

Effective Stress Management through Meditation: An Electroencephalograph-Based Study

Abstract

Introduction: Stress among college students is a common health problem that is directly correlated with poor cognitive health. For instance, cognitive mechanisms required for sustenance can be affected due to stress caused by daily mundane events, not necessarily by chronic events. Thus, it becomes essential to manage stress effectively especially for college students. Meditation is one of the useful techniques that facilitates cognitive flexibility and has consequences at the molecular and endocrinal level to treat stress. **Objectives:** The present study attempts to understand the effect of meditation on the brain waves when participants face stressful events. **Methods:** A randomized controlled pre-post experimental design was used. Total 18 subjects were randomly assigned to control group and experimental group. Subsequently, Electroencephalograph (EEG) data were recorded during the determination test (DT) before and after the meditation. The Control group underwent relaxation music while the experimental group practiced Sudarshan Kriya Yoga (SKY) (a type of meditation). Non-linear EEG signal processing algorithm was applied to capture dynamics and complexity in brain waves. **Results:** Results indicated that the efficacy of meditation was reflected with the improved information processing in the brain. Improved performance and reduced errors were reported in DT Scores in the experimental group. Increased complexity of beta band was observed for non-linear features, signifying efficient utilization of cognitive resources while performing the task. **Conclusion:** Findings implicated the usefulness of the meditation process for effective stress management.

Keywords: Approximate entropy, electroencephalograph, meditation, stress management, Petrosian's fractal dimension

Introduction

Stress is a growing concern in modern society. As the lifestyle of people is changing enormously, people are finding difficulty in facing the challenges of life.^[1] Every day, challenges and global competition have put tremendous pressure on individual mental processes; henceforth, people fail to confront the challenge in adverse situations, and exhausting mental capacity causes psychological stress. Psychological stress is a global public health problem with various adverse health repercussions, comprising anxiety, depression, cardiovascular disease, and suicide.^[2] India enrolls 36.6 million college students, and the prevalence of elevated symptoms of depression and anxiety among Indian college students ranges from 38% to 60%.^[3] Mental health has become a priority in India in recent years, illustrated

by the passage of the National Mental Healthcare Act of 2017 and the ongoing global pandemic of coronavirus disease 2019. To reduce burnout and improve coping skills, various stress management interventions are provided at the institute level. Stress management encompasses a wide range of interventions designed to alleviate stress, such as tolerating stressors and lowering arousals.^[4] However, it seems intuitively appealing to state that existing programs to curb problems arising via stressful events are quite focused on eliminating stressors, but not improving mental resilience. Thus, the importance of practicing meditation arises, which is used to treat stress and stress-related conditions and to promote general health.^[5] Meditation is a psychologically induced, altered state of consciousness. The study of meditation provides insights into cognitive and emotional brain correlates of consciousness,

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which are crucial to understanding the intricacy of the human brain. However, despite almost 50 years of study, a comprehensive empirical and theoretical foundation for meditation is still emerging, and studies of its clinical impact through electrophysiological methods are quite limited. Meditation program at clinical practices is very trivial and varies from person to person. Nevertheless, and despite calls for the importance of understanding meditation implementation coming from a range of areas, at present, the knowledge about the role of process and contextual variables influencing meditation success is rather embryonic.

The present study investigates the effect of meditation on performance while the subject undergoes stressful events through a psychological stress test (determination test [DT]) with simultaneous electroencephalographic (EEG) data acquisition. EEG provides an understanding of the complex inner mechanisms of the brain. Previous studies reported that meditation practices could be correlated with EEG measures.^[6,7] For example, slowing of theta and alpha activation was related to the proficiency of practice. In addition, alteration in the cognitive state was also detectable through event-related potential evaluation. For instance, frontal midline theta activity is linked with the attention-demanding task, showing an effect of meditation in attention allocation.^[8] Meditation could effectively manage stress while performing multitasking as reflected in EEG and sympathovagal index.^[9] An electrophysiological examination of the impact of meditation on a sample comprising 223 novice meditators was provided in a recent study.^[10] Results showed that there was a global increase of 29% of theta power and an 11% increase in gamma power from premeditation to end meditation state. Such studies have measured EEG during meditation, whereas in our case, we have observed the effect of meditation, while participants undergo stressful tasks reflecting their coping mechanism in EEG spectral changes. Since EEG signals are nonstationary, complex, and nonlinear signals^[11] therefore, we have focused on extracting nonlinear EEG features such as approximate entropy (ApEn) and Petrosian's fractal dimensions (D). A study showed that ApEn based on discretized EEG data enhanced classification results during meditation.^[12] Another study showed a decrease in D in the open eye state after the Sajdah in women. "Sajdah," a prostration position, is part of Muslim daily prayers.^[13] Our study would add to research on nonlinear EEG physiological indicators of the meditative experience in individuals with limited meditation experience and with a guided meditation approach.

Methods

Participants

Eighteen subjects volunteered to participate in this experiment, and all were male undergraduate students aged 20–25 years. They were all healthy and did not report any brain disorders. Written informed consent was obtained from the subjects before starting the test protocol, and the study had been approved by the INMAS. Participants were randomly assigned either to the experimental or control group. Participants were matched on age and education. Nine subjects were randomly placed in the control group where they listened to relaxation music for 30 min daily, whereas nine subjects were assigned to an experimental group where they practiced meditation through *Sudarshan Kriya Yoga* (SKY) for 30 min daily.

Stimuli

Determination test

The test examines attentional ability, reactive stress tolerance, and responsiveness between constantly and rapidly changing acoustic and visual stimuli. In this test, subjects underwent a task in which they responded to a stimulus associated with sensory modality (audio or visual) and response methods (hands or feet) along with dexterity (left or right side) as shown in Figure 1. The task of the subject was to respond to incoming stimuli as fast as possible by selecting the appropriate buttons and pedals. Subjects took 6 min to perform the test. The appearance of stimuli was not predictable, and the subjects reacted to them randomly. Stimulus appearance distance was set randomly between 5 and 10 s. The aim of the "adaptive" mode is to ensure that the participant is always working at the limit of his or her ability and that reactive stress tolerance is being fairly measured. The creators of the test^[14] have ascertained that working under such conditions causes the participant to be constantly overstretched and does induce stress within the individual. We examined three key variables: number of correct answers (DT1, raw score), which refers to the ability of the subject how accurately and quickly select the

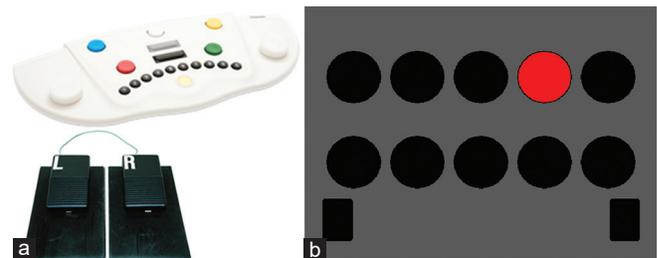


Figure 1: Determination test. Stimuli in circle shape require response through hands (b), different colors can be chosen from the panel (a, Top). Stimuli in the rectangular shape require a response from the foot pedal and the left and right position exhibits responses from the left and right foot, respectively (a, Bottom). In addition, auditory cues in the form of low and high pitch are presented, which is responded via pressing the button on the panel

correct answer under pressure. Further, we examined the number of incorrect scores (DT2, raw score), to determine how the subject is prone to confusion under stress and high pressure, and finally, the number of omitted errors (DT3, raw score) highlights the inability of the subjects to maintain their attention during stress and tend to give up situations.^[15]

Meditation

We employed meditation techniques in *Sudarshan Kriya* (SK) and *Pranayama* (P). The word “Sudarshan” finds its origins in Sanskrit to mean: “Su” = right, “Darshan” = vision and “Kriya” = purifying action. It is a rhythmic breathing activity consisting of the following five stages: *Ujjayi*, *Bhastrika*, *Om Chanting*, SK, and *Yoga Nindra*. SKY promotes wellness^[16] and vigilance by reducing stress.^[17,18] SKY can remove stress by making changes at the endocrine level and molecular level. SKY was used as an intervention to estimate the stress tolerance of the subjects when they voluntarily practiced it for a month (30 days).

Electroencephalograph acquisition system

Emotiv EPOC

EEG from each subject was recorded with a low-cost EEG device Emotiv EPOC, a 14-channel 128 Hz neuro-signal acquisition and processing wireless neuron headset. Channel names based on the international 10–20 locations are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. The 10–20 rule of electrode placement was followed [Figure 2]. Impedance was kept below 5 KΩ. Subjects were told to minimize their body movements, so the signals could be noise-free. Data were acquired in a quiet ventilated room.

Procedure

A randomized controlled pre–poststudy experimental design was used in this study. Subjects were randomly

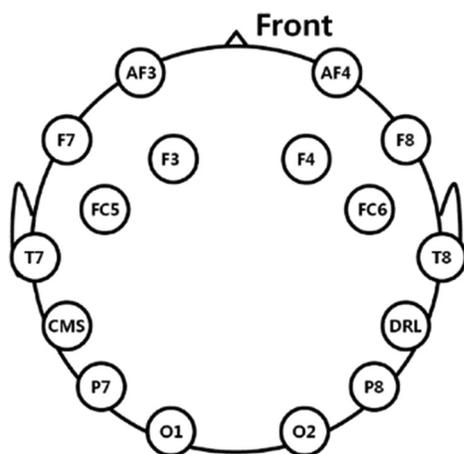


Figure 2: The 10–20 electrode placement system

classified into either experimental group or control group following the filling of the consent form. In the experimental group, a 1-month intervention (SKY) was provided to the subjects. In contrast, the control group was provided no intervention, only relaxation music. Totally, 30 min was spent by subjects on practicing meditation/listening relaxation music. Subjects performed the DT task with simultaneous EEG recording before and after the intervention. EEG signals were acquired throughout the duration of DT (i.e., 6 min continuous acquisition). Both groups performed the task, and scores were automatically saved. Total four types of data were acquired; one is before intervention (precontrol and pre-experimental) and the other was after intervention (postcontrol and postexperimental).

Electroencephalograph signals processing

Preprocessing

The EEG signals were acquired at a sampling rate of 128 samples/s. The acquired EEG signal was processed offline using the EEGLAB software plug-in MATLAB R14b (Version R2014b, MathWorks). The acquired EEG signals were brought in the range of 0.5–40 Hz by using a low pass filter with a cutoff frequency of 40 Hz followed by a high pass filter with a cutoff frequency of 0.5 Hz. The power noise interference was removed by using a comb band stop filter with a notch frequency of 50 Hz. Independent component analysis (ICA) was applied to remove four classes of artifact components – eye blinks, eye movements, muscle activity, and other types of artifacts. ICA isolated and measured these artifacts based on their projection to overlapping electrode subsets.^[19] Thus, ICA is more efficient for artifact rejection.

Feature extraction

Artifact-removed signals underwent Haar wavelet decomposition. The wavelets were scaled and translated copies (known as “daughter wavelets”) of a finite-length or fast-decaying oscillating waveform (known as the “mother wavelet”). Decomposed waves consisted of the approximations (low-frequency components) and the details (high-frequency components). EEG segment at a sampling rate of 128 Hz was decomposed to beta band corresponding to A2 using Daubechies 4 (db4, 2nd Level detail).

Approximate entropy

Entropy is a statistical measure of complexity and does not rely upon a nonlinear description of the data. ApEn is an index that quantifies the irregularity or complexity of a dynamical system. It is particularly effective with short and noisy time-series data. It measures the logarithm of the frequency with which neighborhoods of temporal patterns of length m within a certain distance r in phase space remain close together ($<r$) for patterns that are augmented by one-time point (i.e., for patterns of length $m + 1$).

Thus, smaller values of ApEn imply stronger regularity or persistence in a time series. Conversely, larger values signify greater fluctuation or irregularity in a time series. It is computed from the correlation integral $C_i^{(m)}(r)$, which represents the number of points within a distance r from the i^{th} point of the time series when the signal is embedded in an m dimensional space.

ApEn is calculated in the following steps:^[20,21]

Step 1:

For a given data length N , fix the values of m and r , where m is the length pattern and r specifies as a filtering level.

Step 2:

From the original data of length N , form a series of data $[x(1), x(2), x(3), \dots, x(N - m - 1)]$ where $x(i) = [u(i), u(i + 1), u(i + 2), \dots, u(i + m - 1)]$ and $[u(1), u(2), u(3), \dots, u(N)]$ are the original data sequence.

Step 3:

Compute:

$$C_i^{(m)}(r) = \frac{n_{im}(r)}{N - m + 1} \tag{1}$$

where $n_{im}(r)$ = number of $x(j)$ such that $d[x(i), x(j)] \leq r$ and $d(.)$ represents the distance between the vectors.

Step 4:

Compute:

$$\Phi^m(r) = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \log(C_i^{(m)}(r)) \tag{2}$$

Step 5:

Approximate entropy is then calculated as:

$$ApEn = \Phi^m(r) - \Phi^{m+1}(r) \tag{3}$$

ApEn involves the following parameters: the vector length m , the “filter factor” r , and the number of data points N . The value of N for the ApEn computation is typically between 75 and 5000. ApEn measures the logarithmic likelihood that sets of patterns that are close for m -observations remain close on the next incremental comparisons. ApEn characterizes how different segments of the signal with similar recent histories remain similar in the future. As ApEn decreases, the complexity of the signal is low, and determinism is high. Two input variables, m and r , should be fixed to compute ApEn; Here, we selected $m = 3$ and $r = 20\%$ of the standard deviation (SD) of the EEGs as suitable values. These values were chosen to increase the statistical reproducibility of ApEn.^[12,22,23]

Petrosian’s fractal dimension

Petrosian’s algorithm^[24] is used to provide a fast computation of the fractal dimension of a signal by translating the series into a binary sequence. Several

variations of the algorithm exist. These algorithms primarily differ in the way the binary sequence is created. In the former, consecutive samples in the time series are subtracted, and the binary sequence is created based on the result of the subtraction. A “+1” or “-1” is assigned for every positive or negative result, respectively. In the latter algorithm, the binary sequence is formed by assigning a “1” for every difference between consecutive samples in the time series that exceeds an SD magnitude, and a “0” is assigned otherwise. The D is computed as:

$$D = \frac{\log(N)}{\log(N) + \log\left(\frac{N}{n + 0.4N_s}\right)} \tag{4}$$

where N is the series length and N_s is the number of sign changes in the signal derivative.

Results and Discussion

Paired sample t -test was applied on the correct scores (DT1), number of incorrect scores (DT2), and number of omitted scores (DT3). Results showed significant differences in the experimental group for DT1, $t(8) = 2.293, P < 0.05$, where higher mean scores were found for the postexperimental group [Figure 3].

Results showed significant differences in experimental group for DT2, $t(8) = 1.97, P < 0.05$, where lower mean missed scores were found for postexperimental group [Figure 4]. In addition, reduced omitted errors, DT3, were observed for experimental group, $t(8) = 2.596, P < 0.05$ [Figure 5].

Results showed that for the postexperimental condition, subjects had more correct responses. In addition, they had committed fewer errors. Findings implicated that after meditation, subjects were more able to manage their stress compared to subjects in the control group.

For EEG results, we examined changes in the extracted features, ApEn and Petrosian’s fractal dimension (D), of the signal. Paired sample t -test was applied to the extracted features for all 14 channels. Results showed significant

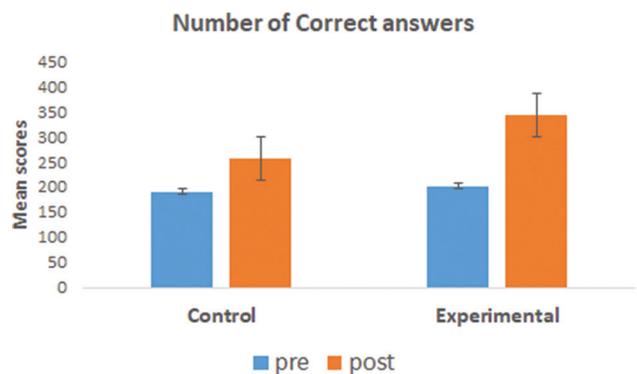


Figure 3: Correct scores between the groups and pre-postcondition. Experimental group had substantial improvement in the correct scores

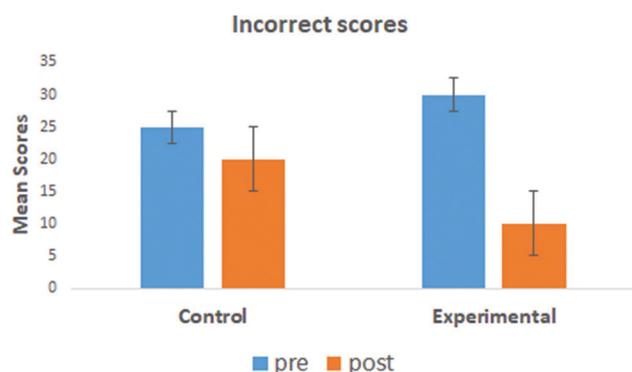


Figure 4: Incorrect scores between the groups and pre–postcondition

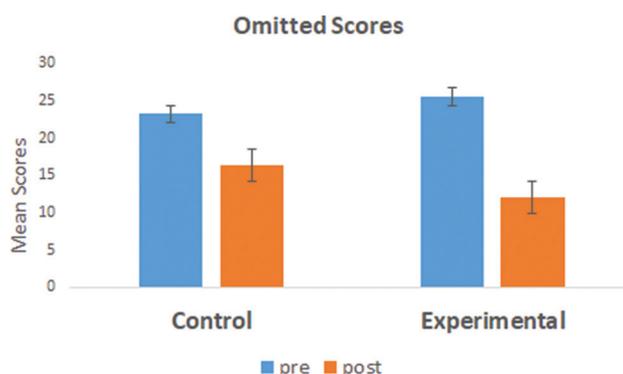


Figure 5: Omitted scores (errors) between the groups and pre–postcondition

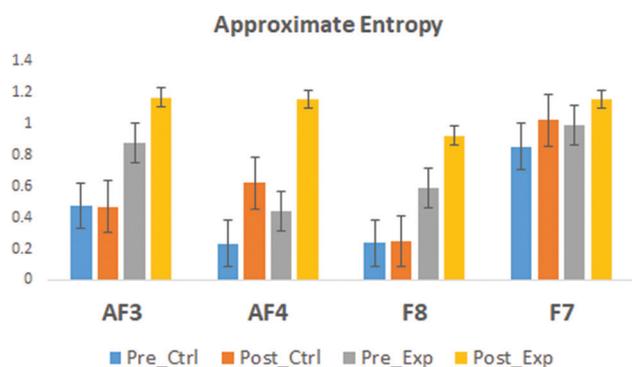


Figure 6: Mean and standard deviation of approximate entropy, averaged over all participants for electroencephalograph channel location, AF3, AF4, F8, and F7, in the two groups (control [ctrl] and experimental [exp]) with two conditions (before meditation [pre] and after meditation [post])

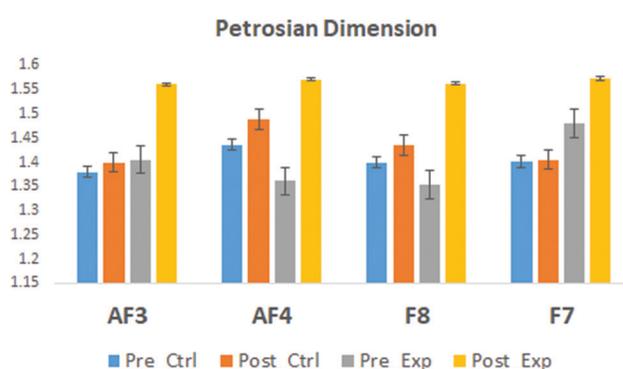


Figure 7: Mean and standard deviation of fractal dimension, averaged over all participants for Electroencephalograph channel location, AF3, AF4, F8, and F7, in the 2 groups (control [ctrl] and experimental [exp]) with two conditions (before meditation [pre] and after meditation [post])

differences for the electrodes in frontal areas: AF3, AF4, F8, and F7 in the experimental group when pre and post-condition were analyzed (at $P < 0.05$). Figures 6 and 7 show ApEn and D, respectively.

During postcondition, ApEn values decreased. ApEn is used to measure the repeatability or predictability within a time series.^[25] ApEn is a nonlinear complexity index that is robust to noise and provides stable results, even when using short data segments, rendering it a potential feature for characterization of EEG signals.^[26] A previous study reported that decrease in the ApEn exhibited more regularity and predictability in the signals.^[27] Results indicated that after meditation, subjects had lesser number of active parallel functional processes, signifying more relaxed state.^[28] Similarly, Petrosian's dimension (D) had shown higher values during postcondition compared to the precondition. Higher values indicated that after meditation, participants were efficiently using required cognitive resources with the better ability to reduce neural noise in the brain. The alert state showed higher complexity of brain activity (as higher values of D) compared to the drowsy state.^[29] In our case, similar results were reported, sustaining vigilance during the stressful condition by practicing meditation. Earlier

studies indicated reduced complexity EEG signals for theta and alpha bands while participants were meditating. Reduction involves “switching off” irrelevant networks for the maintenance of focused internalized attention and inhibition of inappropriate information.^[30] Complexity at the frontocentral region indicates that EEG became high as bioelectric activity turned complex and reached its maximum in wakefulness. Increased complexity of these neuronal interactions in the postexperimental group may be the reason for the higher D values in our results. EEG topographies of beta power from subject-specific reactive bands and occurrence times were displayed to show the distribution on the head [Figure 8]. The topographies were averaged over all subjects. In the experimental group, the distribution of the beta power spectrum had higher activity at frontocentral location after undergoing 1 month meditation training for 30 min daily. However, there were no changes observed in the control group. Significant changes in experimental group showed modulation by task performance. Previous study reported that beta training effects were interpreted as reflecting a tendency toward fast but not necessarily accurate responses due to general arousal increments possibly mediated by increased activation in a noradrenergic alertness/vigilance network of attention.^[31]

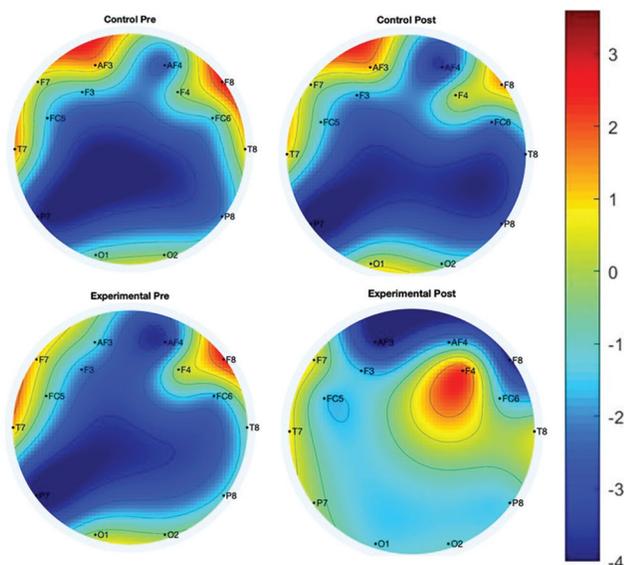


Figure 8: Topoplots showing the topographic distribution of beta bandwidth (16–32 Hz) in the determination test. Red areas represent higher high beta activity, while blue areas represent lower high beta activity. Higher beta activity in frontocentral (especially F4) regions is observed for postexperimental group

Conclusion

In the present study, we provided empirical support for the use of meditation as an effective tool for stress management. In addition, we tried to quantify the changes in the brain signals using nonlinear algorithms. Our results indicated that the efficacy of meditation was reflected with the improved information processing in the brain. Scores in the psychological test were improved, and errors were reduced after using meditation. Increased complexity of beta band was observed for ApEn and D, signifying efficient utilization of cognitive resources while performing the task.

The first limitation for the study could be few numbers of electrodes and lower sampling frequency. Therefore, we cannot claim any causal relationship between hemispheric lateralization or asymmetries. Another limitation could be longitudinal and cross-sectional analysis to assess the quantitative differences. In addition, resting period should be compared with different types of analysis such as event-related synchronization among various cerebral cortex. A combination of both active and resting paradigms should be tested in future trials.

As future work, this method should be validated on a larger database. This includes a collection of EEG signals with increased subject numbers, running different cognitive tasks with a focus on cognitive stress. Altogether, this research is needed to explore the sequence of events in brain activity and the behavioral and physiological changes, as well as the longevity of such a short-term experience.

Ethical clearance

The study was approved by local ethical committee at INMAS.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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