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Automatic Clustering of Students by Level of Situational Interest Based on Their EEG Features

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Abstract: The usage of physiological measures in detecting student's interest is often said to improve the weakness of psychological measures by decreasing the susceptibility of subjective bias. The existing methods, especially EEG-based, use classification, which needs a predefined class and complex computational to analyze. However, the predefined classes are mostly based on subjective measurement (e.g., questionnaires). This work proposed a new scheme to automatically cluster the students by the level of situational interest (SI) during learning-based lessons on their electroencephalography (EEG) features. The formed clusters are then used as ground truth for classification purposes. A simultaneous recording of EEG was performed on 30 students while attending a lecture in a real classroom. The frontal mean delta and alpha power as well as the frontal alpha asymmetry metric served as the input for k-means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithms. Using the collected data, 29 models were trained within nine domain classifiers, then the classifiers with the highest performance were selected. We validated all the models through 10-fold cross-validation. The high SI group was clustered to students having lower frontal mean delta and alpha power together with negative Frontal Alpha Asymmetry (FAA). It was found that k-means performed better by giving the maximum performance assessment parameters of 100% in clustering the students into three groups: high SI, medium SI and low SI. The findings show that the DBSCAN had reduced the performance to cluster dataset without the outlier. The findings of this study give a promising option to cluster the students by their SI level, as well as address the drawbacks of the existing methods, which use subjective measures.

Keywords: student's situational interest; classroom learning; EEG features; k-means clustering; DBSCAN clustering

1. Introduction

The existence of a close relationship between interest and learning has been recognized by literature as early as the beginning of the 19th century. Interest theorists believed that promoting interest in the classroom increases students' essential motivation to learn. They had differentiated between two main types of interest: situational interest and personal interest. Situational interest (SI) appears in response to features in an environment and can be activated immediately [1,2]. In contrast, personal interest has a less spontaneous and dispositional quality and resides in the person across situations. Although research on situational interest in educational psychology has been expanding in the beginning of 20th century, there is a lack of focus on how general contextual factors, such as the condition of the classroom or the type of instruction, can stimulate interest in learning.

The current methods used to assess interest can be divided into two: (1) psychological measures and (2) physiological measures. Usage of a text-based method as one of the psychological measures for situational interest is limited to individual student assessment. This method is not assessing the situational interest within the actual classroom environment. Self-reports and questionnaires are also commonly used tools in psychological measures; however, these tools are known for being susceptible to subjective bias [3]. Mitchell [4] has developed one of the recognized questionnaires to measure situational interest in mathematics classrooms among secondary school students. Rotgans [5] found situational interest is positively related to knowledge acquisition. Fuller [6] highlights a deceptive performance of the self-report assessment method due to students pretending to engage.

Alternatively, physiological measures, such as EEG, Pupil Diameter, and Electrocardiogram (ECG) had overcome the drawbacks of psychological measures. A detailed discussion on the usage of neurophysiological over the traditional methods in experimental design can be found in Borgianni [7]. Not only due to its portability, high temporal resolution, non-invasiveness, and low cost, the EEG is also capable to quantify subjectivity in evaluative situations [8]. The results obtained from EEG cannot be manipulated by participants and this method does not require an interruption during performing the task with the participant's attention, interest, or the session flow [9]. Studies showed that EEG has been increasingly used in interest research related to preference during web searching and advertisement [10,11]. The EEG has also been used to examine the relationship between precursor emotions towards student enthusiasm in learning mathematics and science [12]. This work will positively explore the assessment of situational interest in real classroom settings using the EEG precisely.

Rather than personal interest, this study focuses on SI, since it can have a spontaneous impact on students' learning. It can be effectively activated and assessed using physiological detectors. From Hidi [1], it was reported that the students that accomplished situational interest were better in recalling thought and elaboration. Logical thinking recommends that if the interest of a student is piqued when learning a topic, the student will participate more enthusiastically with that topic when compared to another student who is less intrigued by the topic. Greater commitment will be invested, which would lead to higher academic achievement.

"Situational interest is construed as a motivational response to a perceived knowledge deficit" [5]. Psychological researchers found that situational interest comprises together an attentional and effective reaction to the situation [1,4,13]. Many studies reported the examination of these two aspects alone, but the question of how effective the study is if one of the important elements of SI is abandoned. For example, Sharma [14] observed the influence of SI in increasing an individual's attention but did not examine the effects on the effective reactions. In an EEG-based study on attention, Womelsdorf [15] found that alpha wave synchronization reduces during the attentional process. Both studies did not observe the effects of SI on effective reactions. Other studies have examined students' motivation to learn in response to positive feelings presented in class. For example, Moldovan et al. [16] examined effective states on learning performance in a multimedia-based mobile learning scenario. However, this study did not examine the influence of attentional reactions on SI. Due to these constraints, this study is motivated to provide findings that integrate the cognitive attention and effective motivation of interest during learning. Hence, by measuring motivation and attention, both elements of situational interest will be measured.

In monitoring and examining the level of interest, most of the studies used a combination of questionnaire and classification models to approve, classify, or validate the findings based on physiological sensor data. Among them is the study from Nor et al. [17], which claimed that using neural network multi-layer perceptron (MLP) to examine the features of EEG activity captured while answering mathematics and science questions, it might be able to know the student's interest. A support vector machine (SVM) and MLP were used with self-report on academic emotion prediction based on brain signals, mouse habits, and personality profiles [18]. The classification method's robustness is undeniable; however, this technique requires a complex computation to obtain the output. Furthermore, this method needs predefined classes mainly based on subjective evaluation, which make it impossible to group the data immediately. Thus, to seek the most favorable balance method between uncomplexity and resolve the limitations of existing methods that rely on subjective measures, we suggest the usage of clustering methods to obtain an automatic clustering scheme of situational interests using EEG.

Clustering had been used in classroom assessments. The k-means was used as a prediction of students' academic performance [19], as well as an evaluation model of student's learning outcomes [20]. A study used DBSCAN clustering to cluster the students based on their examination performance in various subjects [21], while fuzzy k-means were used in measuring the accomplishment of Course Outcome in Higher Educational Institutes [22]. In this study, we applied k-means and DBSCAN based on EEG features to assess the SI level of students. The choice of DBSCAN and k-means was motivated by their simplicity and their performances in various fields of previous studies. Since we are expecting the students will be clustered into three classes (high, medium, and low SI), the use of k-means is appropriate. However, if the number of SI classes is unknown, there are other possible clustering methods like hierarchical clustering and Gaussian model that could be used. Good works of literatures can be referred to in Dinh [23] and Jia [24]. The advantage DBSCAN is known to be good in outlier and noise detection. We use density-based clustering specifically DBSCAN to investigate whether the noise will reduce the performance of overall results. This paper proposed a simple framework by replacing subjective bias of psychological measures with clustering method using established k-means and DBSCAN algorithm to be used as predefined classes to classify the students based on their SI level during learning in the class. The contributions of this paper are summarized as follows:

- Contribute to further efforts to integrate EEG and clustering methods on automatically clustering the students by the level of SI in real classrooms.
- The results from clustering methods were then validated for their performance efficiency using a supervised machine learning classifier, and
- The best combination EEG feature-clustering algorithm-classification model is proposed as the scheme to cluster the situational interest automatically during classroom learning without relying on questionnaires.

The remaining section of this study is arranged as follows: Section 2 describes the related work about detecting SI, Section 3 discusses the details methodology, Section 4 presents the results, Section 5 discusses the findings, list the limitations of the study and suggestions for future work, and finally Section 6 summarizes the conclusion.

2. Related Work

A suggested technique to evaluate the student's situational interest is by assessing their attention when the teachers or educators delivered their presentation. A study from Ko et al. [25] showed that EEG beta and theta power ratios were used to distinguish attentive and non-attentive students. Across students and sessions, prolongation of the response time was preceded by an increase in the delta and theta EEG powers over the occipital region, and a decrease in the beta power over the occipital and temporal regions. Meanwhile, Palva [26] reported that attention was indicated by attenuation or reduction of alpha frequency.

Since the EEG features for detecting situational interest during learning have not been well studied, our study stands with the hypothesis on inhibition of alpha frequency as an indication for attention. Besides, the delta band was discovered to be useful in assessing students' situational attention during learning in classrooms [27]. Mohamed et al. [28] found the beta power is manifested in healthy students during focused attention and Ko [25] reported a decrease in beta power during sustained attention. However, these authors set up their experiment by giving the students a visual cognition task and instructing them to stay alert and press the button corresponding to the given stimuli. It contrasts with our study, where the students were instructed to act normally as they were in the real classroom. Therefore, the later analysis will only be focused on the delta and alpha power.

In terms of a brain region, the activities in frontal lobes were found to be significant for the recognition of interest and numerical operations [29,30] and arithmetic tasks [31]. By referring to the EEG electrode's location, Yaomanee et al. [32] and Bono et al. [33] suggested that F3 was one of the ideal locations to gauge the inhibition of alpha frequency during attentional tasks, compared to the relaxation state. Since our aim is to explore the attentional reaction aspect in situational interest, we narrowed down our focus onto the frontal area, represented by the electrode channels of F3 and F4.

In addition, frontal EEG asymmetry has frequently been studied concerning the motivational or emotional states. Early research by Davidson et al. [34] using the Frontal Alpha Asymmetry (FAA) analysis focused on effective manipulations within the stimulus material, reporting negative FAA metrics (interpreted as larger relative left-hemispheric activation) for positive stimuli, while reporting positive FAA metrics for negative stimuli. However, the use of FAA analysis as a predictor tool, which would be desirable for applied contexts such as marketing research, product design, or brain-computer-interfacing (BCI) is inadequate [35]. In the context of learning, Rajanen et al. [36] have applied FAA as an index of approach/withdrawal motivation, during the natural reading of a newspaper on the traditional print medium and a tablet computer.

A review from Soni [37] reported that there was a relationship between the ability of focus attention and screen-out emotional distractions. The more unfocused we are, the more the prefrontal cortex inhibits a phase-locking response to external stimuli. In his book, Gazzaniga [17] had concluded that emotion regulation was dependent on the interaction of frontal cortical structures and subcortical brain regions. Based on the literatures that describe the emotion, which integrated into cognitive control, occurring at prefrontal and frontal area of the brain [17,37], we further examined the alpha asymmetry in this region.

We hypothesize the increases in delta and alpha power in the frontal brain region are correlated to the reduction of cognitive attention and low situational interest in learning the topics. We hypothesized negative alpha asymmetry metric at the frontal region as being associated with positive emotion that increased the interest in learning. In this study, the FAA was employed for the first time as a tool to assess the effective reaction in SI to the situation, especially in the classroom learning setting.

3. Methodology

This section describes in detail the participant's information and stimuli that had been given to the participants. The analysis steps on EEG signals were discussed. Moreover, clustering algorithms and classification models used were briefly introduced. Figure 1 presents the flow of experiments completed in this study.

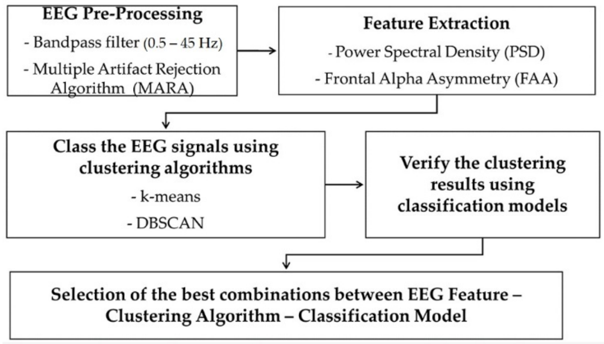


Figure 1. Suggestion scheme to cluster the situational interest automatically during classroom learning.

3.1. Dataset

For this study, we used the dataset of Experiment 2 and Experiment 3 from Babiker et al. [38]. The dataset was chosen based on careful inspection of the experimental design. Each experiment was conducted in two similar sessions. Overall, 30 (M:26, F:4) volunteered undergraduate students, whose ages were between 18 to 25 years of age from the Universiti Teknologi PETRONAS (UTP), had participated in this experiment. The participants were first-year undergraduate students from different engineering disciplines. In this study, the EEG data from 30 students that were given the same Laplace Transform lecture presentation topics were chosen for analysis. However, the other 13 students from the original dataset source were excluded, as they were given different lecture topics.

One student's data was excluded from the analysis due to technical errors. Each student contained the acquired signals, while performing the following blocks: 4 min of eyes closed, 4 min of eyes opened and 22 min of the learning task. Upon arrival in the experiment room, the students were given explanations about the experiment and signed consent forms. The EEG signal was recorded by using Enobio 8 channels headset with a 500 Hz sampling rate. The channels used were: FP1, FP2, F3, F4, T7, T8, Pz, and P4. Since our objective is to allow for later determination of the level of situational interest, only EEG signals during the learning task were used.

3.2. Stimuli

In this subsection, we briefly discuss the original experiment flow used on the students. Upon the arrival of participants, they signed informed consent and completed a pre-knowledge test, as well as a Personal Interest (PI) survey. This was performed to verify that there was little to no knowledge of the presented topic, as well as to confirm the degree of PI. The EEG was captured while the students were given an approximately 22 min lecture on Laplace Transform, where interesting elements in the presentation slides were introduced (i.e., colors, fonts, and animations). A total of 16 subtopics were designed in a way to trigger situational interest in students, as shown in Figure 2.

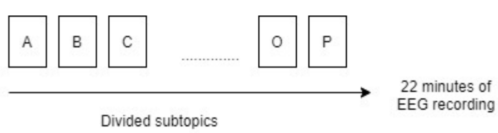


Figure 2. Subtopics in the lecture's presentation.

The presentation began with an introduction to the Laplace Transform, the learning objectives, an explanation on the definition, notation, and example of the topic. Then, the students were given challenge questions, the summary, and the application of Laplace Transform. Once the experiment was completed, a self-report questionnaire score was obtained to rate the level of interest in the presentation of the subtopics delivered. A 5-Likert presentation questionnaire was designated, based on the subtopics to identify which were the most interesting subtopics for each student.

3.3. EEG Data Analysis

3.3.1. EEG Pre-Processing

The EEG signal was filtered using a bandpass filter between 0.5 Hz to 45 Hz. In the author's dataset, the signals were epoched 460 s out of 22 min presentation. Rotgants [2] reported that "if one wishes to quantify situational interest, one must select a unit of analysis that is sufficiently small." Therefore, in this study, the signal was segmented according to subtopics during the presentation. We realized each subtopic has an impact to situational interest. However, the subtopics were not chosen based on the results of questionnaire. These subtopics were rather chosen based on the durations. We chose two subtopics that had different durations, and the other two subtopics that had the same durations. The clustering results were not compared to the questionnaire. The detail of the selected subtopic's length is tabulated in Table 1.

Table 1. Subtopics of the delivered Laplace Transform lecture.

Subtopic	Details	Length (s)
D	Definition of Laplace	124
F	History of Laplace Transform	142
H	Unit step function	68
I	Challenge question	68

Since the obtained raw EEG was contaminated with noise and artefacts, such as electrooculography (EOG), electromyography (EMG), power frequency interference, etc. it was necessary to pre-process the data before performing the multi-feature extraction. Artefacts were eliminated using the Multiple Artifact Rejection Algorithm (MARA) [39]. It is an open-source MATLAB-based EEGLAB [40] plug-in that automatically recognizes the artifact-contaminated independent components for artefact rejection [39,41]. The MARA can deal with a wide range of electrode configurations, time-consuming, and can identify multiple types of artefacts with a high reliability [41]. The artefact rejection process was made only after the signal was segmented into the subtopic to ensure that each student had the same signal length, in the respective subtopic.

3.3.2. EEG Power Spectral

EEG signals have changes that cannot be shown solely in the temporal domain. To extract these fluctuations, we converted the obtained EEG signals to the frequency (spectral) domain. The Fast Fourier Transform (FFT) was applied, and the raw EEG signal was decomposed into delta (0.5–4 Hz) and alpha (8–13 Hz) frequencies. The power was calculated using Welch's [42] periodogram method and the Hanning window function [43]. Power spectral density (PSD) [42] was calculated to obtain the absolute power for each frequency band.

The average of the squared Fourier transform of the EEG signal is shown in Equation (1). Denoting the m th windowed frame from the signal x by:

$$x_m(n) = w(n)x(n + mR), n = 0,1, \dots, M - 1, \qquad m = 0,1, \dots, K - 1$$

where R is the window *hop size*, the periodogram of the m th block, and K number of frames can be written as:

$$P_{x_{m,M}}(w_k) = \frac{1}{M}\left|\sum_{n=0}^{N-1} x_m(n)e^{-j\frac{2\pi kn}{N}}\right|^2 \tag{1}$$

The Welch estimate of the PSD can then be obtained by averaging the periodograms of successive blocks as shown below:

$$\hat{s}_x^w(k) = \frac{1}{K}\sum_{m=0}^{K-1} P_{x_{m,M}}(w_k) \quad (2)$$

The averaged power was calculated for single channel F3 and F4 and then the power was averaged across the frontal region.

3.3.3. Frontal Alpha Asymmetry Analysis

The FAA was analyzed to see whether it could be used as an effective reaction predictor of situational interest during real classroom learning. The FAA has been described in detail by Allen et al. [44] as a specific approach to evaluate EEG data. The alpha signal was a natural log adjusted to lessen kurtosis and positive skewness. The FAA was calculated using the following equation:

$$\ln(R) - \ln(L) \quad (3)$$

The FAA metric is determined to summarize the difference between relative activity at right hemispheric to the left hemispheric. Hence, positive FAA values denote higher relative right-hemispheric power, which reflects greater cortical activation compared to the left hemisphere. In this study, the FAA was determined at prefrontal region (FP1 and FP2) and frontal (F3 and F4) regions. The overall FAA of the frontal region was calculated by averaging the FAA at FP1-FP2 and the FAA at F3-F4.

3.4. Clustering Analysis

In this study the classes of the EEG data were unknown. Thus, we utilized an unsupervised learning approach. The clustering algorithms used in this study were k-means and DBSCAN. The choice of DBSCAN and k-means was motivated by their simplicity and their performances in various fields in previous studies. Overall, three features were analyzed. These features were multiplied by three different channel locations and four different subtopics. Each feature vector was applied to the k-means and the DBSCAN algorithm. Students' situational interest level clustering results had produced the output of the proposed framework. The complexity of the proposed framework was measured by the amount of time required by the algorithm to run an input of a given size (n).

The objective of the k-means method is to label n number of points into k groups or clusters, in which the sum of distances between each point belongs and the centroid is minimized. The algorithm was adopted from Arthur [45]. The optimal number of data clusters was evaluated using silhouette criterion values. In this study, k-means was chosen as a clustering tool, since this approach is widely used in the literature related to EEG [46–48] with the highest accuracy of 98.80%. Besides, the k-means algorithm can guarantee convergence and is able to manage dataset that consists of variable density clusters [46].

Conversely, DBSCAN defines clusters depending on density connectivity and density reachability among data points. The input parameters of the algorithm are the radius (ε) and the minimum number of objects in it (*MinPts*). The *MinPts* were selected by considering a value greater than or equal to one plus the number of dimensions of the input data, while optimum ε was determined using a *sorted k-dist* graph [49]. With this method, clusters were formed within the radius, and those pieces that were far from the main volume were called outlier data. The number of objects in its radius made it possible to categorize an object into three groups: a noisy, a marginal, and a center object. The mean delta and alpha power at frontal lobes and the FAA for each subtopic were fed as inputs for both k-means and DBSCAN algorithm to cluster the student's SI level. The situational interest classes examined in this study were high, medium, and low (class 1, class 2, and class 3).

3.5. Statistical Analysis

The distribution of the students based on their SI level was assessed using the Shapiro-Wilk test to check if the data were normally distributed. The Shapiro-Wilk normality test was recommended for a sample size of less than 50 [50]. Since the distributions of data were not normal, the differences between the high, medium, and low SI groups were analyzed on each EEG feature by using a non-parametric test; Wilcoxon signed rank. The statistical findings were reported by significant values (p). All the computations of the statistical tests were performed using SPSS software (version 24.0.0.0, IBM Corp., Armonk, NY, USA). The confidence level was set at 95%, representing that there was a 5% risk of significant difference.

3.6. Classification

The classes predicted from k-means and DBSCAN clustering would be used as a priori information for classification via several classification models. The classification of the situational interest results was performed using the Classification Learner Application in MATLAB 2021a (MathWorks, Natick, MA) using nine predictors:

- the mean delta power at single channel F3,
- the mean delta power at single channel F4,
- the mean delta power at the combination of channel F3 and F4,
- the mean alpha power at single channel F3,
- the mean delta power at single channel F4,
- the mean alpha power at the combination of channel F3 and F4,
- the FAA at FP1-FP2,
- the FAA at F3-F4, and
- the FAA at overall frontal region.

A total of 29 machine learning models with multiclass classification were trained in the domain of Neural Network, Ensemble classifiers, Nearest Neighbour Classifiers (*kNN*), Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, Discriminant Analysis, and Decision Tree. For easy reviewing, all the classification models used were labeled according to Table 2. The EEG data signals from 29 students was split into small overlapping regions before being randomly divided into 70:30 of training and validation sets. To avoid overfitting in the classification, 10-fold cross-validation was used in all model verification. It was useful in extracting as much useful information as possible from the limited data.

Table 2. Label for classification models.

Label	Domain	Name of Classification Model	Label	Domain	Name of Classification Model
1	Decision Tree	Fine Tree	16	*kNN*	Coarse *kNN*
2		Medium Tree	17		Cosine *kNN*
3		Coarse Tree	18		Cubic *kNN*
4	Discriminant Analysis	Linear Discriminant	19		Weighted *kNN*
5		Quadratic Discriminant	20	Ensemble Classifiers	Boosted Tree
6	Naïve Bayes	Gaussian Naïve Bayes	21		Bagged Tree
7		Kernel Naïve Bayes	22		Subspace Discriminant
8	SVM	Linear SVM	23		Subspace *kNN*
9		Quadratic SVM	24		RUSBoosted Tree
10		Cubic SVM	25	Neural Network	Narrow Neural Network
11		Fine Gaussian SVM	26		Medium Neural Network
12		Medium Gaussian SVM	27		Wide Neural Network

13		Coarse Gaussian SVM	28	Bilayered Neural Network
14	*kNN*	Fine *kNN*	29	Trilayered Neural Network
15		Medium *kNN*		

3.7. Performance Assessment

Table 3 shows a square matrix called a confusion matrix, which was used to represent the classification results. The columns of the matrix contain counts of predicted classes, while the rows of this matrix contain counts of the true classes or vice versa.

Table 3. Confusion matrix with three classes.

Actual Value	Predicted Value		
	High SI (1)	**Medium SI (2)**	**Low SI (3)**
High SI (1)	L	M	N
Medium SI (2)	O	P	Q
Low SI (3)	R	S	T

True positives; True negatives; Misclassified class.

From the confusion matrix, several additional statistical comparison metrics, such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) rates are defined as:

- True Positive (TP): The label belongs to the class, and it is correctly predicted.
- False Positive (FP): The label does not belong to the class, but the classifier is predicted as positive.
- True Negative (TN): The label does not belong to the class, and it is correctly predicted.
- False Negative (FN): The label does belong to the class but is predicted as negative.

There are seven performance assessments measured in this study including accuracy, sensitivity, specificity, precision, recall, F-measure, and Geometric Mean. The corresponding formulas are described as follows:

$$Accuracy\ (Acc) = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Sensitivity\ (Sn) = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity\ (Sp) = \frac{TN}{TN + FP} \quad (6)$$

$$Precision\ (P) = \frac{TP}{TP + FP} \quad (7)$$

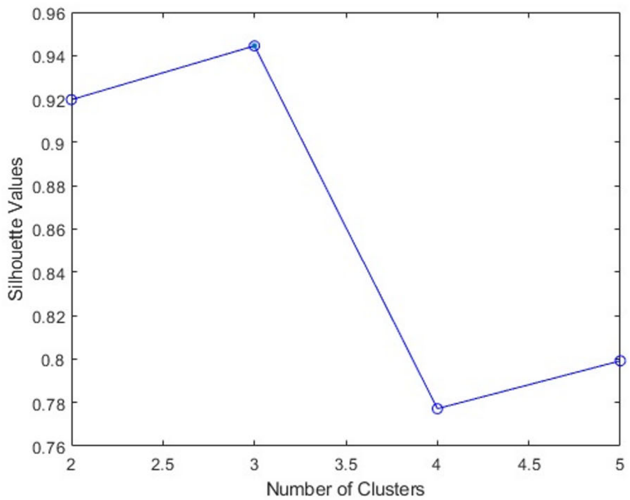
$$Recall\ (R) = \frac{TP}{TP + TN} \quad (8)$$

$$F - measure\ (FM) = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

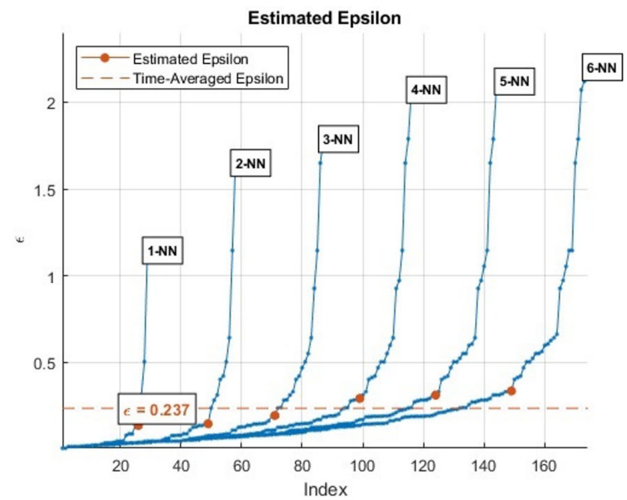
$$Geometric\ mean\ (GM) = \sqrt{}(TP \times TN) \quad (10)$$

4. Results

The findings were presented in the following subsections: clustering analyses, power spectral analyses, asymmetry analyses, statistical analyses, and performance analyses. Initially, before the k-means algorithm was applied, it was important to know the optimal number of clusters to be assigned. The silhouette criterion values could be used to find the optimal number of clusters. Figure 3a showed that the highest silhouette value occurred at three clusters; from what we inferred, the appropriate number of clusters was k = 3. This gave a percentage of 94%. Since the number of clusters examined must be three (high, medium, and low SI), the silhouette value showed the same. Furthermore, an appropriate value of ε needed to be assigned before the DBSCAN algorithm was applied. Figure 3b showed an example of the clustering threshold, ε, that could be estimated and displayed by using *k-dist* graph.



(a)



(b)

Figure 3. (**a**) Evaluating the optimal number of clusters, *k* for k-means. (**b**) Estimated clustering threshold, ε, determined for DBSCAN.

4.1. Clustering Analyses

To analyze the attentional reaction aspect in situational interest, the mean delta power and mean alpha power in each subtopic (Subtopic D, F, H, and I) were used as the input to k-means and DBSCAN. These features were tested on single frontal channels F3 and F4, as well as their combination. The k-means managed to cluster the data successfully into three classes in each case. An example of k-means results for mean delta and alpha power is shown in Figure 4.

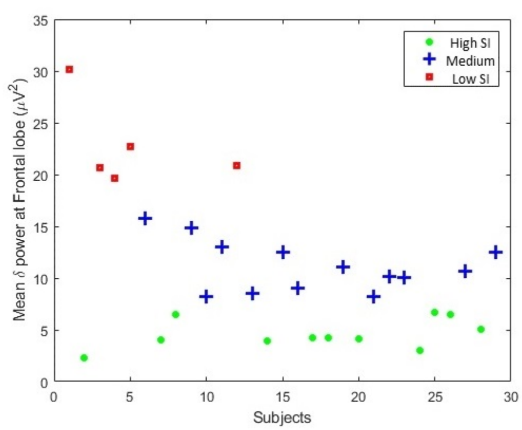


Figure 4. An example of k-means clustering that managed to separate the data completely into three clusters.

Alternatively, the DBSCAN algorithm managed to cluster the data successfully into three classes in all cases, except in channel F3 when the mean delta power was used. Here, there were misclasses detected between the high and low SI groups. However, no outlier or noise detected in the data observation. The examples of DBSCAN clustering results are shown in Figure 5.

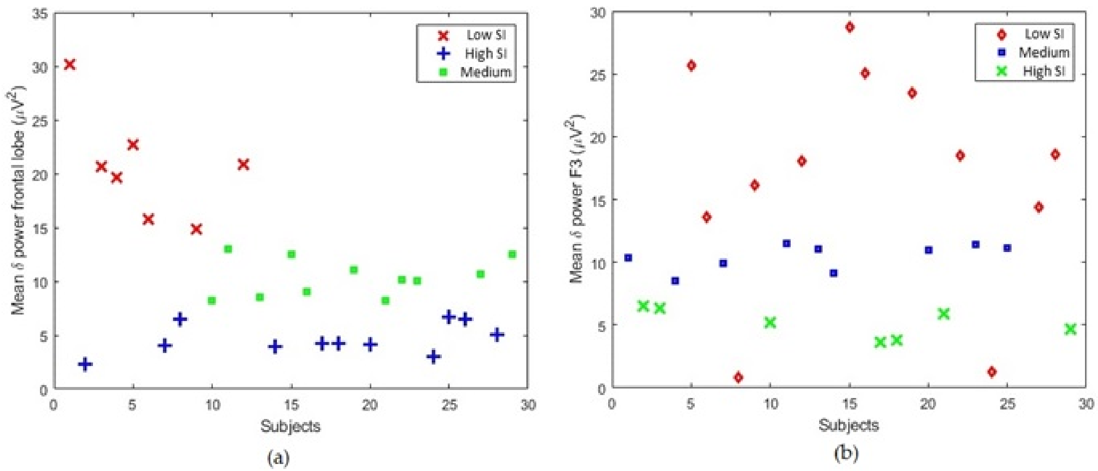


Figure 5. Example of DBSCAN clustering results: (**a**) the clusters are well separated; (**b**) misclasses detected.

To analyze the FAA as an effective reaction predictor of situational interest, the asymmetry was calculated on a pairing of prefrontal channels (FP1-FP2) and frontal channels (F3-F4). The average asymmetry from these two combinations had also been calculated to represent the FAA for the overall frontal region. These features in each subtopic (Subtopic D, F, H, and I) were used as input to k-means and DBSCAN. The k-means managed to cluster the FAA successfully into three classes in each case.

Furthermore, the results from DBSCAN for FAA were shown in Figure 6. These figures revealed that the DBSCAN algorithm was managed to cluster the data successfully into three classes, only at the combination of the channels (see Figure 6c). Misclasses were detected between the high and low SI groups in each pairing of FP1-FP2 and F3-F4. Again, no outlier detected in the data distribution. The other example of clustering results for all EGG features (see Figures S1–S6) can be found in the supplementary material. A summarization of clustering results was tabulated in Table 4. The numbers in the clusters were imbalanced. Regarding the comparison between the duration of the subtopic, we found that the duration had no impact on the clustering results.

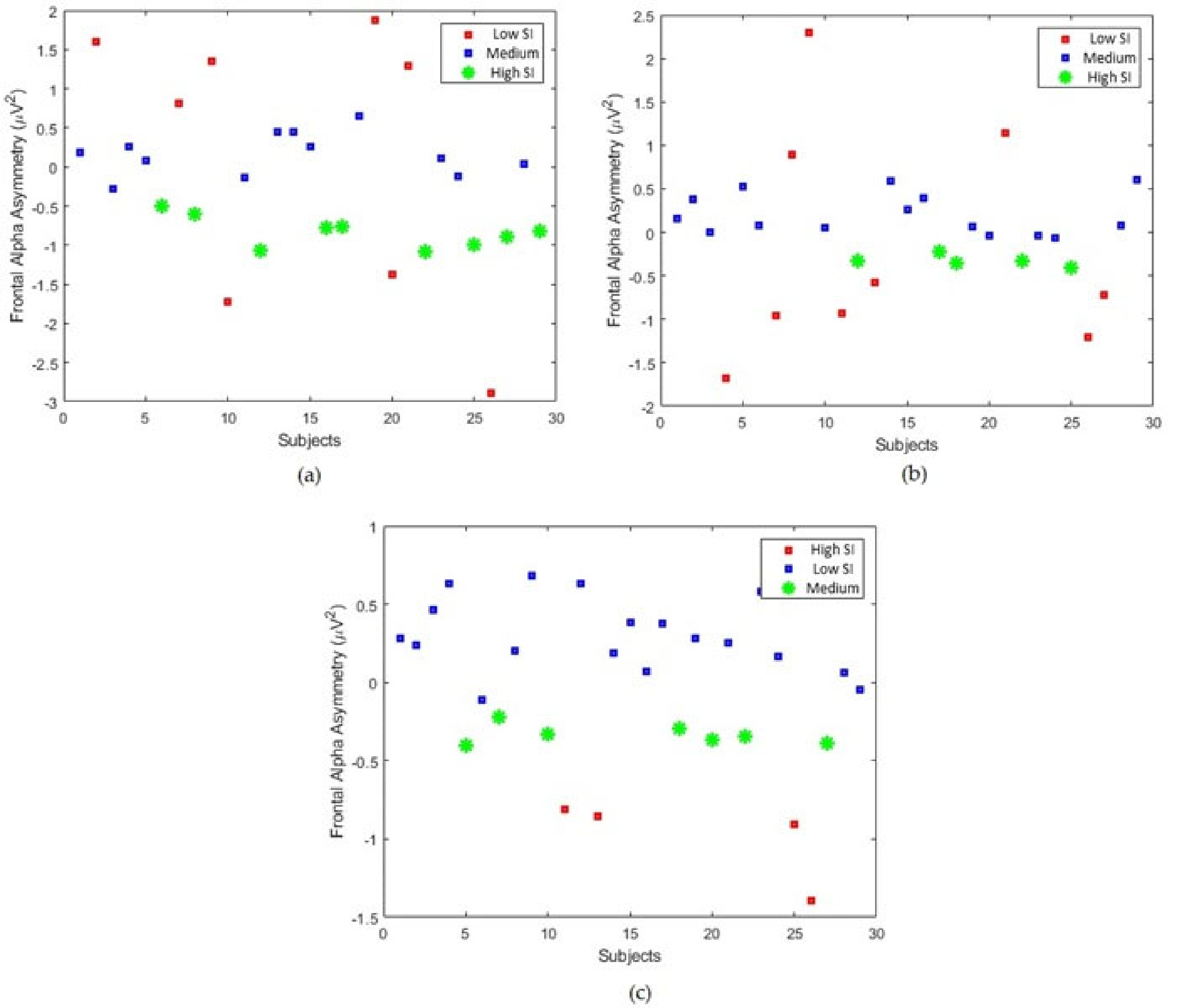


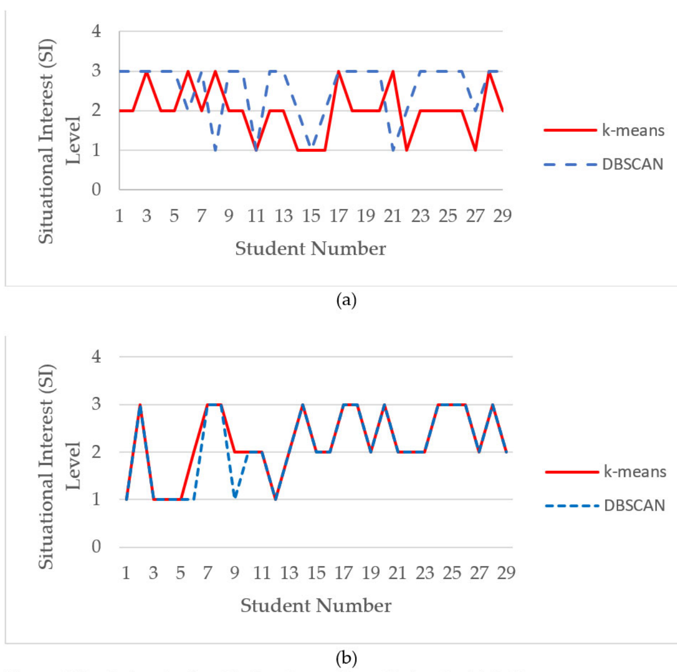
Figure 6. Example of DBSCAN clustering results for FAA metrics at the following electrode: (**a**) FP1-FP2, (**b**) F3-F4, and (**c**) combination of channel prefrontal and frontal.

Table 4. A summarization of the clustering results for each EEG feature used in every subtopic.

EEG Features	**Subtopics**	**k-Means**			**DBSCAN**		
		Low SI	**Medium SI**	**High SI**	**Low SI**	**Medium SI**	**High SI**
Mean δ power at F3	D	7	17	5	4	5	20
	F	5	12	12	12	8	9
	H	7	15	7	6	3	20
	I	7	13	9	13	9	7
Mean δ power at F4	D	1	16	12	3	9	17
	F	1	8	20	3	6	20
	H	3	14	12	3	15	11
	I	3	8	18	12	8	9
Mean δ power at F3 and F4	D	1	7	21	9	14	6
	F	5	13	11	7	10	12
	H	7	8	14	9	3	17
	I	3	11	15	11	7	11
	D	3	9	17	6	7	16

Mean α power at F3	F	2	9	17	3	8	18
	H	2	10	17	9	4	16
	I	1	13	15	8	9	12
Mean α power at F4	D	1	8	20	5	6	18
	F	1	5	13	8	8	13
	H	1	13	15	8	13	8
	I	1	7	21	3	5	11
Mean α power at F3 and F4	D	1	13	15	6	6	17
	F	2	12	15	5	10	14
	H	2	5	22	8	9	12
	I	3	7	19	4	6	19
FAA at FP1-FP2	D	3	21	5	10	14	5
	F	4	7	18	15	9	5
	H	16	11	2	9	7	13
	I	18	3	8	6	4	19
FAA at F3-F4	D	4	12	13	8	14	7
	F	5	12	12	8	12	9
	H	4	11	14	10	8	11
	I	14	2	13	21	4	4
FAA at Combined Pairs	D	7	9	13	12	10	8
	F	8	15	6	21	4	4
	H	17	9	3	20	5	4
	I	12	16	1	20	5	4

From this clustering result, the SI level for each student was monitored by comparing SI levels classified from two different approaches. Figure 7a shows that the k-means and DBSCAN were classified differently when a single electrode was used; however, both algorithms showed an agreement in the combination of electrodes, as shown in Figure 7b.



Note – SI level: class 1 – low SI; class 2 – medium SI; class 3 – high SI.

Figure 7. The SI level classified for the same student with different approaches. (**a**) Both algorithms show a difference; (**b**) both algorithms show an agreement.

To verify that the proposed framework was simple and of low complexity, the processing times of the applied clustering was calculated. All the runtime experiments were checked on a PC with an AMD™ Ryzen 7 processor with 2.90 GHz and 8 GB RAM. Table 5 shows the average speed of this clustering for nine EEG features selected across subtopics. The average time taken for k-means algorithm was about 1.24 CPU sec for the entire dataset. For the DBSCAN, the average test was about 1.73 CPU sec. Therefore, the proposed framework allowed SI monitoring throughout the learning session easily and quickly, which was not feasible with the questionnaire method. Besides, the data could be processed from multiple electrode channels.

Table 5. Average speed of the applied clustering.

EEG Features	EEG Channel	Clustering Algorithm	
		k-Means	DBSCAN
Mean δ power	F3	1.28 s	1.28 s
	F4	1.22 s	1.22 s
	F3 and F4	1.21 s	1.21 s
Mean α power	F3	1.23 s	1.23 s
	F4	1.25 s	1.25 s
	F3 and F4	1.28 s	1.28 s
FAA	FP1-FP2	1.30 s	1.30 s
	F3-F4	1.22 s	1.22 s
	Combine Pairs	1.17 s	1.72 s
Average time		1.24 s	1.73 s

4.2. Power Spectral Analyses

The averaged EEG power across all subtopics (subtopic D, F, H, and I) were examined with three SI groups (high, medium, and low) multiplied by two frequency bands (delta and alpha) multiplied by three different electrodes (single F3, single F4, and combination of F3 and F4) using Wilcoxon signed-rank test. Figure 8 shows the box plot indicating the significant pattern between a high, medium, and low SI group for the delta and alpha power. Based on box plot, the data has no outlier. The distinct median level could be observed for the three groups, where the median of the low SI group of students was higher than the median of the medium SI and high SI group of students for the delta power, which was similarly observed for the alpha power case.

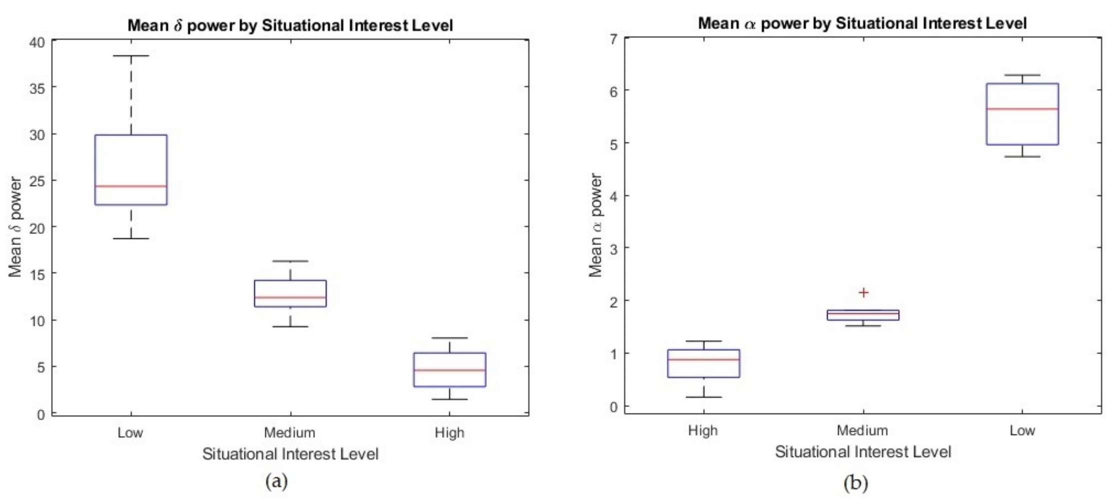


Figure 8. Box plot of mean power for (**a**) delta (**b**) alpha for the high, medium, and low SI student groups.

The summary of the Wilcoxon signed-rank test for delta and alpha mean power was shown in Table 6. The Wilcoxon signed-rank test evidenced that the mean delta power at the combination of frontal electrodes, regardless of the subtopics in the low SI group was significantly higher than in the medium and high SI group with p = 0.029 and p = 0.0285 in k-means and DBSCAN, respectively. From this data, it can be concluded that the mean delta and alpha power at all electrode positions were significantly higher than in the medium and high SI groups when both clustering algorithms were used.

Table 6. The p-value of Wilcoxon signed-rank test for the mean delta and mean alpha power at respective electrode position.

Electrode Position	Delta		Alpha	
	k-Means	DBSCAN	k-Means	DBSCAN
F3	0.1583	0.2895	0.0160 *	0.0073 *
F4	0.0383 *	0.1401	0.0026 *	0.0021 *
Combination of F3 and F4	0.0029 *	0.0285 *	0.0175 *	0.0178 *

* Significant at the 0.05 level (2-tailed).

4.3. Asymmetry Analyses

Wilcoxon signed-rank test was used to examine the FAA across all subtopics (subtopic D, F, H, and I) using three SI groups (high, medium, and low) and three different electrodes pairs (FP1-FP2, F3-F4, and a combination of these two pairs). Figure 9 shows a box plot of the significant pattern between the high, medium, and low SI groups for the FAA. The median of the low SI students was more positive than the median of the high SI students, indicating that a unique median level could be observed for the three groups.

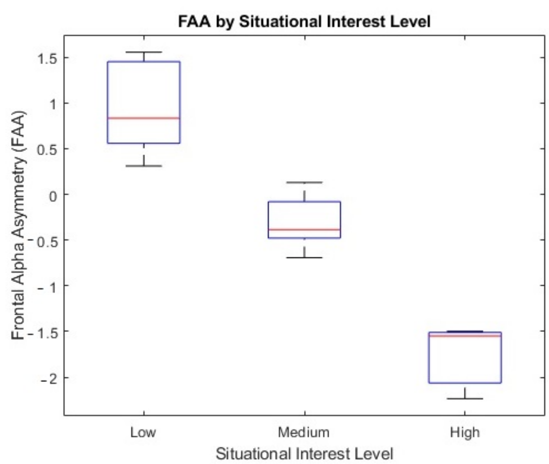


Figure 9. Box plot of FAA metric for the low, medium, and high SI student groups.

Table 7 shows the result from the Wilcoxon signed-rank test for the FAA. From the data, it can be concluded that only FAA in k-means at the combination of FP1-FP2 and F3-F4 electrode pairs was significantly more positive than in medium and high SI groups.

Table 7. The p-value of Wilcoxon signed-rank test for the FAA at respective electrode pairs.

Electrode Pair	FAA	
	k-Means	DBSCAN
FP1-FP2	0.1087	0.0536
F3-F4	0.1741	0.1075

Combination of pair FP1-FP2 and F3-F4	0.0353 *	0.2086

* Significant at the 0.05 level (2-tailed).

4.4. Performance Analyses

To evaluate the model performance, seven performance assessment parameters were computed, including: accuracy, sensitivity, specificity, precision, recall, F-measure, and geometric mean. A total combination of EEG, feature-EEG, and channel-clustering algorithm-classification models that have all had the highest value performance assessment matrices was tabulated in Table 8. The most frequent classification models that appeared to have the highest values in all performance assessment matrices were models 10, 14, 23, and 25. However, in several situations, no classification model could give the highest value in all seven performance matrices. It can be seen in the DBSCAN clustering algorithm when the mean delta power and mean alpha power were used for single channel F4. The same situation was detected in the DBSCAN clustering algorithm when all EEG features were used in the combination of F3 and F4 channels.

Table 8. The classification model with the highest value in all performance assessment parameters across the subtopic.

EEG Features	EEG Channel	Clustering Algorithm	Classification Model Label	Total Model	Acc	Sn	Sp	P	R	FM	GM
Mean δ power	F3	k-means	2, 14, 22	3	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	F4		10	1	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	F3 and F4		11, 14, 21, 23	4	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
Mean δ power	F3	DBSCAN	None	0	0.969 ± 0.063	1.000 ± 0	0.938 ± 0.125	0.958 ± 0.083	1.000 ± 0	0.977 ± 0.046	0.967 ± 0.067
	F4		None	0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	F3 and F4		None	0	0.969 ± 0.063	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	0.875 ± 0.250	0.978 ± 0.147
Mean α power	F3	k-means	1–12, 17,19, 20, 21, 23–27	21	0.969 ± 0.063	1.000 ± 0	0.917 ± 0.125	0.958 ± 0.083	1.000 ± 0	0.977 ± 0.046	0.954 ± 0.092
	F4		None	0	0.906 ± 0.120	1.000 ± 0	0.750 ± 0.500	0.929 ± 0.143	1.000 ± 0	0.948 ± 0.068	0.750 ± 0.500
	F3 and F4		5, 23	2	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
Mean α power	F3	DBSCAN	5, 6, 7, 9, 10. 12, 19, 26	8	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	F4		None	0	0.906 ± 0.120	1.000 ± 0	0.792 ± 0.250	0.938 ± 0.125	1.000 ± 0	0.914 ± 0.102	0.839 ± 0.150
	F3 and F4		None	0	0.969 ± 0.063	1.000 ± 0	0.917 ± 0.167	0.958 ± 0.083	1.000 ± 0	0.977 ± 0.046	0.954 ± 0.092
FAA	FP1-FP2	k-means	29	1	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	F3-F4		14, 25, 26, 28	4	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	Combine Pairs		10, 19, 22, 25, 28	5	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0

FAA	FP1-FP2		25	1	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	F3-F4	DBSCAN	27, 28	2	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
	Combine Pairs		None	0	0.875 ± 0.144	1.000 ± 0	0.917 ± 0.167	0.667 ± 0.577	1.000 ± 0	1.000 ± 0	1.000 ± 0

5. Discussion

5.1. Presence of Interest

In this section, the cluster performed by the k-means and DBSCAN algorithm will be discussed in detail. We have proposed the mean delta and alpha power at the frontal lobe as an attention reaction predictor for SI detection. Figure 4 indicates that the k-means was able to cluster the students into three groups completely when delta power was served as the input. Based on the results obtained, the students who had a lower mean delta power were clustered as high SI, while students with a higher mean delta power were clustered as medium, and the highest mean delta power were clustered as the low SI group. The results highlighted the scientific finding of an increase in delta power mainly in frontal leads in different tasks during cognitive processing [51]. These findings were corroborated with findings from the original database authors, where the grouping of the SI was finished using a questionnaire [38].

Meanwhile, when the same features were used as the input for the DBSCAN clustering algorithm, they were misclassed in the student's SI groups detected (see Figure 5b). Based on the finding from Babiker [27], the high SI student should have the lower delta power at the frontal region when compared to the low SI student. However, two students that had a low delta power were misclassified as low SI group. For further performance evaluation, the class given by the clustering was retained as it was even though the class was mismatched.

Both k-means and the DBSCAN algorithms could cluster the mean alpha power in three groups. The student with the highest alpha power represented the low SI group and vice versa. The suppression in alpha in the frontal lobe for high SI students indicated the tense state, compared to increases in alpha in the frontal lobe for low SI students who were more relaxed. These findings were consistent with an alpha inhibition hypothesis from Klimesch [52] and Pfurtscheller [53], who proposed that an indicator of active neuronal processing regions was reflected by a small amplitude of alpha oscillation; however, large-amplitude alpha oscillations reflected the reduction and disconnection of task-irrelevant cortical areas.

Aside from the mean delta and alpha power, we also proposed the FAA metrics as an effective reaction predictor for SI detection. The k-means clustering results using FAA metrics as input showed that the students could be clearly distinguished into three clusters. The k-means was working well in all electrode pairs. Students with more negative FAA metrics were clustered as having high SI, while students with more positive FAA metrics were clustered as having low SI. The results from DBSCAN clustering are shown in Figure 6. This figure indicated that the DBSCAN algorithm was unable to cluster the data properly. There were students with more negative asymmetry that were misclassified as low SI at channel pair of FP1-FP2 and F3-F4.

The present study showed that changes in the frontal EEG alpha asymmetry depended on students' situational interest levels. Students with a low level of SI exhibited relatively high right-hemispheric activation (positive FAA metrics). By contrast, a high level of SI students showed relatively high left-hemispheric activation. Notably, students with high situational interest would have positive emotions, while low situational interest students had negative emotions. Realistically, when someone had a positive feeling on some topic, that they would show more interest to gather information about that topic. These statements were supported by a previous study from Reznik [54], who reported changes in FAA metrics recognized by EEG that could correspond with passionate or inspirational character attributes. Hence, the proposed method achieved a quantitative result, which was incorporating two important elements (i.e., attentional and effective reaction) in assessing situational interest.

5.2. Automatic Clustering Scheme of Situational Interest during Classroom Learning

The classification was used to validate the cluster performed by the clustering for all the EEG features mentioned previously. The performance assessment parameters have been calculated in all the subtopics across all the channel positions. However, Table 8 only reported the classification model with the highest averaged value in all performance assessment parameters across the subtopic. Overall, both k-means and DBSCAN clustering gave their best performance with a minimum accuracy of 87% in clustering the students by their level of situational interest. Nevertheless, the k-means had performed better than the DBSCAN, since it had obtained the maximum value of one in all performance assessment parameters. The k-means was in its maximum capability to cluster the student's SI level when the mean delta and mean alpha power were used as the input.

Based on Table 8, the performance of DBSCAN was slightly lower than the k-means. Even though studies reported that DBSCAN reached its highest accuracy of 99.2 ± 0.7 in measuring stroke clinical outcomes [55], our findings presented the opposite. This might be due to our data being homogenous, and no outlier being detected (see Figure 8 and 9). Although DBSCAN had been found to give good performance in outlier and noise detection to classify dataset with outlier [56,57], this algorithm had a poorer performance in our present study when compared to the k-means method.

If we further compared the performance of the k-means algorithm across the electrode channel, the k-means achieved the highest accuracy at all the electrode positions in the mean delta power. In contrast to when the alpha power was used as the input, the results showed that the k-means obtained its highest performance only in the combination of F3 and F4 channels, but not in the single channels F3 and F4. Since the frontal lobe played a significant function in the recognition of interest, especially on an arithmetic task [32] and numerical operation [21,22], the usage of combination channels F3 and F4 was better compared to the single channel used. However, the result from Wilcoxon signed-rank test showed that there was a significant difference between the three groups, only at the combination of F3 and F4.

In terms of the classification model, the results showed that the model no. 23 (Subspace *k*NN) was the most efficient model to classify the cognitive attention reaction of situational interest features, since it had all the maximum value performance assessments when it was applied together with the combination of F3 and F4 channel and the k-means clustering. This model showed its highest efficiency in both mean delta and mean alpha power.

To validate the effective reaction aspect of situational interest, both the k-means and DBSCAN algorithms achieved their maximum efficiency at single pair of prefrontal channels (FP1-FP2) and frontal channels (F3-F4). If we compared the performance of the algorithms in the combination of pairs, only the k-means achieved its maximum value in all performance parameters. Even though the DBSCAN had its maximum sensitivity, it was noticed that it had a lower accuracy, specificity, and precision compared to the k-means. A study from Schmid [58] revealed that greater left frontal asymmetry calculated from several frontal pairs was reliably related to approach learning. Thus, we proposed the average FAA on the combination pair was better compared to the FAA on a single pair. This selection was supported by the significant results from Wilcoxon signed-rank test ($p = 0.0353$).

There were five classification models (model 10, 19, 22, 25, and 28) that gave the highest efficiency when evaluating the effective reaction of situational interest features, since it had all the maximum value performance assessments when it was applied together with the average FAA in the combination of prefrontal and frontal channels and the k-means clustering. This model sat in the domain of SVM, *k*NN, ensemble classifiers, and Neural Network.

The combination of frontal delta and alpha power + k-means clustering + subspace *k*NN classification model was proposed as a scheme to validate the attentional reaction of SI. Further, the combination of average frontal alpha asymmetry + k-means clustering, and several classification models was proposed as a scheme to validate the effective reaction of SI. The summary of the best combination proposed is listed in Table 9. These findings open the door for the development of a system that was capable to automatically cluster the level of students' situational interest in an everyday classroom scenario.

Table 9. The proposed combinations to cluster the situational interest in classroom learning.

EEG Feature	Clustering Algorithm	Classification Model
Mean δ power at F3 and F4	k-means	Subspace *k*NN
Mean α power at F3 and F4	k-means	Subspace *k*NN
Average FAA at FP1-FP2 and F3-F4	k-means	Cubic SVM Weighted kNN Subspace Discriminant Narrow Neural Network Bilayered Neural Network

The integration of EEG and the implemented clustering technique was able to group the students according to their SI level almost instantaneously during learning in the classroom. The ease-of-use and learning motivation observed from the EEG clustering scheme suggested that this approach was a good platform for teachers and educators in assessing their students' interests immediately. Appropriate action can be taken to increase the audience's interest level during the learning session. This is useful for them to choose the right teaching material and teaching technique assessment, which will motivate classroom learning enhancement.

In line with World Sustainable Development 2030 (Goal 4: Quality of Education) if student's interests can be detected easily and quickly, students will enjoy learning with the positivity in the classroom. The teaching and learning processes will be more proactive and the teacher-student barrier can be decreased. Hence, quality of education can be enhanced specifically in classroom learning.

The study has a few limitations. First, since this approach is dependent only on the EEG features used as the input, the right EEG features that represent the changes of SI need to be carefully selected. Furthermore, all features used in this study were extracted based on the EEG frequency band. Future studies are encouraged to expend the exploration based on time series analysis and time-frequency analysis features. Next, to improve the classification result, the length of data segmentation and input algorithm parameters should be further investigated for recommending the most appropriate selection. For further exploration, the level of each student's situational interest can be assessed through all subtopics of the presentation. This could be used as a real-time indicator for teachers and educators to ensure the level of students' interests remain high during classroom learning.

6. Conclusions

This research proposed a novel approach to cluster the students based on their situational level during learning in a classroom. Our approach is more rapid and simple compared to existing classification methods, which necessitates a predefined class and a lengthy computational time. The obtained results showed the ability of an unsupervised machine learning as a clustering tool to cluster the student's interest level. The ability of physiological measures to cluster the situational interest in the classroom had been explored, and its performance to replace the usage of psychological measures was promising. Furthermore, we addressed the disadvantages of psychological measures that suffer from susceptibility bias. Several combinations have been proposed to be used as the scheme to cluster the student's situational interest automatically during classroom learning. The results revealed that the k-means algorithm had better efficiency in clustering the students compared to DBSCAN algorithm.

This study explored the features of identifying SI using EEG. Since situational interest consists of attentional reaction to the situation, we found that mean delta and alpha power at the combination of channel F3 and F4 was the best feature to represent this component. We had observed the relationship between increased cognitive attention with high situational interest in learning the topics. It was indicated by the low attenuation of alpha power over the frontal region.

The ability of the FAA as an EEG feature on situational interest to identify different emotional perceptions during real classroom learning was also investigated. Negative FAA metrics associated to high situational interest, while positive FAA metrics led to low situational interest. The FAA can fulfill the component of effective reaction in detecting situational interest, especially during learning in a classroom.

Supplementary Materials: The following are available online at www.mdpi.com/article/10.3390/app12010389/s1. Figure S1: Example of k-means clustering results for mean delta power at the following electrode: (a) channel F3, (b) channel F4 and (c) combination of channel F3 & F4, Figure S2: Example of k-means clustering results for mean alpha power at the following electrode: (a) channel F3, (b) channel F4 and (c) combination of channel F3 & F4, Figure S3: Example of DBSCAN clustering results for mean delta power at the following electrode: (a) channel F3, (b) channel F4 and (c) combination of channel F3 & F4, Figure S4: Example of DBSCAN clustering results for mean alpha power at the following electrode: (a) channel F3, (b) channel F4 and (c) combination of channel F3 & F4, Figure S5: Example of k-means clustering results for FAA metrics at the following electrode: (a) FP1-FP2, (b) F3-F4 and (c) combination of channel prefrontal and frontal, Figure S6: Example of DBSCAN clustering results for FAA metrics at the following electrode: (a) FP1-FP2, (b) F3-F4 and (c) combination of channel prefrontal and frontal.

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Abbreviations

Physiological Measures		**Confusion Matrix**	
EEG	Electroencephalogram	EEG	Electroencephalogram
ECG	Electrocardiogram	ECG	Electrocardiogram
EOG	Electrooculography	EOG	Electrooculography
EMG	Electromyography	EMG	Electromyography
Interest Type		**Input Parameters**	
SI	Situational Interest	FFT	Fast Fourier Transform

PI	Personal Interest	PSD	Power Spectral Density
		FAA	Frontal Alpha Asymmetry
Clustering and Classifier			
DBSCAN	Density-Based Spatial Clustering of Applications with Noise	**Others**	
MLP	Multi-layer Perceptron	BCI	Brain-Computer-Interfacing
SVM	Support Vector Machine	UTP	Universiti Teknologi PETRONAS
kNN	Nearest Neighbour Classifiers	MARA	Multiple Artifact Rejection Algorithm

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