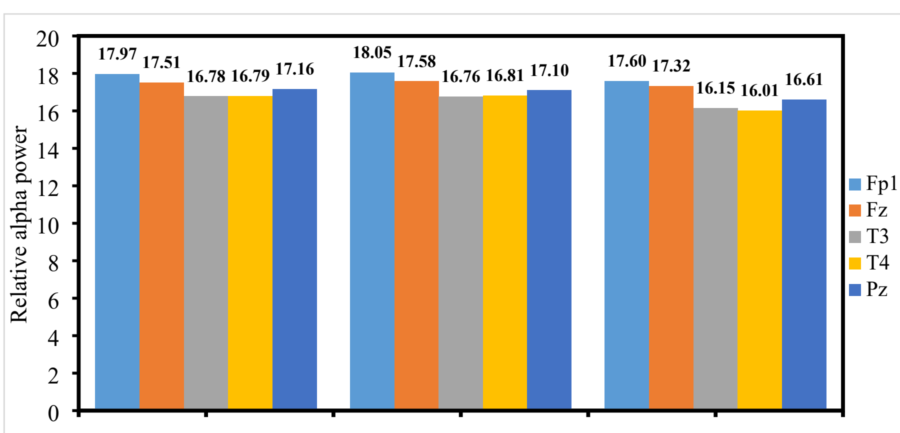

Fig. 13. Relative alpha power for 2nd level visual assessment at different audio stimulation.

obtained for Mozart's music stimulation for both assessments. Therefore, it is recommended that the white noise stimulation significantly influenced subject memory more than Mozart's Sonata music. The 1st level visual assessment achieved better scores than the 2nd level for all audio stimulations in terms of task level. This happens due to the different number of items that need to be remembered. The 2nd level had more items than the 1st level, which reduced the subject's memorizing ability. However, by listening to the audio, the memorizing performance of the subject was improved than the control condition. The difference in score performance of the subject under the different influences of audio stimulation was caused by attenuation and suppression of relative rhythm power. Activation of certain brain rhythms led to the improvement of adult memory. In this case, four major types of rhythms are focused. It found that the white noise stimulation had the highest relative gamma and theta powers, improving subject memory. As discussed earlier, these rhythms are essential for sensory processing

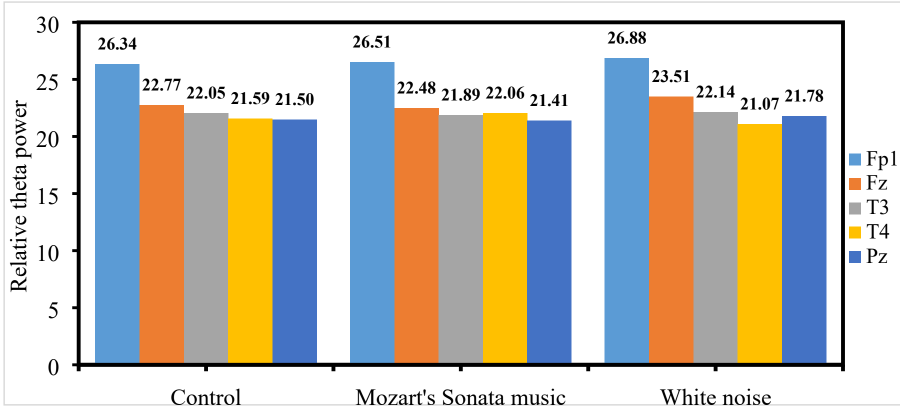

Fig. 14. Relative theta power for 1st level visual assessment at different audio stimulation.

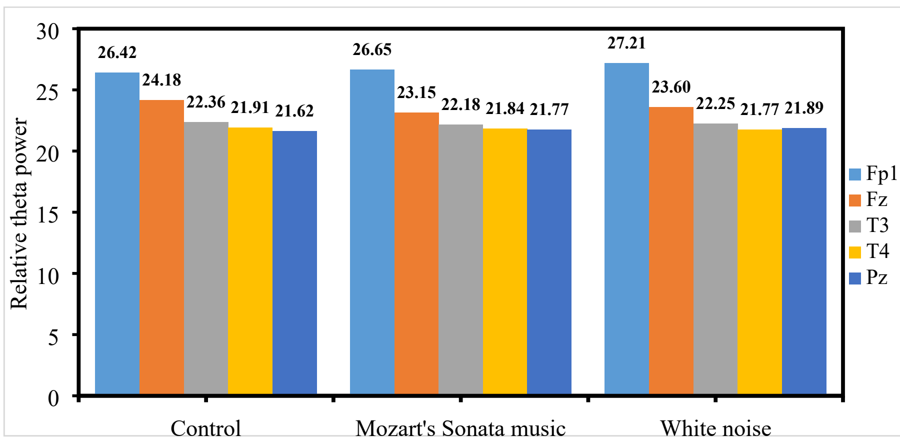

Fig. 15. Relative theta power for 2nd level visual assessment at different audio stimulation.

Audio stimulation	Mean score of visual stimulation	Sign test analysis (*p*-value)
Control (no audio)	7.28/10	-
Mozart's Sonata music	8.07/10	0.203
White noise	8.56/10	0.009*

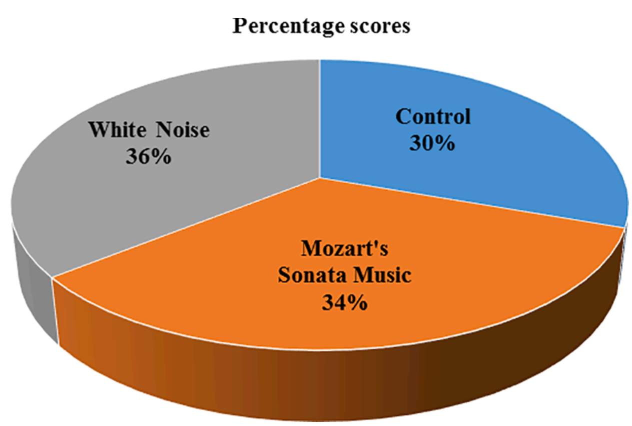

Fig. 16. Score evaluation for 1st level visual stimulation.

and internal focus. Therefore, the main reason the subject performed better in white noise stimulation was caused by improvement of sensory processing and inner focus.

4. Discussion

This research investigates the influence of audiovisual stimulation on adult memory. Two types of audio were used: Mozart's Sonata music and white noise. These audios were chosen by professionals because they have been shown to increase memory and cognitive processes in humans. However, relatively few research have been conducted on their effects on visual memory. Visual memory is one of the vital parts of the brain that stores visual information. Therefore, improving visual memory is crucial for increasing the ability to remember or recall previously viewed information such as words, pictures, and activities that have been viewed in the past [14,76]. In this research, we used two different assessment task levels that consist of a different amount of items. The memory capacities of subjects are determined using EEG features and assessment test scores. The EEG datasets were processed using SWT and DWT methods to extract the required features.

From score evaluation, the subjects performed better in white noise stimulation than Mozart's Sonata music and control condition at both

Audio stimulation	Mean score of visual stimulation	Sign test analysis (*p*-value)
Control (no audio)	2.91/10	-
Mozart's Sonata music	3.63/10	0.061
White noise	4.23/10	0.001*

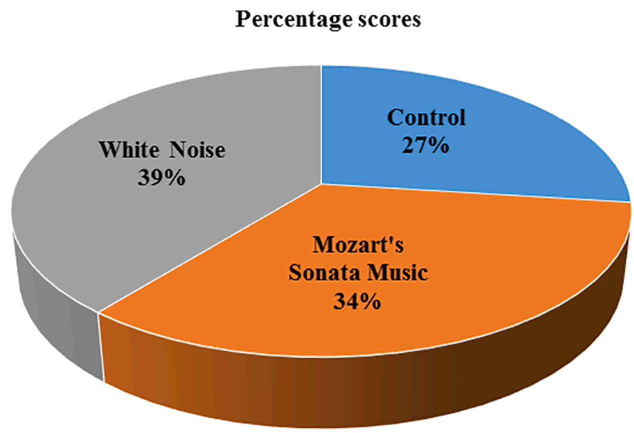

Fig. 17. Score evaluation for 2nd level visual stimulation.

levels of visual assessment. Sign test analysis revealed a substantial relationship between the score result of white noise and control conditions. The 2nd level had more impact than the 1st level, which indicates the white noise assists people in focusing their attention on the job. This could contribute to the increased quantity of items that need to be remembered in the 2nd level of the assessment task. In comparison to control conditions, both audio stimulation positively influenced adult memory as their scores are better. The extraction of EEG features is discussed to scientifically understand the correlation between audio stimulation and visual memory performance.

Based on EEG features, it was discovered that the audiovisual stimulation produced different increasing and decreasing patterns of mean, standard deviation, and peak-to-peak amplitude. To have a better understanding of the effect of stimulation, the relative power of four major types of brain rhythms such as alpha, beta, theta, and gamma is determined. As illustrated in Table 5, the most influential rhythms are theta and alpha, which exhibit the highest relative power. The activation of these rhythms may be due to the subjects' increased internal focus, attention, and awareness in response to stimuli [36,37]. For instance, white noise stimulation used in the 2nd level visual assessment gains a lower relative alpha power than others, indicating that subjects are paying attention to the task. This could be because the sensation disturbs the white noise, necessitating increased concentrate to memorize the items. However, in 1st visual evaluation, white noise has the highest relative alpha, indicating that the subject is in a relaxed and tranquil state when memorising the items, as opposed to Mozart's Sonata music and the control condition.

Most people believe that remembering in the quiet state is the best place to avoid external distraction, but this research proved that the quiet/control condition is not efficient for learning. As we can see, the relative alpha power of the control condition was the lowest among the others, which revealed that the subject feels a little bit distracted or bored. The other possible reason was the difference in relative gamma and beta power. The relative gamma power was higher in white noise than Mozart's Sonata music and control condition, indicating that visual information captures by eyes can be processed more effectively in white noise at both visual assessment levels. Additionally, the relative beta power was greater under audio stimulation than under control. This suggested that subjects were more attentive and concentrated when listening to audio. As a result, it may be concluded that Mozart's Sonata music and white noise altered brain activity that resulted in improved visual memory in subjects. Thus, white noise is the optimal audio stimulus for assessing visual memory.

The fact that Mozart's Sonata music and white noise perform better visually can be explained using the Trion model and stochastic resonance concept. Mozart's Sonata music is classified as classical music because composed of the high organization structure necessary for stimulating the cortical firing patterns associated with in-memory processing [38,77,78]. This kind of classical music consists of three characteristics: eight-bar phrases of harmony, the beats are separated at a fixed tempo, and a single composition of various voices and equipment. Trion model state that the music modified the neuron's synaptic weight in a particular pattern based on Hebbian learning principles [34,79]. These principles describe the involvement of brain regions during the cognitive process, which believes listening to music can strengthen the neuron firing. Thus, the input information transmitted into memory can be processed successfully, decreasing information loss. The involvement of noises is usually associated with stochastic resonance concept or noise improve signaling. Prior, this concept was found in any non-linear dynamic system, but the newest is observed in the nervous system. Soderlund, 2007 [42] stated that stochastic resonance could improve auditory, touch, and visual stimuli processing. This concept explained that the input information caught by human senses is considered a weak signal requiring force to make it more detectable. The addition of white noise led to the interaction with weak stimuli, which increased the signal-to-noise output. The stochastic noise improves human sensory discriminability [80].

This study included three significant strengths. First, it investigates the influence of music and noise source on adult visual memory. The majority of past research has relied solely on audio-based music or noise genres rather than incorporating both. This research can determine the best audio for adult visual memory. Second, this study evaluates the effect of audiovisual stimulation using two parameters which are score performance and EEG analysis, which offers comprehensive information about the influences. This overcomes the constraint of Bottiroli et al., [46], who only considers score performance as the major variable. The activation and suppression of selected EEG features can be known through EEG analysis, and their relation with good and bad score performance is determined. Finally, this research also investigates the influence of audios on the difficulty of visual memory tests. Therefore, the exact impact of audios can be discussed for both difficulties, and the effect can be investigated. This research suggested that listening to white noise can help adults improve their visual memory. It is a relatively low-cost, non-invasive technique that can be incorporated into regular habits that boost memory.

5. Conclusion

This research successfully investigated the effect of audiovisual stimulation on adult memory performance. Brain activity and score analysis revealed that audio stimulation improved visual memory performance when compared to the control/no audio condition. This was explained using the Trion model and the concept of stochastic resonance. Due to the presence of audio, weak signals become more detectable, resulting in improved memory performance. This occured as a result of the subject's increased attention, alertness, and internal focus. This contributes to Mozart's Sonata music and white noise receiving the highest score for visual stimulation. On the other hand, increasing the number of visual items to memorize resulted in a decrease in subject performance. The 2nd level of visual assessment yielded fewer scores. The relative beta rhythm associated with attention level was reduced in the 2nd level of visual evaluation when Mozart's Sonata music and white noise were compared to the 1st level. However, in the 2nd level of visual stimulation, the relative beta rhythm of white noise stimulation was improved. This suggests that when the number of items increases, white noise stimulation can help the subject maintain their attention. Additionally, gamma and alpha activation revealed that white noise is the most appropriate type of noise to listen to while memorizing visual items. This research indicated that white noise can be heard during learning and non-learning activities. The limitations of this recent research are that it focuses exclusively on adult visual memory and extracts fewer types of EEG features. Future research should consider the influence of white noise and Mozart's Sonata music on children's and older people's cognitive and memory functions. This allows for the investigation of the effect of audio stimulation on other cognitive or memory abilities and on different age groups to determine whether it has a similar effect on adults. Another suggestion is to classify EEG features into three domains: time domain, frequency domain, and time–frequency domain. Additional extracted features will result in a more complete representation of the information contained in EEG signals.

CRediT authorship contribution statement

Syarifah Noor Syakiylla Sayed Daud: Conceptualization, Methodology, Investigation, Data curation. **Rubita Sudirman:** Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that there is no conflict of interest in this article.

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References

[1] A. Jaeger, C.A. Galera, L.M. Stein, E.J. Lopes, Human memory research: current hypotheses and new perspectives, Estud. Psicol. 21 (2) (2016) 92–103, https://doi.org/10.5935/1678-4669.20160010.
[2] Z.M. Reagh, C. Ranganath, What does the functional organization of cortico-hippocampal networks tell us about the functional organization of memory? Neurosci. Lett. 680 (2018) 69–76, https://doi.org/10.1016/j.neulet.2018.04.050.
[3] S. Ballesteros, J.M. Reales, E. Garcia, M. Carrasco, Selective attention affects implicit and explicit memory for familiar pictures at different delay conditions, Psicothema 18 (2006) 88–99.
[4] S. Malanowski, Is episodic memory uniquely human? Evaluating the episodic-like memory research program, Synthese 193 (2016) 1433–1455, https://doi.org/10.1007/s11229-015-0966-z.
[5] B. Vervliet, Y. Boddez, Memories of 100 years of human fear conditioning research and expectations for its future, Behav. Res. Ther. 135 (2020) 1–9, https://doi.org/10.1016/j.brat.2020.103732.
[6] C. Martín Gómez, Essentials of human memory, Int. J. Educ. Psychol. 5 (2016) 1–4, https://doi.org/10.17583/ijep.2016.1909.
[7] N. Cowan, P. Brain, R. Author, What are the differences between long-term, short-term, and working memory? NIH Public Access Author Manuscript, Prog. Brain Res. 169 (2008) 323–338.
[8] D.G. Norris, J. Hall, S.E. Gathercole, Can short-term memory be trained? Mem. Cogn. 47 (2019) 1012–1023, https://doi.org/10.3758/s13421-019-00901-z.
[9] G. Van Houdt, C. Mosquera, G. Nápoles, A review on the long short-term memory model, Artif. Intell. Rev. 53 (2020) 5929–5955, https://doi.org/10.1007/s10462-020-09838-1.
[10] G. Jones, L.V. Justice, F. Cabiddu, B.J. Lee, L.S. Iao, N. Harrison, B. Macken, Does short-term memory develop? Cognition. 198 (2020) 1–16, https://doi.org/10.1016/j.cognition.2020.104200.
[11] G.A. Miller, The magical number seven, plus or minus two: some limits on our capacity for processing information, Psychol. Rev. 63 (2) (1956) 81–97, https://doi.org/10.1037/h0043158.
[12] M. Gyllenberg, J. Jiang, L. Niu, Chaotic attractors in Atkinson-Allen model of four competing species, J. Biol. Dyn. (2020) 440–453, https://doi.org/10.1080/17513758.2020.1779828.
[13] Norah Hadi Alsaeed, Wish you were here: a psychological analysis using Atkinson-Shiffrin memory mode, J. Lit. Art Stud. 6 (5) (2017) 521–527, https://doi.org/10.17265/2159-5836/2017.05.004.
[14] J.K. Hartshorne, T. Makovski, The effect of working memory maintenance on long-term memory, Mem. Cogn. 47 (4) (2019) 749–763, https://doi.org/10.3758/s13421-019-00908-6.
[15] S.J. Alsunaidi, N.A. Saqib, K.A. Alissa, A comparison of human brainwaves-based biometric authentication systems, Int. J. Biom. 12 (4) (2020) 411–429, https://doi.org/10.1504/ijbm.2020.110814.
[16] C. Sun, Y. Bao, J. Xu, D. Kong, H. Zhou, Q. Wang, H. Shang, W. Wang, M. Jin, X. Wang, Y. Duan, The effects of different types of music on electroencephalogram, Int. Conf. Bioinfor. Biomed. (2013) 31–37.
[17] S. Jothimani, A. Suganya, Denoising of EEG gesture using DWT, Int. J. Electrical Comp. Eng. 8 (2019) 522–527.
[18] A. Biasiucci, B. Franceschiello, M.M. Murray, Electroencephalography, Curr. Biol. 29 (2019) 80–85, https://doi.org/10.1016/j.cub.2018.11.052.
[19] H. Gu, Q. Chen, X. Xing, J. Zhao, X. Li, Facial emotion recognition in deaf children: evidence from event-related potentials and event-related spectral perturbation analysis, Neurosci. Lett. 703 (2019) 198–204, https://doi.org/10.1016/j.neulet.2019.01.032.
[20] R. Upadhyay, P.K. Padhy, P.K. Kankar, EEG artifact removal and noise suppression by Discrete, Comput. Electr. Eng. 53 (2016) 125–142, https://doi.org/10.1016/j.compeleceng.2016.05.015.
[21] O.A. Rosso, A. Mendes, R. Berretta, J.A. Rostas, M. Hunter, P. Moscato, Distinguishing childhood absence epilepsy patients from controls by the analysis of their background brain electrical activity (II): a combinatorial optimization approach for electrode selection, J. Neurosci. Methods. 181 (2) (2009) 257–267, https://doi.org/10.1016/j.jneumeth.2009.04.028.
[22] Y. Zhang, Y. Wang, Research on feature extraction algorithm commonly used in brain-computer interface technology, J. Phys. Conf. Ser. (2021) 1–9, https://doi.org/10.1088/1742-6596/1861/1/012027.
[23] N.K. Al-qazzaz, S. Hamid, B. Mohd, S.A. Ahmad, Signal Analysis during a working memory task, (2015) 29015-29035. doi:10.3390/s151129015.
[24] Z.A.A. Alyasseri, A.T. Khader, M.A. Al-Betar, A.K. Abasi, S.N. Makhadmeh, Z. Abdi, A. Alyasseri, S. Member, EEG signals denoising using optimal wavelet transform hybridized with efficient metaheuristic methods, IEEE Access 8 (2020) 10584–10605, https://doi.org/10.1109/ACCESS.2019.2962658.
[25] T. Alotaiby, F.E.A. El-Samie, S.A. Alshebeili, I. Ahmad, A review of channel selection algorithms for EEG signal processing, EURASIP J. Adv. Signal Process. 66 (2015) 1–21, https://doi.org/10.1186/s13634-015-0251-9.
[26] K. Suresh Manic, A. Saadha, K. Pirapaharan, C.V. Aravind, Characterisation and separation of brainwave signals, J. Eng Sci. Technol. (2015) 32–44.
[27] B.O. Watson, Sleep, memory & brain rhythms, Daedalus. 144 (1) (2015) 67–82, https://doi.org/10.1162/DAED_a_00318.
[28] R. VanRullen, J. Dubois, The psychophysics of brain rhythms, Front. Psychol. 2 (2011) 1–10, https://doi.org/10.3389/fpsyg.2011.00203.
[29] S.L. Kappel, D. Looney, D.P. Mandic, P. Kidmose, Physiological artifacts in scalp EEG and ear-EEG, Biomed. Eng. Online 16 (103) (2017) 1–16, https://doi.org/10.1186/s12938-017-0391-2.
[30] G. Bernardi, M. Betta, E. Ricciardi, P. Pietrini, G. Tononi, F. Siclari, Regional delta waves in human rapid eye movement sleep, J. Neurosci. 39 (14) (2019) 2686–2697, https://doi.org/10.1523/JNEUROSCI.2298-18.2019.
[31] D. Mantini, M.G. Perrucci, C. Del Gratta, G.L. Romani, M. Corbetta, Electrophysiological signatures of resting state networks in the human brain, Proc. Natl. Acad. Sci. U. S. A. 104 (32) (2007) 13170–13175, https://doi.org/10.1073/pnas.0700668104.
[32] V. Gopejenko, I. Mihailovs, Neurocomputer interface, the classification of the brain waves and virtual reality control, in: 9th Int. Conf. Appl. Inf. Commun. Technol. AICT 2015 - Proc., 2015, pp. 1–4, https://doi.org/10.1109/ICAICT.2015.7338595.
[33] S.N.S. Sayed Daud, R. Sudirman, Artifact removal and brain rhythm decomposition for eeg signal using wavelet approach, J. Teknol. 78 (2016) 7–15, https://doi.org/10.11113/jt.v78.9460.
[34] F.H. Rausher, G.L. Shaw, K. K.N., Music and spatial task performance, Nature. 6447 (1993) 611-620.
[35] B.E. Rideout, S. Dougherty, L. Wernert, Effect of music on spatial performance: a test of generality, Percept. Mot. Skills. 82 (1998) 427–432, https://doi.org/10.2466/pms.1998.86.2.512.

[36] N. Jaušovec, K. Habe, N. Jausovec, K. Habe, The influence of auditory background stimulation (Mozart's Sonata K.448) on visual brain activity, Int. J. Psychophysiol. 51 (2004) 261–271, https://doi.org/10.1016/S0167-8760(03)00227-7.
[37] N. Jausovec, K. Jausovec, I. Gerlic, The influence of Mozart music on brain activity in the process of learning, Clin. Neurophysiol. 117 (2006) 2703–2714.
[38] J.M. Taylor, B.J. Rowe, The Mozart effect and the mathematical connection, J. Coll. Read. Learn. 42 (2012) 51–66.
[39] L. Perlovsky, A. Cabanac, M.C. Bonniot-Cabanac, M. Cabanac, Mozart effect, cognitive dissonance, and the pleasure of music, Behav. Brain Res. 244 (2013) 9–14, https://doi.org/10.1016/j.bbr.2013.01.036.
[40] C.F. Chabris, Prelude or requim for the Mozart effect? Nature. 400 (1999) 826–827.
[41] K.M. Steele, J.D. Brown, J.A. Stoecker, Failure to confirm the Rausher and Shaw description of recovery of the Mozart effect, Percept. Mot. Skills. 88 (1999) 843–848.
[42] G. Soderlund, S. Sikstrom, A. Smart, Listen to the noise: noise is beneficial for cognitive performance in ADHD, J. Child Psychol. Psychiatry. 48 (2007) 840–847.
[43] G.B.W. Flodin, S., Hagberg, E., Persson, E., Sandbacka, L., Sikstrom, S., and Soderlund Lateralization Effects of Auditory White Noise on Verbal and Visuo-Spatial Memory Performance, in: Proc. 2012 Swedish Phonetics Conf., 2012: pp. 1-5.
[44] S.K. Helps, S. Bamford, E.J.S. Sonuga-Barke, G.B.W. Söderlund, Different effects of adding white noise on cognitive performance of sub-, normal and super-attentive school children, PLoS One. 9 (2014) 1–10, https://doi.org/10.1371/journal.pone.0112768.
[45] G.B.W. Söderlund, S. Sikström, J.M. Loftesnes, E.J. Sonuga-Barke, The effects of background white noise on memory performance in inattentive school children, Behav. Brain Funct. 6 (2010) 1–10, https://doi.org/10.1186/1744-9081-6-55.
[46] S. Bottiroli, A. Rosi, R. Russo, T. Vecchi, E. Cavallini, The cognitive effects of listening to background music on older adults, Front. Aging Neurosci. 284 (2014) 1–7.
[47] H. Javaid, M. R, E. Kumarnsit, S. Chatpun, Decision Tree in Working Memory Task Effectively Characterizes EEG Signals in Healthy Aging Adults, IRBM. In Press (2021) 1-10.
[48] M.L. Oldoni, T. Catecati, E.J. Legal, M.G.G. Ferreira, A.R.G. Ramirez, Measuring working memory usage on aphasic individuals and analysis of emotional valence through electroencephalography, Comput. Methods Programs Biomed. 1 (2021) 1–10, https://doi.org/10.1016/j.cmpbup.2021.100006.
[49] T. Tempel, C. Frings, B. Pastötter, EEG beta power increase indicates inhibition in motor memory, Int. J. Psychophysiol. 150 (2020) 92–99, https://doi.org/10.1016/j.ijpsycho.2020.02.008.
[50] M. Näpflin, M. Wildi, J. Sarnthein, Test-retest reliability of EEG spectra during a working memory task, Neuroimage. 43 (2008) 687–693, https://doi.org/10.1016/j.neuroimage.2008.08.028.
[51] J.E. Hajonides, A.C. Nobre, F. van Ede, M.G. Stokes, Decoding visual colour from scalp electroencephalography measurements, Neuroimage. 237 (2021) 1–8, https://doi.org/10.1016/j.neuroimage.2021.118030.
[52] M.J. Mollakazemi, D. Biswal, S. Sunderam, A. Patwardhan, EEG segments synchronized to be temporally farthest from the R-waves in ECG are more informative during listening to music, Biomed. Signal Process, Control. 68 (2021) 1–10, https://doi.org/10.1016/j.bspc.2021.102660.
[53] W.J. Chai, A.I. Abd Hamid, J.M. Abdullah, Working memory from the psychological and neurosciences perspectives: A review, Front. Psychol. 9 (2018) 1–16, https://doi.org/10.3389/fpsyg.2018.00401.
[54] S.H. Wang, P. Phillips, Z.C. Dong, Y.D. Zhang, Intelligent facial emotion recognition based on stationary wavelet entropy and Jaya algorithm, Neurocomputing. 272 (2018) 668–676, https://doi.org/10.1016/j.neucom.2017.08.015.
[55] Y. Zhang, S. Wang, Y. Sui, M. Yang, B. Liu, H. Cheng, J. Sun, W. Jia, P. Phillips, J. M. Gorriz, Multivariate approach for Alzheimer's disease detection using stationary wavelet entropy and predator-prey particle swarm optimization, J. Alzheimer's Dis. 65 (2018) 855–869, https://doi.org/10.3233/JAD-170069.
[56] S.-H. Wang, Y.-D. Zhang, Z. Dong, P. Phillips, Wavelet families and variants, (2018) 85-104. doi:10.1007/978-981-10-4026-9_6.
[57] R. Naga, S. Chandralingam, T. Anjaneyulu, K. Satyanarayana, Denoising EOG signal using stationary wavelet transform, Meas. Sci. Rev. 12 (2) (2012) 46–51, https://doi.org/10.2478/v10048-012-0010-0.
[58] M. Merah, T.A. Abdelmalik, B.H. Larbi, R-peaks detection based on stationary wavelet transform, Comput. Methods Programs Biomed. 121 (3) (2015) 149–160, https://doi.org/10.1016/j.cmpb.2015.06.003.
[59] M.E. Palendeng, Removing Noise From Electroencephalogram Signals For BIS Based Depth of Anaesthesia Monitors, Master of Engineering Research (MENR), University of Southern Queensland, Australia, 2011.
[60] X. Kang, D.O.D. Handayani, H. Yaacob, Comparison between Butterworth bandpass and stationary wavelet transform filter for electroencephalography signal, IOP Conf. Ser. Mater. Sci. Eng. 1077 (2021) 1–11, https://doi.org/10.1088/1757-899x/1077/1/012024.
[61] M. Adib, A new method for removing electrical vestibular stimulation induced artifacts from electro-encephalographic recordings, The University of British Columbia, Canada, 2012. Master of Applied Science.
[62] M.O.K. Särkelä, M.J. Ermes, M.J. Van Gils, A.M. Yli-Hankala, V.H. Jäntti, A. P. Vakkuri, Quantification of epileptiform electroencephalographic activity during sevoflurane mask induction, Anesthesiology. 107 (2007) 928–938, https://doi.org/10.1097/01.anes.0000291444.68894.ee.
[63] M.S. Choudhry, R. Kapoor, A survey on different discrete wavelet transforms and thresholding techniques for EEG denoising, in: International Conference on Computing, Communication and Automation, 2016, pp. 1048–1053.
[64] M. Balamareeswaran, D. Ebenezer, Denoising of EEG signals using discrete wavelet transform based scalar quantization, Biomed. Pharma. J. 8 (2015) 399–406.
[65] M. Li, W. Chen, T. Zhang, Classification of epilepsy EEG signals using DWT-based envelope analysis and neural network ensemble, Biomed. Signal Process Control. 31 (2017) 357–365, https://doi.org/10.1016/j.bspc.2016.09.008.
[66] S.M. Park, K.B. Sim, A study on the analysis of auditory cortex active status by music genre: Drawing on EEG, in: Proc. - 2011 8th Int. Conf. Fuzzy Syst. Knowl. Discov. FSKD 2011, 2011, pp. 1916–1919, https://doi.org/10.1109/FSKD.2011.6019916.
[67] I. Ullah, R.U. Khan, F. Yang, L. Wuttisittikulkij, Deep learning image-based defect detection in high voltage electrical equipment, Energies. 13 (2) (2020) 1–17, https://doi.org/10.3390/en13020392.
[68] I. Rakhmatulin, The electronic board to replace the reference voltage on the earlobe for EEG measurement, Meas. J. Int. Meas. Confed. 173 (2021) 1–8, https://doi.org/10.1016/j.measurement.2020.108673.
[69] J. Jödicke, S. Olbrich, C. Sander, J. Minkwitz, T. Chittka, H. Himmerich, U. Hegerl, Separation of low-voltage EEG-activity during mental activation from that duringtransition to drowsiness, Brain Topogr. 26 (4) (2013) 538–546, https://doi.org/10.1007/s10548-013-0287-9.
[70] D.K. Lee, J. In, S. Lee, Standard deviation and standard error of the mean, Korean J. Anesthesiol. 68 (3) (2015) 220–1213, https://doi.org/10.4097/kjae.2015.68.3.220.
[71] J. Cannon, M.M. Mccarthy, S. Lee, J. Lee, C. Börgers, M.A. Whittington, N. Kopell, Neurosystems: Brain rhythms and cognitive processing, Eur. J. Neurosci. 39 (5) (2014) 705–719, https://doi.org/10.1111/ejn.12453.
[72] J.D.K. Negara, S. Mudjianto, A. Budikayanti, P.P. Adhitya Nugraha, The effect of gamma wave optimization and attention on hitting skills in softball, Int. J. Hum. Mov. Sport. Sci. 9 (1) (2021) 103–109, https://doi.org/10.13189/saj.2021.090114.
[73] M. Kim, S.H. Cheon, Y. Kang, Use of electroencephalography (EEG) for the analysis of emotional perception and fear to nightscapes, Sustain. 11 (1) (2019) 1–15, https://doi.org/10.3390/su11010233.
[74] M. Murugappan, N. Ramachandran, Y. Sazali, Classification of human emotion from EEG using discrete wavelet transform, J. Biomed. Sci. Eng. 3 (4) (2010) 390–396, https://doi.org/10.4236/jbise.2010.34054.
[75] H. Zhang, A.J. Watrous, A. Patel, J. Jacobs, Theta and alpha oscillations are traveling waves in the human neocortex, Neuron 98 (6) (2018) 1269–1281, https://doi.org/10.1016/j.neuron.2018.05.019.
[76] S. Magnussen, Visual memory and psychology, Int. Encycl. Soc. Behav. Sci. (2001) 16264–16266.
[77] Y.N. Su, C.C. Kao, C.C. Hsu, L.C. Pan, S.C. Cheng, Y.M. Huang, How does mozart' s music affect children's reading? The evidence from learning anxiety and reading rates with e-books, Educ. Technol. Soc. (2017) 1–12.
[78] R. Yuspitasari, Rahmawati, R.Z. Dalimunthe, The effect of using music classic (Mozart) towards Student Anxiety Before The Exams, J. Fam. Sci. 5 (1) (2020) 47–56, https://doi.org/10.29244/jfs.5.1.47-56.
[79] G.L. Shaw, D.J. Silverman, J.C. Pearson, Model of cortical organization embodying a basis for a theory of information processing and memory recall, Proc. Natl. Acad. Sci. U. S. A. 82 (8) (1985) 2364–2368, https://doi.org/10.1073/pnas.82.8.2364.
[80] S. Yang, Z. Fan, R. Ren, The stochastic resonance phenomenon of different noises in underdamped bistable system, Adv. Math. Phys. (2021) 1–9, https://doi.org/10.1155/2021/4614919.