Assessment of attention in real classroom environment: An EEG based study

Abstract

Attention is a critical factor for academic success in the classroom environment. However, any interruption or distraction can significantly affect students' attention levels. The fundamental challenge for both classroom and online learning is to maintain attention in the midst of distractions or interruptions. The present study is an attempt to assess attention level in the classroom setting by using EEG on twenty four students.

Objectives:The study assesses the students' attentiveness in the presence of distractions introduced through the external interruptions during academic lectures and compare distraction-free and manually-distracted lectures. **Method:** Pre-frontal EEG powers are utilized to determine the student's attention index. The significance of attention level variation from non-distracted to distracted lecture and vice versa is tested using one-sample T test at the significance level $p<0.05$. **Result**:Our approach found statistically significant variation in students' attention during classroom lecture, when they are manually distracted. The findings reveal that attention level of students during classroom lecture affects from the distractions and it enhances or deteriorates for different individuals.

Conclusion:The findings suggest that the effect of distractions be considered when assessing students' attention. It alsosuggests that using distraction during a lecture can provide useful information about a student's attention profile. Students' attention is assessed in this manner for detailed profiling to assist teachers in understanding their cognitive processes and needs. However, the approaches described above are not appropriate for virtual learning environments and can be overwhelming when attempting to understand each student's learning style and academic abilities.

Keywords: *Attention Profile, Distraction, Interruption, Learning style, and Prefrontal cortex*

Introduction :

The ability to maintain attention in a classroom learning environment is an important factor in academic achievement, as students with stronger attention skills tend to perform better academically.Studies(Gallen et al., 2023; Ko et al., 2017; Lodge & Harrison, 2019) revealed that the classroom learning requires sustained attention in relevant information while filtering out distractions effectively. Furthermore, due to limited peer interaction, face-to-face communication with teachers, and technology issues introduced duringonline learning in the virtual classroom environment, resulting in social isolation for students. The students get easily distracted by social media, email, or other online activities while taking an online class, which affects their attention and retention. As a result, the presence of distracting information captures attention while also impairing classroom and academic achievement. (Zickerick et al., 2020). Some recent studies (Demirbilek & Talan, 2018; May & Elder, 2018; Wang, 2022) alsopresenteddetrimental effectsof distractions on attention. A recent study(Wetzel et al., 2021) highlighted the age-related impact of auditory novel information on attention and revealed the greater impact of distraction on children than adults. Therefore, the identification of goal-relevant information and focusing on it using limited attentional resources is important aspect of learning (Lindsay, 2020).

Teachers have traditionally assessed students' attention levels during classroom lectures by observing their facial expressions, relying on self-reported feedback, and evaluating academic achievements. There have been few studies that have assessed students' attention levels during classroom lectures by observing their facial expressions. Such as, D'Melloet. al.found differential facial expressions for the states of boredom and confusion during a computer-based learning task, where the study revealed head nods and eye blinks associated with boredom and eyebrow furrowing and head tilts associated with confusion(Lehman et al., 2013).However, a few studies explainthe common methods for measuring the students' attention using self-reported feedback and evaluating academic achievements. Baker et al. revealed the positive correlation between academic achievement and self-reported rating of student's engagement and attention during a lecture measured using a Likert scale or other self-report measure(Baker et al., 2010). Similarly, Yan et.al. found a positive correlation between students' academic achievement andself-regulation and feedback(Yan, 2020).

However, the approaches described above are not appropriate for virtual learning environments and can be overwhelming when attempting to understand each student's learning style and academic abilities. Sustained attention tests have been used to assess the ability of the attention system to maintain a high level of alertness for an extended period of time(Blotenberg & Schmidt-Atzert, 2019). Temporal and spectral features of EEG signals have been widely used to assess the level of attention (Hamadicharef et al., 2009; Horschig et al., 2015; Liu et al., 2013), these studies have reported significant variations in the EEG band powers and their association with the changes in attention level. Studies have found a decrease in alpha power activity during engagement of attentional circuitry and visual attention(Ergenoglu et al., 2004; Kelly et al., 2003; Klimesch, 1999; Uusberg et al., 2013). The time-frequency analysis on EEG signals has been usedin several studies(Bauer et al., 2014; Haegens et al., 2014)to estimate attention indices of volunteers by analyzing different frequency bands such as theta, alpha, and beta. Multiple indices have been proposed and employed(Al-Nafjan & Aldayel, 2022; Fahimi et al., 2018; Jin et al., 2019; Rajan et al., 2019; Toa et al., 2021; Wan et al., 2021), including β/α, $\beta/(\alpha+\theta)$, and $1/\alpha$, which are extracted during attention tasks or lectures.These indices are designed to represent the attention of volunteers in the task by taking into account the characteristics of different EEG band powers. The Beta frequency band, in particular, is linked to an increase in mental task-related brain activity, as well as visual and motion planning activity. Increases in Alpha and Theta activity, on the other hand, are associated with decreased mental vigilance and alertness. These findings imply that changes in EEG band powers can provide useful information about an individual's cognitive state during a task or activity.

In this paper, we use an EEG headset to compute students' attentional engagement in a classroom setting. We also compare distraction-free and manually-distracted lectures, as well as their attentiveness in the presence of distractions introduced by external interruptions during academic lectures. EEG band powers (theta, alpha, and beta) are estimated using EEG data collected from multiple students during classroom lecture in both contexts, distraction free lecture and manually distracted lecture, to assess students' attentiveness. Our findings show that distracting contexts influence students' attention levels, emphasizing the importance of taking distractions into account when assessing students' attention. A detailed profiling of students' attention levels in the presence and absence of distraction during a classroom lecture will undoubtedly assist teachers in understanding their cognitive processes and needs.

Materials and methods:

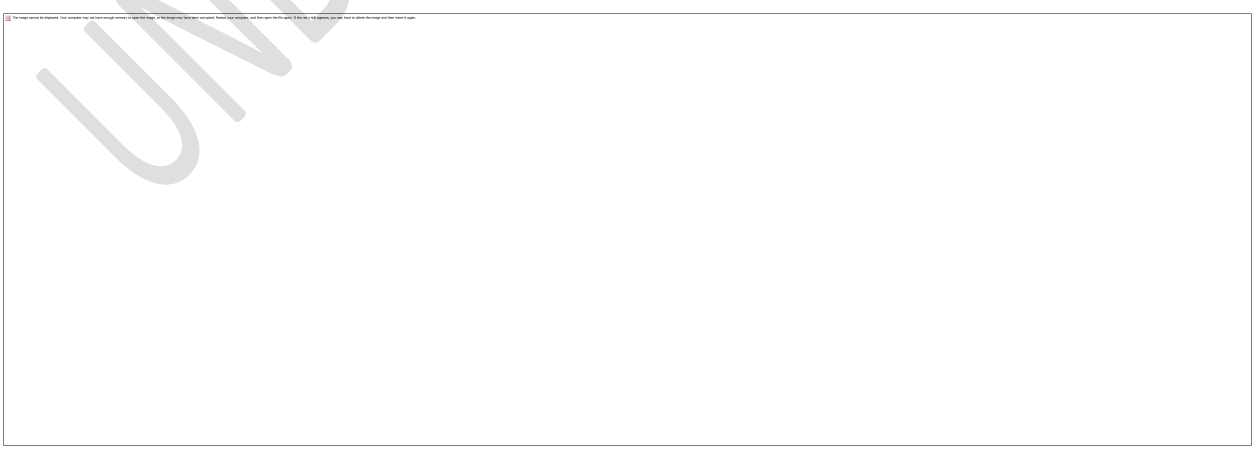
Participants:

Twenty-four subjects (14 males, 10 females, mean age: 14years) participated in the study. All subjects wereright-handed and had normal or corrected-to-normal vision. They were informed about the purpose of this experiment and signed the informed consent forms before participating in the experiments. None of them suffered from a chronic disease, mental disorder, drugs or alcohol abuse, depression or anxiety, hearing defects or neurological disorder at the time of experiment and none of them were on medication. All experiments involved non-invasive safe procedures and resembled a computer survey while using the non-invasive commercially-available EEG devices. The procedures were also described in the recruitment phase, where students and staff of several academic institutions were offered to participate in experiments involving EEG BCI.

Stimuli:

To access the sustained attention of school students, the experiments are carried out in classroom environment. In this, a lecture of Physics subject was designed and presented to the student in audio-visual presentation in a meaningful and simplistic way. The course content was designed as per their curriculum. The participants were instructed at the beginning of the experiment to pay attention to the lecture for good academic performance.

All subjects' data were collected at three stages of each experimental trial: pre-task eyes closed for 60 seconds, multiple trials of lecture, and post-task eyes closed for 60 seconds. Experiment tasks included a total of 10 minutes of audio-visual lecture presentation, as shown in Figure 1.



During the lecture, participants were interrupted by asking them basic questions about the ease of the experiment, their interest, understanding of the lecture, and so on. The students were only distracted for 15 seconds; no other distractions were used in the study. To avoid any impact on coursework scoring, experimental results were kept confidential.

EEG data acquisition:

EEG was recorded using the Emotiv Insight 2.0 headset consisting of 5 monopolar felt-based gold-plated electrodes placed approximately in locations AF3, AF4, T7, T8, Pz according to 10–20 system. The impedance of the electrode contact to the scalp was visually monitored using Emotiv Control Panel software. The data were digitized using the embedded 16-bit ADC (0.1275μV step for 8400 mV dynamic range) with 128 Hz sampling frequency per channel and sent to the computer via Bluetooth.The pre-frontal area is representedin Emotiv by electrodes AF3, and AF4. These two electrodes are of main interest in ourresearch. Each time, the headset was carefullypositioned, it wasespecially difficult for participants with smaller heads and/or thick hair. The additional common mode sense (CMS)electrode on the left mastoid is the global reference channel,and the driven right leg (DRL) electrode on the right mastoid isused as a feedback for noise cancellation.

EEG-Preprocessing:

The pre-processing analyses were carried out using Python 3 with NumPy and SciPy packages. Firstly, a notch filter at 50 Hz, based on IIR filters is applied to remove the background noise. Further, to identify the channel's malfunction and unusablenoisy data, channels are marked as 'bad channel' without deleting from data. Following the bad channel rejection, raw EEG data is subsampled to 125 Hz and re-referenced to the one common average reference to and reduce environmental noise. Further, to remove a direct current offset and high-frequency muscle activity, channel data isfiltered with a high-pass 0.5 Hz and subsequently with a low-pass 30 Hz. EEG segments were then segmented as per events of interest. For this, 1-s segments for whole lecture duration with 200ms prior are extracted for baseline correction. Epochs were then baseline corrected by subtracting the -200 to 0 milliseconds pre-stimulus baseline from all data points in the epoch. EEG trial epochs were then corrected for eye movements and blinks based on the electrooculogram channels. For the correction of ocular artifacts, first eye blinks are detected in EEG channels by computing the projections and then detected information is applied to filtered data. The projection commutation and their application of filtered data returns the effect of eye blinks during data collection. For this, it uses band-pass filter from 1-10 Hz on prefrontal channel. The artifact collected is further analyzed.

Data Analysis:

Time-Frequency Analysis:

The EEG data for prefrontal channels (AF3 and AF4) associated with whole lecture (10 minutes)were segmented into 1-s epochs spanning300 milliseconds before the tone onset to 1 secondafter it. Trials where the distractions were introduced were labelled as distracted-lecture phase and rest as lecture phase.The study employed a Morlet wavelet analysis to the EEG epochs to examine the oscillatory powers associated with the alpha, theta and beta oscillations during lecture in classroom setting. The Morlet wavelet is a complex wavelet, comprising real and imaginary sinusoidal oscillations, that is convolved with a Gaussian envelope so that the wavelet magnitude is largest at its center and tapered toward its edges. It is defined by setting parameters for the general ‘‘mother wavelet,’’ which is then used to generate the family of wavelets covering the frequencies to be extracted during the spectral decomposition of EEG data. To focus on theta (4–8 Hz), alpha (8–13 Hz) and beta (13–30 Hz) bands, the study limited the frequency range examined to 4–30 Hz. It also limited the time of interest to a range beginning at -200 milliseconds pre-stimulus to 1000 milliseconds post-stimulus.

Assessment of attention duringclassroom lecture:

The attention level of students in classroom lecture is calculated by estimating the attention index derived from pre-frontal EEG powers (AF3 and AF4 channels). The index value determines whether students are attentive or inattentive during the classroom lecture. For this,attention index was computed using theta, alpha, and beta band powers as:

$$\text{Attention index} = \text{Beta}/(\text{Alpha} + \text{Theta})$$

Computation of attention index was suggested as alpha–beta–theta ratio (ABTR) by Daniele (Szafir & Mutlu, 2012) and Wang (Wan et al., 2021).The spectral powers-based attention index was calculated for the whole 10-minute lecture recording and provided index values for every second of recorded signal.

Estimation of variation in level of attention:

To explore the variations in the attention level in classroom lecture, change of attention indices for lecture to distracted-lecture phases are estimated and subjected to theone sample T-test for statistical significance at $p<0.05$. For this,lecture phase is sub-divided into three subparts as start (15 seconds), mid (15 seconds) and end (15 seconds) of the phase, the attention indices calculated for each lecture phase (15 seconds) and variations are estimated from distracted-lecture phase(15 seconds).Multiple trials consisting of lecture and distracted-lecture phases for each volunteer are studied to understand any significant variation in attention level with the distraction.

Results and discussion:

EEG activity is recorded using an Emotive headset during a real classroom lecture lasting approximately 10 minutes to monitor students' dynamic attention levels in the classroom (Fig. 1). The artifacts corrected data is investigated for consistency and reliability. Previous research efforts have shown that time frequency analysis has the potential to assess the level of distinct cognitive states of human volunteers (Morales & Bowers, 2022). Therefore, the study first used time frequency analysis to calculate the EEG band powers for the lecture and distracted-lecture phases. The baseline is set to prior and post lecture recordings for this purpose. Figure 2 depicts the topographic distribution of EEG spectral power during various stages of a classroom lecture.

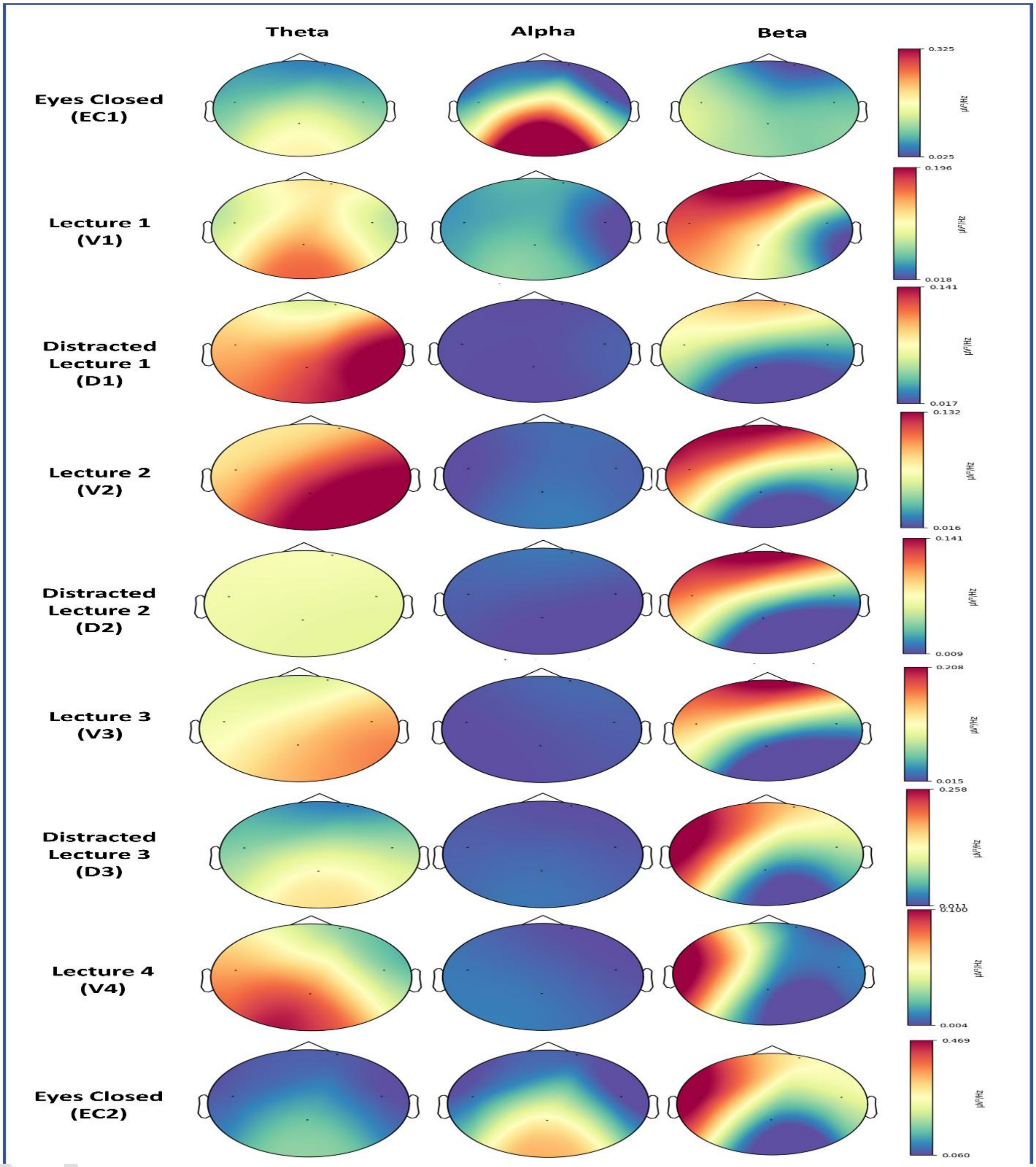


Figure2: Condition under different wavelength

The graph depicts normalized alpha, theta, and beta EEG powers, as well as changes from closed eyes to lecture and distracted-lecture phases. Additionally, the attention level of students is studied using pre-frontal EEG powers to determine the student's attentiveness or inattentiveness during the classroom lecture. The attention index is a combination of alpha, theta, and beta powers that has been used in several studies to assess attention level(Al-Nafjan & Aldayel, 2022; Fahimi et al., 2018; Jin et al., 2019; Rajan et al., 2019; Toa et al., 2021; Wan et al., 2021)**.**The detailed attention level analysis revealed variations in the attention index values during the lecture. The hypotheses were tested using a one-sample test analysis, and the prediction was that incorporating manual distractions or interruptions during the lecture would result in noticeable changes in attentiveness. These changes could manifest as either increased attention or a shift towards inattention.

The study observed a statistically significant variation in students' attention levels when comparing distracted-lectures to lectures without any distraction. The one-sample T test is used to assess the significance of variation in attention level from lecture to distracted-lecture and vice versa. Table 1 shows significant relationships (t-values) at the $p<0.05$ significance level. The findings show that distractions affect students' attention levels during lectures, which improves or deteriorates for different individuals. The variation in attention from difference phases on individual volunteers (volunteer 1 to volunteer 24) are tabulated in table 1and Table 2 and that explains the variation of attention level from eyes closed to non-distracted lecture (EC1-V1), non-distracted to distracted lecture (V1-D1) and so on. Nonsignificant resultsarenot shown in table and marked with zero(0).

Table 1: Significant variations in attention level changes for 24 volunteers in classroom lecture at the significance p<0.05.

	Eyes closed to lecture (EC1-V1)	Lecture to Distracted Lecture (V1-D1)	Distracted Lecture to Lecture (D1-V2)	Lecture to Distracted Lecture (V2-D2)	Distracted Lecture to Lecture (D2-V3)	Lecture to Distracted Lecture V3-D3	Distracted Lecture to Lecture (D3-V4)	Lecture to Eyes closed (V4-EC2)
Vol1	8.782	3.804	0	6.190397	-9.65407	4.429693	-3.27281	-6.9645
Vol2	2.69734	0	0	0	0	0	-2.36454	-4.93517
Vol3	0	0	3.264939	0	0	-5.04662	-3.95046	-5.42611
Vol4	5.947831	3.871233	-4.53225	2.55262	-2.66992	0	-3.9648	-2.83212
Vol5	-4.64388	-8.16591	-2.99468	0	0	0	4.784378	2.81087
Vol6	-4.47169	3.895586	3.297482	0	-3.00861	3.315086	-4.64354	-14.1232
Vol7	-4.47169	4.009696	3.422008	0	-3.36293	3.314299	-4.64354	-14.1232
Vol8	-3.16976	-2.51486	-3.69304	2.491917	-5.85358	-2.55243	-2.68244	2.522887
Vol9	-3.16976	-2.51486	-3.69304	2.491917	-5.85358	2.912629	-2.68244	2.522887
Vol10	0	0	0	2.24493	0	2.634439	0	0
Vol11	0	0	3.7469	-2.21437	-4.07267	-3.33822	-2.36825	-2.2825
Vol12	-3.16976	0	3.688878	-2.46581	-4.15052	-4.51214	-	2.75578
Vol13	-2.44053	4.686421	3.857015	2.645378	-7.08565	-5.07288	6.41974	-2.39804
Vol14	3.715386	-2.77508	-5.11466	-7.37454	6.089454	5.217872	0	-2.85522
Vol15	2.90794	3.374399	-3.32353	2.786	0	0	0	2.333166
Vol16	-4.74183	3.552221	-3.08171	0	0	-2.2111	4.291465	3.764601
Vol27	-2.83132	-2.57234	2.234868	0	0	0	0	2.733425
Vol18	0	3.07681	-8.01868	-2.26243	0	3.14452	-3.56645	0
Vol19	0	-2.68217	7.539907	0	-3.89633	-2.73231	2.597996	-4.07637
Vol20	-4.96519	3.739135	-5.774	5.224919	-3.21282	-3.69292	0	4.95922
Vol21	2.732572	0	0	0	0	3.047009	-2.76869	-2.84466
Vol22	-4.78577	2.645208	-2.44329	8.405429	-7.35608	3.049074	-4.64448	-5.98498
Vol23	2.705404	0	-3.60795	4.921672	-3.24774	0	-2.28703	0
Vol24	2.705404	3.499264	-2.83286	2.699448	0	2.209612	0	-2.48033

Table 2: Group results: Significant variations in attention level changes in classroom lecture at the significance $p<0.05$.

Eyes closed to lecture (EC1-V1)	Lecture to Distracted Lecture (V1-D1)	Distracted Lecture to Lecture (D1-V2)	Lecture to Distracted Lecture (V2-D2)	Distracted Lecture to Lecture (D2-V3)	Lecture to Distracted Lecture V3-D3	Distracted Lecture to Lecture (D3-V4)	Lecture to Eyes closed (V4-EC2)
-2.330	-2.656	2.204	-4.467	8.356	-3.748	3.556	3.687

Inter subject analysis shows different directionality through the positive and negative values and suggest varying individual's cognitive behavior. Different cognitive behavior refers to the increase or decrease in attention level during different phases of a lecture. Except for volunteer 10, the findings show significant differences.

The findings demonstrated the capability of EEG technology to assess students' attention levels in a classroom setting. The current study sought to examine students' attention levels in the classroom under normal and distracting conditions. During the lecture, it is found that all of the students' EEG powers and estimated attention levels varied significantly. The audio-visual oddball paradigms are used to investigate the previously mentioned distraction (Escera et al., 2000; Wetzel et al., 2012; Wetzel &Schröger, 2007, 2014).Later, several studiescharacterized the impact of irrelevant salient sounds as distraction on ongoing task in children and resulted as allocation of attention and resources to salient sound and then a reallocation of attention and resources towards the task (Bidet-Caulet et al., 2015; Escera et al., 2000; Näätänen, 1992). Further studies revealed the behavioral benefits due to burst of phasic arousal according to the sound properties (Bidet-Caulet et al., 2015; Masson & Bidet-Caulet, 2019; Max et al., 2015a; Näätänen,91 1992; Wetzel et al., 2012). The current study has shown that attention level estimation is robust to inter-subject variability. The study investigated whether any manual distraction could be a driving force behind the change in the attention level of students and found that distraction during lecture drive a significant variation in neural engagement of frontal brain regions. In all the transitions from non-distracted lecture to distracted lecture and vice versa, students showed significant attention differences. This difference obtained due to transition of phasescould be explained by the fact that the any distraction during attentive task lead to affect the underlying cognitive processes. Distracting events are referred as potential threat to the reliability and validity of any assessment procedure by interfering with an individual's ability to complete a task at peak performance.Earlier studies have shown the effect of interruptions and distracting events on attention levelleading to the disengagement in ongoing task. Specifically, cognitive tasks such as visuo-spatial and working memory tasks have shown detrimental effects of distraction in earlier studies (Lavie,2005;Tremblayetal.,2005). Later, study(Wyss et al., 2013)observed that the toddlers with no-distraction condition were more attentive, with high sustained attention level during session. However, the toddlers in thedistraction condition increased their attention to the task and decreased theirattention to the distractor in the second half of the session. Further another study(Nagaraj, 2021) found thatmore efficient processing deployed in the presence of noise appeared to have led to improvements in working memory performance and making inferences in a listening comprehension task.

In traditional classroom learning, environment is designed forminimal interruptions. However, virtual learning environment is with enormous interrupting events capable of triggeringirrelevant thoughts. In this case, students distract more by the presence of task-irrelevant information and activities such as YouTube bookmarks advertisements and suggestions constantly and sooner or later divert the attention. Therefore, there is a crucial need to design ideal online learning environment capable of minimizing the presence of potential distractions and maintaining their focused attention. Hence, teachers must aware of distractions and their effect on students for strategizing and helping distracted students.

The current studysuggestsconsidering the effect of distractions and interruptions for assessing students' attention. It also suggestsdesigningattention checking protocols under distracting contexts.For example, when any individual student isdistracted during lecture, individuals with a strong attention towards lecture may be better sustainability compared to those who have either expertise or least interest in the lecture. In distracting contexts, the dynamic nature of allocation behaviors, (Atkinson & Birch, 1978) is observed. As a result, the findings suggest that using distraction during lectures provides useful information about students' attention. It also implies that while investigating students' attention profiles in the classroom, individual differences with the introduction of distractions is a way to better understand attentional demands.

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