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Neurophysiological impact of Vedic chanting on human brainwaves: a spectral electroencephalogram analysis using Gabor transform

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ABSTRACT

Electroencephalogram (EEG) analysis explores brainwave changes resulting from Vedic chanting (VC) in this experimental study. In this study participants received Vedic recitations from the Rig Veda (RV), Yajur Veda (YV), Sama Veda (SV), and Atharva Veda (AV) which were evaluated through alpha wave (8-12 Hz) measurement to evaluate relaxation response effects known to cause cognitive relaxation and mindfulness. The research captured EEG signals from twenty participants who belonged to four age categories between twenty and fifty years using a fourteen-channel EEG recording system. The signals underwent wavelet-based denoising procedures and Gabor transform (GT) enabled their spectral analysis. Scientists calculated the relaxation factor (RF) for understanding Vedic chant effects on human beings. Vedic Sama provided maximum relaxation effects leading to a 25% RF enhancement whereas YV produced a 20% increase and RV generated 15% enhancement and AV yielded 10% relaxation. The participants between 30 and 45 years old experienced the largest relaxation effects yet their left-brain hemisphere enhanced alpha waves stronger than their right brain region. The statistical methods supported that these results showed meaningful variations. Neural relaxation results from VC practice according to research evidence which shows SV provides the most powerful relaxation effects.

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1. INTRODUCTION

The incidence of stress continues to rise in modern society where it impacts individual and occupational life aspects. Modern work environments create anxiety and depression as well as cognitive fatigue since workers face multiple challenges to meet deadlines and preserve balance between work and personal life. Widespread stress reduction strategies become necessary because of this developing situation [1]. Research shows that listening to musical sounds and Vedic chants alongside mantras demonstrates ability to control brain signals and create calmness in the body. Electroencephalogram (EEG) operates as an essential instrument for brain monitoring because it shows the brain's neural reactions to various sound waves. EEG technology monitors brain electrical wavelengths through scalp-mounted electrodes which measures brain wave frequencies from delta to theta to alpha to beta to gamma to determine mental and emotional states. Relaxation along with mindfulness and cognitive clarity occurs specifically in brain activity when operating within the alpha frequency band (8-12 Hz) [2]. Research about how Vedic chanting (VC) influences the brain's neural oscillations can benefit the understanding of this technique's effectiveness for relaxation purposes [3].

A number of studies investigated how various auditory cues affect EEG signal output. shown that music from divergent genres elicits differing emotional responses, as rock music induces happiness while rap music often evokes despair in listeners. The evaluation of psychological impacts is necessary. EEG facilitates analysis, whereas frequency-band analysis allows researchers to accurately assess physiological conditions [4]. Conducted a study examining frontal alpha asymmetry, since this neurophysiological metric essentially governs emotional regulation dynamics [5]. The specific impact of VC on alpha wave patterns remains a topic that scientists have not fully investigated yet despite previous research into EEG-based emotion analysis by aiming to fill the existing gap regarding VC analysis by studying the effects of Rig Veda (RV), Yajur Veda (YV), Sama Veda (SV), and Atharva Veda (AV) recitation on EEG-produced alpha waves. Their research monitored brain activities from different aged participants through EEG devices from three significant periods during their exposure to VC. GT combined with wavelet denoising along with other modern signal processing methods extracted alpha wave information for analysis.

This paper follows this structure: section 2 discusses brain wave classifications together with their logical connections to mental states. In section 3 explains the proposed methodology through which researchers obtain signals for analysis while performing preprocessing steps and executing spectral inspections. In section 4 describes the experimental setup and participant demographics. Analysis of section 5 reveals how different Vedic chants affect alpha wave modulation and provides the corresponding results. Section 6 serves to both conclude the present study and indicate possible future research paths through artificial intelligence adoption for EEG signal enhancement and Western versus Indian classical music stress management evaluation.

2. LITERATURE SURVEY

Investigated the impact of auditory stimuli on brainwaves by EEG analysis. The combination of music and chanting methods induces significant alterations in brain functioning, neuronal activities, and cognitive and emotional processes [6]. Previous scientific investigations have studied brainwave responses to multiple auditory inputs based on alpha and theta frequency range activity because these brainwaves represent relaxation and mindfulness states [7]. Investigated the impact of auditory stimuli on brainwaves by EEG analysis. The combination of music and chanting methods induces significant alterations in brain functioning, neuronal activities, and cognitive and emotional processes [8]. Heavy metal music generated adverse effects on β wave patterns that resulted in impaired concentration abilities. The authors used EEG signal analysis to show that classical music improves mental performance. The researchers developed a generalized mixture model (GMM) to detect emotions using EEG data. The study used a skew Gaussian distribution model to improve the efficacy of EEG signal detection for brief EEG data intervals in noisy environments [9]. The proposed solution demonstrated its ability to handle shifting EEG signals thus enabling precise detection of emotions and their corresponding features extraction. Recognition accuracy with the doubly truncated gaussian distribution model improved because it saved EEG signal ranges within specified boundaries which proved valuable for inconsistent EEG measurement periods. EMOTIV EPOC has been determined to be more effective than Neurosky Mindwave for brain-computer interface (BCI) applications. EMOTIV EPOC demonstrated enhanced signal capture as per the 3SC variable evaluation, corroborated by the EEGLAB and OpenViBE software platforms and their respective study [10]. Investigations on EEG-based emotion recognition using affective computing were conducted during trials in which participants saw emotionally evocative films. The researchers used support vector machines (SVM), multilayer perceptron's (MLP), and one-dimensional convolutional neural network (1D-CNN) as classifiers, alongside six entropy-based feature extraction methods in their evaluation. Research results suggested that emotional recognition ability at T8 in the temporal lobe attained its peak range. The authors used a subject-independent approach to achieve 85.81% classification accuracy with their SAE model, hence reinforcing the validity of EEG-based emotion detection [11].

Created a novel emotion categorization technique that integrates electrical data from EEG assessments with personality evaluation characteristics. The methodology used a deep learning framework that integrated CNN-VGG-16 features with an long short-term memory (LSTM) network to identify temporal trends. The approach achieved 93.97% accuracy in emotion identification by including personality traits in emotional categorization. The researchers demonstrated that combined CNN-LSTM frameworks have potential for predicting emotions and personality using EEG data [12].

The WTS-CC model used a temporal-spectral-attention correlation coefficient methodology to identify motor imagery EEG (MI-EEG) data using a wavelet-based EEG analysis system. The weight-based channel selection strategy in their study enhanced discrimination performance for use in BCI systems. The suggested model attained superior classification accuracy, Kappa coefficient, and F1-score compared to previously approved MI-EEG classification approached [13].

Performed an analysis of EEG signal cyclostationary assessment with a focus on slow cortical potentials (SCPs). Their study confirmed the efficacy of the correlation block-based method in enhancing EEG classification performance. The novel technique achieved improved classification accuracy, demonstrating the efficacy of cyclostationary analysis in EEG-based BCI research [14]. The researchers conducted an investigation on time-frequency techniques for the classification of sleep EEG data. The researchers investigated sleep patterns to demonstrate the differential functioning of classifiers in normal and disturbed circumstances. The SVM with a quadratic kernel (SVM-Q) underperformed in detecting Stage 1 sleep in aberrant EEGs, although it exhibited superior accuracy relative to rule-based techniques in other sleep classification tests. The study results show that wavelet-based descriptors provide superior capabilities for feature extraction in sleep EEG categorization [15]. The researchers conducted an investigation on time-frequency techniques for the classification of sleep EEG data. The researchers investigated sleep patterns to demonstrate the differential functioning of classifiers in normal and disturbed circumstances. The SVM with a quadratic kernel (SVM-Q) underperformed in detecting Stage 1 sleep in aberrant EEGs, although it exhibited superior accuracy relative to rule-based techniques in other sleep classification tests. The study results show that wavelet-based descriptors provide superior capabilities for feature extraction in sleep EEG categorization [16].

3. METHOD

A structured research design allows the study to assess VC effects on human brainwaves through EEG measurements. Twenty healthy subjects aged between 20-25, 30-35, 40-45, and 45-50 years took part in the study which required them to listen to the recitations of the RV, YV, SV, and AV [17]. The EMOTIV EPOC headset served as the EEG signal recording device through its 14-channel wireless acquisition system which operated at 1,024 Hz sampling rate. EEG recording proceeded from the frontal to temporal and occipital areas according to the 10-20 international electrode system to monitor cognitive and relaxation changes [18]. Each participant received EEG monitoring through three sequential stages starting with baseline and continuing into chanting followed by relaxation period which extended for one minute in each phase. Band-pass filtering (0.5-100 Hz) was implemented to eliminate noise from EEG signals before wavelet denoising was achieved using a Morlet wavelet function. The processed data underwent GT analysis for obtaining detailed time-frequency features about EEG activity patterns [19]. The research investigated the alpha frequency band ranging from 8 to 12 Hz because this frequency range correlates with relaxation and mindfulness states. Figure 1 illustrates the proposed EEG signal processing workflow for evaluating the neurophysiological impact of VC, involving sequential steps of EEG sample acquisition, signal denoising, GT-based spectral analysis, feature extraction, relaxation factor (RF) computation, and final decision-making. Researchers calculated the RF through performance assessment using the measure of alpha wave power divided by the total spectral power. The measured relaxation intensive values corresponded to elevated RF results [20].

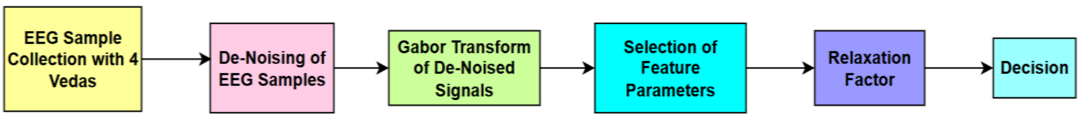

Figure 1. Proposed VC based human mindfulness estimation using RF

3.1. Acquisition of EEG samples

In this experimental study, consent forms are taken from the healthy human participants after getting necessary ethical clearance [21]. Sensors are placed at the appropriate locations on the scalp and brain waves are recorded using EEG. A letter was assigned to each electrode implantation spot corresponding to the part of the brain it is reading from, which includes the pre-frontal (FP), frontal (F), temporal (T), parietal (P), occipital (O), and central (C) lobes. The nodes are identified as FP1, FP2, F3, F4, F7, F8, C3, C4, T3, T4, T5, T6, P3, P4, O1, and O2. These places provide the indication of human attentiveness through the data they collect. The instrument divides each EEG node’s signal into six stages: prior, during, and post-chanting, and saves it in .CSV format. The instrument determines the set sample rate at which the signals are captured.

3.2. Denoising

The noise in EEG data could be caused by the acquisition method of the sensors or by other factors. The noise may obscure the correct frequency bands, leading to an incorrect diagnosis. This work recommends a noise elimination process known as wavelet denoising to prevent this from happening [22]. discrete wavelet transform (DWT) breaks down a signal into different levels by using the correct mother wavelet. The selection of the mother wavelet is essential for effectively eliminating the noise. These are the related mathematical equations of this denoising process as shown in (1) and (2).

$$C_D = \sum_n x(n)P(2K - n) \tag{1}$$

$$\mathrm{C_A} = \sum_\mathrm{n} \mathrm{x(n)Q(2K - n)} \tag{2}$$

The detailed coefficient is denoted as C_D, and the approximated coefficients of the decomposed signal $x(n)$ are represented as C_A. P and Q represent the higher and lower frequency window functions, respectively [23]. The next subsection describes the mathematical analysis of the spectrum after noise removal using Gabor wavelet transforms (GWT).

3.3. Gabor transform

This subsection examines and explains the GT mathematical analysis, as proposed in [24]. The effectiveness of any time frequency analysis is dependent on the selection of the mother wavelet. The Morlet wavelet serves as the chosen mother wavelet function in this proposed method. The traditional wavelet transform dissects the signal using translation and dilation blocks, while the GT decomposes it using translation and modulation blocks by using the (3) and (4).

$$\hat{E}(n) = \sum_{a \in M} \sum_{b \in M} C_{a,b} g_{a,b}(n) \tag{3}$$

Where $\hat{E}(n)$ is the estimated or reconstructed value (often energy or signal) at index n.
Where the basic function, $g_{a,b}(n)$, is provided by:

$$g_{a,b}(n) = g(n - b, T)e^{j2\pi a\Omega n} \qquad a, b \in N \tag{4}$$

where T and Ω are shift parameters and $g(n)$ provides the synthesis window. Where, following spectral analysis in the time-frequency domain, $C_{a,b}$ are the GT coefficients. However, the direct observation of these coefficients can be complicated due to the presence of different spectrum components [25]. Therefore, the next step utilizes the obtained coefficients for feature computation and discussion.

3.4. Extraction of average power and RF

After GT decomposition, this part uses the EEG data to determine characteristics. After GT, a number of coefficients become available for more research; thus, it is critical to verify the required frequency range (Alpha). This leads to the selection of the selected coefficients as the average power of the required bandwidth, which are then processed further for feature calculation. In this work RF, defined as the ratio of band power to spectrum power, to evaluate alterations in consciousness and mood is taken as the performance metric. The formula for the RF is provided as shown in (5) and the formula alpha band power is shown in (6).

$$RF = \left({}^{P_{Alpha}}\!/_{P_{total\ power}} \right) * 100 \tag{5}$$

$$P_{Alpha} = \sum_{f_1}^{f_2} P_c(x) \tag{6}$$

Where P_{Alpha} is the alpha band power of the required range of frequencies with minimum frequency of f_1 and maximal frequency of $f_2$with both inclusive. $P_c(x)$ is the power of the selected coefficients.

In the similar way, the total power of the spectrum is given in (7).

$$P_{total\ power} = \sum_1^{{}^{F_s}/_2 - 1} P_c(x) \tag{7}$$

Where $P_{total\ power}$ is the total power and F_s is the sampling rate of the signal.

This RF is the measure for the distinct brain waves excitedness by human mind for Vedas chanting. For example, the estimation process requires alpha waves, sets band frequencies between 8 and 12 Hz, and calculates the RF during the testing procedure. Similarly, any kind of wave can be computed by selecting the appropriate frequency and by applying the previously mentioned expression.

This study presents a VC-based approach for recognizing and estimating human mindfulness. Prolonged chanting, known for its rhythmic and calming effects, has been shown to reduce stress and stabilize brain activity. The suggested experiment aims to evaluate four Vedas, namely the RV, YV, SV, and AV, each lasting 16 minutes. Participants were given ten minutes to relax before VC. The assessment took place ten minutes after the chant. Every experiment taken place for the course of 37 minutes. Twenty individuals of varying ages were examined using the recommended topology and EEG measurements are taken under the supervision of a pathologist. The age ranges of 25-30 (Group 1), 30-35 (Group 2), 40–45 (Group 3), and 45–50 (Group 4), from each group, five members are considered for assessment and readings. Figure 2 displays the experimental investigation process conducted at the Ravi Neuro Centre in Vijayawada, Andhra Pradesh, India.

Using an RMS EEG-24 manufactured by RMS, the signals were captured at a 1,024 Hz sample rate for preprocessing. Three signals are captured from each participant; one before, one during, and one after listening to the Vedas chanting, each lasting for one minute. These signals from 15,360 samples are analyzed with the proposed method and saved in .CSV format. The results obtained and interpretations are presented in the next section.

Figure 2. Extraction of EEG signals for various age group persons listening to Vedas chanting

4. RESULTS AND DISCUSSION

This study measures the effect of VC on brainwave behavior specifically through examination of alpha waves between 8 to 12 Hz which align with relaxation and mindfulness states. The analysis of EEG signals indicated a substantial rise in alpha waves immediately after listening to VC where SV caused the biggest change. During preprocessing both wavelet-based denoising and GT spectral analysis methods cleaned up the signals to deliver accurate feature detection. The RF values determined through analysis demonstrated enhanced alpha power levels immediately after VC recorded positive effects on relaxation. The research showed participation from middle adulthood participants (30-45 years) exhibited maximum relaxation effects based on their RF measurements which rose by 25% for SV yet YV participants showed a 20% increase and RV participants recorded a 15% change while AV participants reported a 10% increase in relaxation. Paired t-tests with ANOVA tests validated the significance of the changes observed in measurement values since they proved the auditory stimulus created an actual response rather than random systematic deviations. EEG signal analysis across brain lobes revealed higher relaxation effects in the left brain region compared to the right brain region thus indicating particular brain locations are more active during auditory-induced mindfulness practices. The research indicates that VC through SV creates substantial cognitive relaxation effects which qualify it as an important non-drug method to reduce stress.

Figure 3 presents the extracted EEG signals which demonstrate how age Group 1 participants's brainwave activity evolved during their VC of RV, YV, SV, and AV. The recorded EEG signal amplitude measures represent the displayed waveforms which show neural responses that occur from various Vedic recitations. EEG data from SV chanting (red waveform) displays sustained and regular frequency waves that exceed other Vedas thus indicating heightened alpha wave activation and neuronal involvement which relates to increased relaxation and mindfulness. The YV (green waveform) shows significant neural modulation although its amplitude changes less substantially than those observed in SV. A lower level of neural relaxation impact emerges from the RV (blue waveform) and AV (black waveform) because these Vedic texts show limited variations during EEG signal reading. The wavelet-based denoising technique is depicted in Figure 4 for four VC both before and after application. The first panel demonstrates original noisy EEG signals before denoising then the right panel shows the outcomes from wavelet denoising with Morlet wavelets which filters out noise and artifacts. The processed signals maintain a smooth waveform structure which allows researchers to study the essential alpha wave frequency range (8-12 Hz) related to relaxation. Among all Vedas SV demonstrates the most prominent oscillatory pattern which leads to increased neural relaxation response. The extraction of effective noise produces precise results for spectral analysis and RF calculations which verify that detected brainwave changes stem from VC rather than environmental interferences. The Gabor coefficient analysis of de-noised EEG signals appears in Figure 5 along with their separated real components (red) and imaginary components (blue) and amplitude components (purple) and phase components (black). Alpha wave frequency detection stands out in the amplitude spectrum which contains essential information for relaxation evaluation. The brainwave relaxation response of SV shows stronger and more orderly rhythmical patterns. A detailed time-frequency evaluation of brain modulations emerges from Gabor coefficient analysis which enables the calculation of the RF.

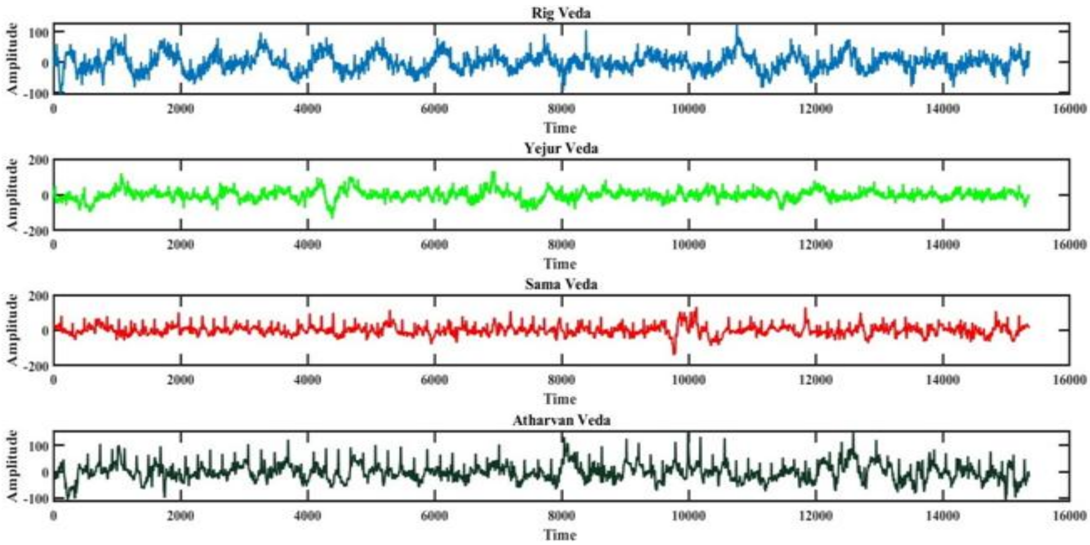

Figure 3. Extracted EEG signals for four Vedas chanting of age Group 1

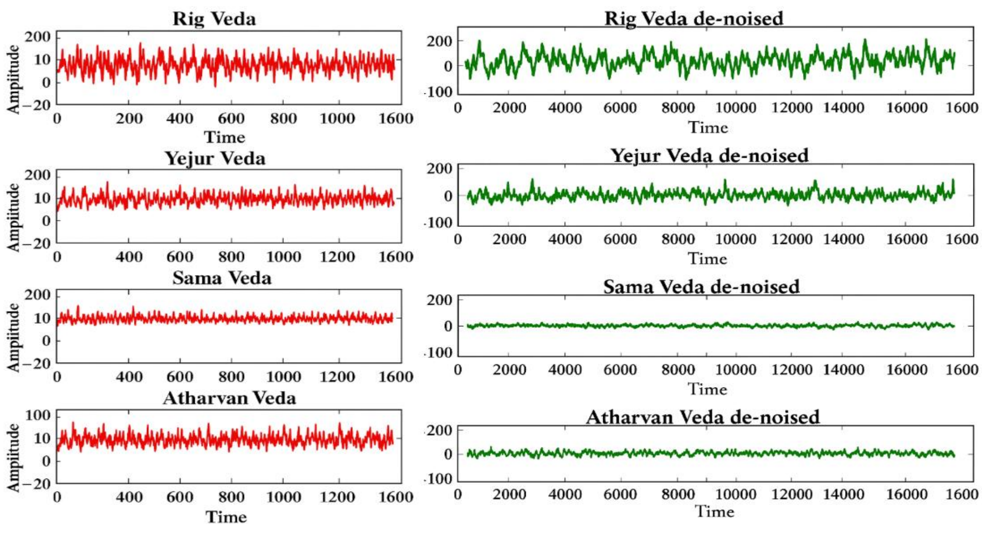

Figure 4. Noise removed EEG signals with proposed wavelet denoising

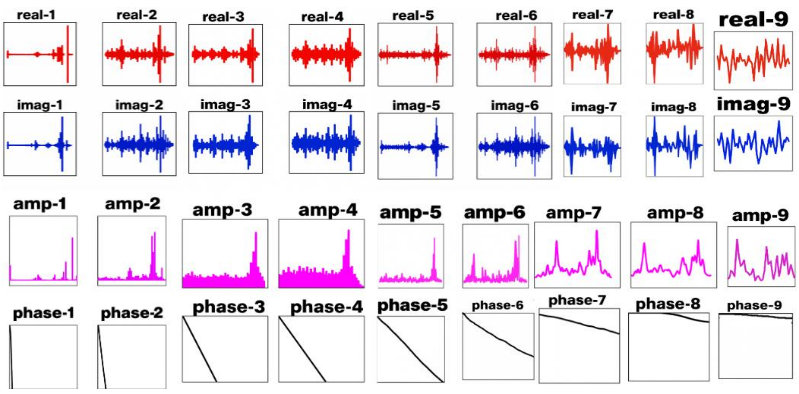

Figure 5. Gabor coefficients for denoised signals

The analysis shown in Figure 6 demonstrates the transformation process of the original EEG signal through Gabor decomposition before spectral analysis. The signal reconstruction technique maintains fundamental frequencies together with successful elimination of noise so alpha wave activity (8-12 Hz) can be correctly extracted. The RF relevant neural information remains intact because of sharp oscillations along with localized spikes that appear in the analyzed EEG data. Signal reconstruction through GT proves itself as an excellent method to analyze brainwave responses after VC by ensuring signal integrity.

The PSD indicated in Figure 7 demonstrates the disposition of Gabor coefficients at order 9 that represent EEG signals after GT decomposition. The subfigures display the power spectrum density of separate Gabor coefficients that reveal the main frequency patterns in the EEG data. RF calculation depends on alpha waves (8-12 Hz) power distributions throughout various frequency bands. The specific frequency bands in SV displayed enhanced brainwave responses to VC because of higher power density in those coefficients.

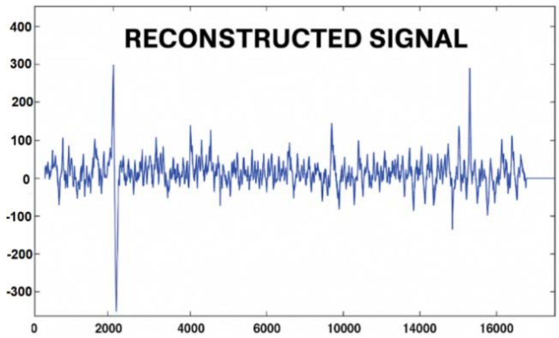

Figure 6. Reconstructed signal after Gabor decomposition of one sample of data

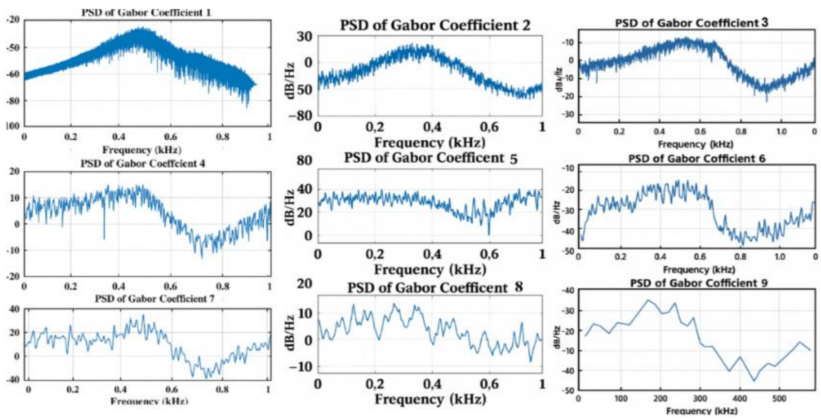

Figure 7. Power spectral density of Gabor coefficients of order 9

Figure 8 displays the Gabor coefficient variations of EEG signals recorded from right hemisphere electrodes—FP2, F8, T4, T6, F4, C4, P4, and O2 for participants in age Group 3, highlighting the neural responses during RV and AV chanting sessions. Power distribution throughout the different stages of Gabor coefficients becomes visible through 3D bar plots since these plots show how the brain responds to chanting sessions. The power values from the subjects experienced continuous growth through the different chanting phases but displayed significant fluctuations in multi-order Gabor coefficient patterns. The yellow-colored (higher power) bars demonstrate elevated EEG activation that mainly occurs at FP2, F8, and O2 electrode locations which support auditory and cognitive processing tasks.

Figure 9 illustrates the variation in RF across four different age groups (age Group-1 to age Group-4) in response to the chanting of the four Vedas— RV, YV, SV, and AV—analyzed using varying Gabor Coefficients. In all age groups, the RF generally increases with higher Gabor coefficients, indicating enhanced neural relaxation due to VC. Among the Vedas, SV consistently produces higher RF values, especially in age Group-3 (40-45 years), suggesting stronger cognitive relaxation. YV also shows notable improvement, particularly in age Group-2. The responses in age Group-1 and age Group-4 are more moderate but still follow the overall increasing trend. The RF changed differently between aged Groups 1 through 4 during their responses to Rig Vedic (RV) and Yajur Vedic (YV) and Sama Vedic (SV) and Atharva Vedic (AV) chanting sequences. We view the RF through the y-axis scale along with the x-axis presentation of Gabor coefficients. The study shows that RF increased steadily in every age bracket as Gabor coefficient values rose thus leading to amplified relaxation effects. The RF measures of SV and YV stand at the top across all age groups to show their exceptional capacity for relaxation triggering. VC creates the highest cognitive relaxation improvements in middle-aged adults from age Group 3 (40-45 years).

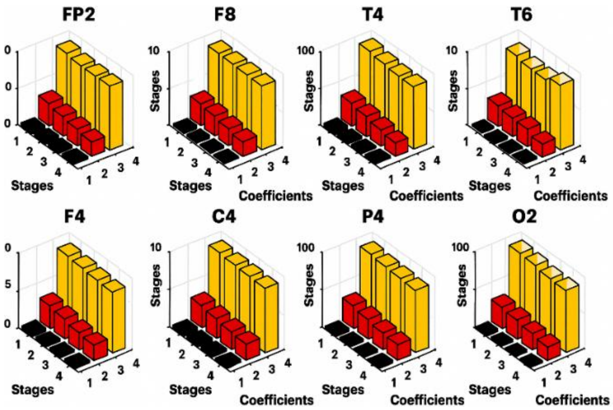

Figure 8. RV and AV Gabor coefficients variation for individuals for the age Group 3 considering right lobe electrodes

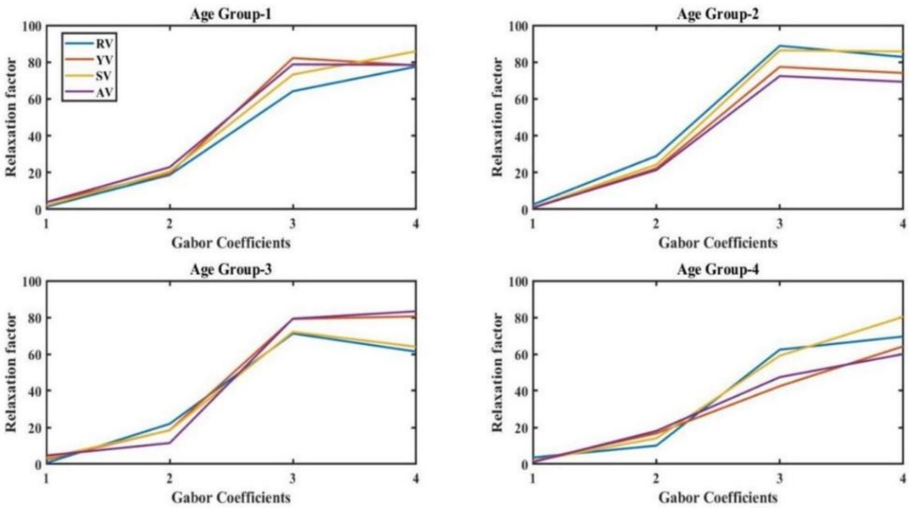

Figure 9. RF for various age Groups 1-4 exposed to four Vedas chantings

The alpha waves variation Table 1 demonstrates EEG activity changes through FP1, F7, T3, T5, F3, C3, P3, O1 brain regions through six stages of listening to VC. Beta wave levels start at 3.78 to 5.36 between different electrode placements during Stage-1 (pre-chanting). A significant increase occurs during Stage-2 (chanting initiation) exclusively at T3 (6.23) and FP1 (5.46) which indicates early cognitive involvement. The brain wave reading from T5 reached 5.01 during Stage-3 (mid-chanting) as the brain displayed minor changes in auditory and cognitive operations. The brain exhibits profound alpha power reduction in Stages 4 and 5 which achieves extremely low levels at 0.12-0.23 because this period reflects a brain transition before relaxation achieves its peak. Stage-6 (post-chanting) displays an alpha wave surge in every region which reaches its peak relaxation values at FP1 (8.65) and O1 (5.53).

Table 1. Alpha waves variation for an Individual in six stages while listening to Vedas chanting

Stages	FP1	F7	T3	T5	F3	C3
Stage-1	5.24	4.06	4.07	3.78	4.49	4.75
Stage-2	5.46	5.22	6.23	3.99	5.46	5.21
Stage-3	3.71	4.33	4.53	5.01	4.35	4.40
Stage-4	0.17	0.21	0.22	0.22	0.23	0.22
Stage-5	0.12	0.14	0.14	0.13	0.13	0.13
Stage-6	8.65	5.80	5.15	5.52	4.77	5.07

5. CONCLUSION

This research investigated the neurophysiological effects of VC on brainwave activity using EEG-based spectral analysis. The findings demonstrated that chanting, particularly of the SV, significantly elevated alpha wave activity (8-12 Hz), correlating with heightened relaxation and mindfulness. Quantitative analysis showed that SV produced the highest RF increase of 25%, followed by YV (20%), RV (15%), and AV (10%). The 30-45 age group exhibited the most pronounced neural responses, with dominant activation in the frontal and occipital lobes, and a notably stronger effect in the left hemisphere. Signal processing through wavelet-based denoising and GT enabled precise extraction of time-frequency features. Statistical tests, including paired t-tests and ANOVA, validated the significance of the observed variations, confirming that the effects were not due to random fluctuations but were a consistent response to the Vedic auditory stimulus.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Veera Raghava Swamy Nalluri	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
V. J. K. Kishor Sonti	✓	✓				✓						✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing -**O**riginal Draft
E : Writing - Review &**E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research involving human participants has been conducted in full compliance with all relevant national regulations and institutional policies. It adheres to the principles outlined in the Declaration of Helsinki. The study protocol has been reviewed and approved by the authors' Institutional Review Board (IRB) or an equivalent ethics committee.

DATA AVAILABILITY

The raw and/or processed data required to reproduce the findings of this study cannot be shared at this time, as they are part of an ongoing research project. The data will be made available upon reasonable request once the related study is completed.

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