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Summative EEG-based assessment of the relations between learning styles and personality traits of openness

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Abstract

Learning styles (LS), being one of the important attributes of a learner's profile, are relevant to different aspects of teaching and learning such as the learner's achievement and motivation. Equally important is the personality traits of 'Openness', which relate positively to knowledge and skill acquisition, thus making them relevant to learning and learners differences. Recognizing the importance of LS and Openness in profiling learners, the researchers carried out this study to examine the relationship between these two factors using a novel method based on Electroencephalogram (EEG) technology. In this research, Kolb's Learning Style Inventory (KLSI) was used to determine 131 participants' LS: *Diverger, Assimilator, Converger* or *Accommodator*. The EEG technology was used to record the participants' brain signals (with their eyes closed) to generate the dataset of EEG Beta band of baseline condition. Later, the dataset was processed and classified based on the LS using the *2-Step Cluster Analysis*. The result showed that the brain signals could be processed effectively to classify the participants' LS. More importantly, among the LS studied, convergers and assimilators were observed to have positive and strong relation with Openness. Between the two learning styles, assimilators were found to have stronger relation with Openness than convergers.

Keywords : Learning Style; Cluster Analysis, Learning Styles, Openness, Summative EEG;

1. Introduction

Learning styles (LS) reflect the cognitive, affective and psychological characteristics of learners, which to certain extent, determine their perception, interaction and reaction style [1]. From the cognitive perspective, learning styles determine how the learner assimilate and process new information to construct meaning [2]. Likewise, the learning style of a learner defines the cognitive strategy that he or she will invoke in assimilating new information and in retrieving the acquired knowledge for later use [3]. Many studies have found that students' academic performances

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are invariably linked to the LS they use in the learning process in classrooms [4-6]. Likewise, there are studies that have been conducted to examine the impacts of LS in broader contexts beyond the classroom settings, such as e-learning [7], health information [8] and physical therapy [9]. In terms of classifying the LS, the is a dearth of research in using novel methods, particularly on tapping neurological signals, as compared to the traditional, paper-based instruments.

In light of this need, EEG technology, which has been used successfully in related disciplines, seems a viable technology in harnessing the brain waves in educational research [10-13]. The results of previous studies suggest that this technology, when carefully and craftily utilized, could be an efficient tool to detect and process brain signals for educational purposes. More precisely, EEG technology when used in some innovative ways could capture brain signals, which would be processed to determine the LS of learners during learning. Beside LS, another important aspect of learners profile is the personality traits. In psychological domain, there is an overwhelming consensus regarding the description of personality, which could be classified into *extraversion, agreeableness* (also referred to as *sociability*), *conscientiousness, neuroticism* and *openness* to experience (also referred to as intellect or culture) [14]. Essentially, openness describes a broad, general dimension of personality involving vivid fantasy, artistic sensitivity, depth of feeling, behavioural flexibility, intellectual curiosity, and unconventional attitudes [15]. In addition, openness is a known marker for individual differences in intellectual curiosity, need for cognition, and cognitive ability [16]. In fact, openness has been interpreted as a major "investment trait", meaning it is causally and positively linked to knowledge and skill acquisition; hence, its relevance to learning and individual differences is highly emphasized in educational realm [17]. Similar to LS, the biological basis of learners' openness has been studied using EEG in which significant and negative correlations were reported for Beta band of closed eyes [18]. Premised on these encouraging findings, this study focuses on determining the relation between LS and openness using EEG as a technique to record brains signals and process this input for Beta band analysis.

2. Method

2.1. Participants

The study sample consisted of 131 healthy undergraduates who were randomly selected from the Sultan Idris Education University, Malaysia. Their participations were voluntary, and they were assured that the experiment was safe and would not cause any health risk. In addition, they were also briefed on the research's scope and activities before the experiment.

2.2. Research Instruments

2.2.1. Kolb's Learning Style Inventory (KLSI)

Kolb's Learning Style Inventory (KLSI) is based on the Experiential Learning Theory, comprising four learning modes: Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE) [19]. These learning modes when combined yields a bi-polar spectrum (i.e., vertical and horizontal dimensions), discerning on how a learner takes in and deals with experience. Referring to the bi-polar score, a particular LS could be ascribed to the learner, namely Diverger (CE and RO dominant), Assimilator (RO and AC dominant), Converger (AC and AE dominant) and Accommodator (AE and CE dominant) [20]. The latest KLSI version 3.1, which was used in the research is more robust by having a set of new normative data derived from a diverse and a greater number of representative participants, comprising 6977 LSI users. Essentially, KLSI contains a brief questionnaire of 12 items, asking participants to rank four sentences corresponding to the four learning modes [21].

2.2.2. WaveRider

The hardware 'WaveRider' and the accompanying software 'WaveWare' version 2.5 were used to record and to process the brain signals of the participants, respectively. Capturing these signals entailed attaching several electrodes of the hardware to the participants' scalps at the frontal areas of Fp1 and Fp2 using. At the same time, the hardware was linked live to the computer system using USB connection to establish the 'handshake' between WaveRider and WaveWare. The EEG data were filtered using band pass filter set from 0.5 Hz to 30 Hz to produce common EEG fast waves, namely Beta band frequency in a range of 13 to 30 Hz. The 1024 length Fast Fourier Transform (FFT) with Hamming window set to 256 with 50% overlapping was applied to calculate the power of the beta band. The EEG Beta band power spectral density (PSD) values were recorded in 0.125-second intervals for 5 minutes (i.e., 300 seconds). Finally, the summative PSD of each participant was calculated and analyzed.

2.3. Statistical Analysis

The statistical analysis was conducted using SPSS version 16, involving the Two Step Cluster Analysis for classifying the data. Conventionally, this approach is used to cluster objects of a mixed attributes of dataset. In this study, the LS were set as the categorical variable, and the EEG Beta band PSD values were treated as the continuous variable [22, 23]. Under the Two Step Cluster Analysis, LS groups were generated based on dedicated mean values, enabling comparative analysis. In addition, the significance and influence of LS in the clustering process were highlighted.

3. Results and Discussion

The participants' LS and EEG were derived from the analyses of the data obtained through the questionnaire and experiment in the study. For the EEG, the focus of the research was on the Beta band power of the baseline condition of closed eyes [18]. In this case, the Beta summative PSD was clustered based on the 'participant-by-participant' basis to classify the corresponding LS. The summative mean power of each LS was then utilized to determine its relation with Openness.

3.1. Participants' LS classification

An on-line KLSI was used by the participants (N = 131) to classify their respective learning styles as summarized in Table 1. The fulfill the sampling requirement, each group had to be restricted to a minimum number of 30 participants. Table 1 shows that among the participants, there were 36 assimilators, which account for 27.5% of the participants (accounting the highest number); and there were with 30 accommodators, which account for 22.9% of the participants (accounting the lowest number). In addition, there were 33 divergers and 32 convergers, which account for 25.2% and 24.4% of the participants, respectively.

Table 1: Classification of the participant's learning styles

Learning Style	Count	%
Diverging	33	25.2
Assimilating	36	27.5
Converging	32	24.4
Accommodating	30	22.9
Total	131	100

3.2. EEG Classification

After the participants had been classified according to their LS (refer to Table 1), their corresponding Beta band values were then analyzed using SPSS Two-Step Cluster analysis to ascertain that the participants' EEG was correctly clustered based on the LS group. The clustering process was carried using the recorded EEG Beta band summative PSD dataset in closed eyes condition at two frontal scalp locations, left and right. As shown in Figure 1a and Figure 1b, 100% classification was achieved in each case, but with different LS arrangement. As for the left frontal scalp position (see Figure 1a), the divergers were grouped in Cluster 1, accommodators in Cluster 2, assimilators in cluster 3, and convergers in Cluster 4. In contrast, for right frontal scalp position (see Figure 1b), Cluster 1 was completely filled by the assimilators, Cluster 2 by the accommodators, Cluster 3 by the convergers, and Cluster 4 by the divergers.

3.3. Relation of LS and Openness

In order to determine the relation between LS and Openness, the mean value of the summative Beta PSD for each construct was analyzed. The analysis indicated that the LS with the lowest mean was most related to Openness, suggesting a significant negative correlation between the two [18]. For the closed eyes at the left scalp position (see Figure 2a), three clusters (i.e., Clusters 1, 3 and 4) lie below the overall mean reference line of 11090.27. These clusters correspond to the LS of diverger, assimilator, and converger, respectively (see Figure 1a). Among the three LS, convergers that reside in Cluster 4 was found to attain the lowest mean of 9285.13. This particular finding provides strong evidence that convergers, among the LS studied, was highly related to Openness. On the other hand, for the closed eyes at the right scalp position (see Figure 2b), the overall mean reference line delineates the four clusters in such a way that only one cluster (i.e., Cluster 1), which has a mean value of 9721.17, is placed well below the reference line. Hence, this finding strongly indicates that the LS of assimilator was highly related to Openness (See Figure 1b).

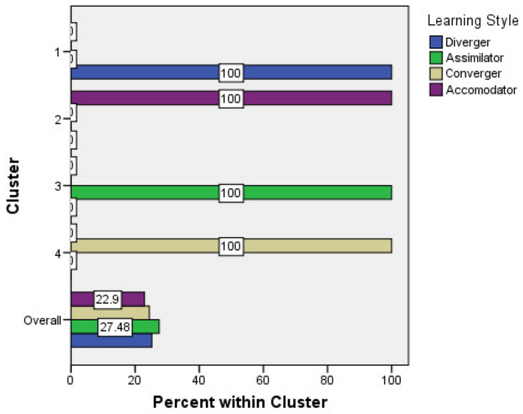

Fig. 1(a) : LS clustering by summative PSD Beta for closed eyes at left frontal scalp position

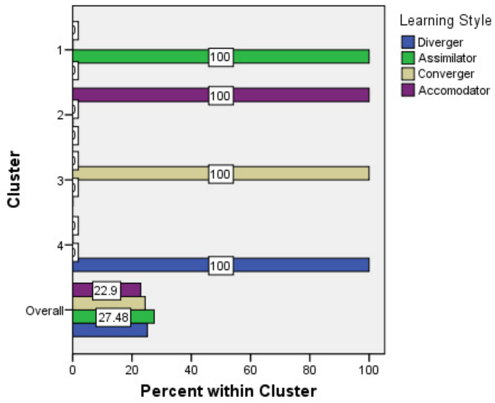

Fig. 1(b) : LS clustering by summative PSD Beta for closed eyes at right frontal scalp position

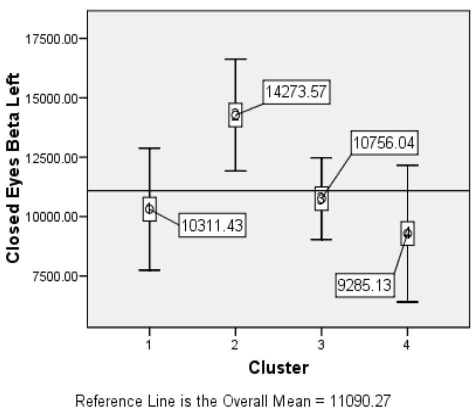

Fig. 2(a) : Comparison of Beta summative PSD mean for closed eyes at left scalp frontal location

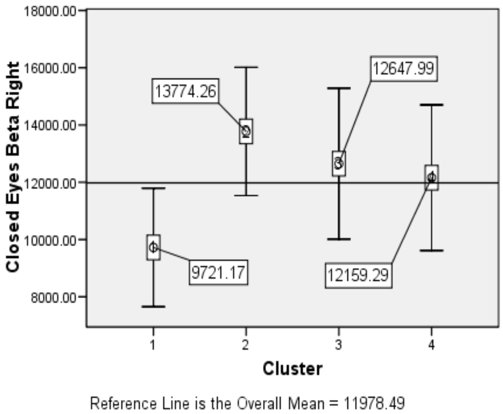

Fig. 2(b) : Comparison of Beta summative PSD mean for closed eyes at right scalp frontal location

The summative Beta PSD was used to classify the participants according to their LS. Table 2 shows that the classification of the LS was successfully carried out. The clustering process also produced the summative Beta PSD mean comparison to highlight the lowest mean cluster.

Table 2: LS classification at different construct using Summative Beta PSD

No	EEG Summative PSD	Condition	Scalp Position	LS Clustering	Lowest mean LS
1	Beta	closed eyes	Left	100%	Convergers
2		closed eyes	Right	100%	Assimilators

For both convergers and assimilators, their different impacts on cluster formation were evaluated using *student's t test*. As shown in Figure 3a and Figure 3b, the impact of each cluster on the overall classification formation was evaluated against the critical value of the significance test statistics. Figure 3a shows the cluster importance between clusters for Beta summative PSD mean in closed eyes condition at left scalp frontal location. Cluster 1 (diverger), Cluster 3 (assimilator), and Cluster 4 (convergers) were the clusters that had negative values of the t-test statistic, where the latter deviated furthest from the critical value line by 1.66 points. In contrast, Cluster 2 was the only group that exceeded the critical value with a t-test statistical value of 3.6. Referring to Figure 1a, this cluster was formed by the accommodators, asserting that this group of the LS could be significantly distinguished as compared to the other clusters, including the convergers. On the other hand, an opposite pattern was observed for the Beta summative PSD mean in closed eyes condition at the right scalp frontal location as depicted in Figure 3b. Cluster 1 was the only group that attained a negative t-test statistical value as compared to Cluster 1, Cluster 2, and Cluster 3. Nevertheless, Cluster 1, which had a negative t-test statistical value of -2.87, seemed the best group in the clustering process among the other LS groups. Referring to Figure 1b, this cluster was formed by the assimilators, which was significantly related to Openness (see Table 2).

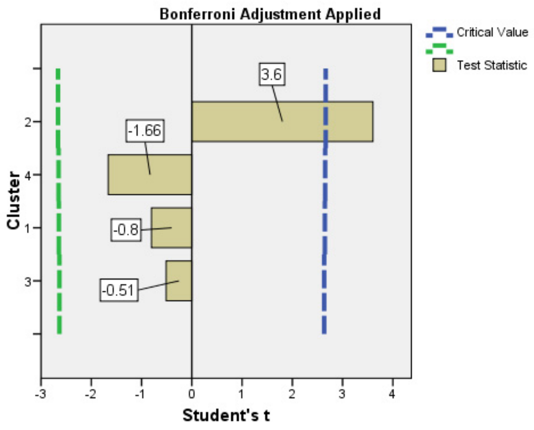

Fig. 3(a) : Cluster importance for Beta summative PSD mean for closed eyes at left scalp frontal location

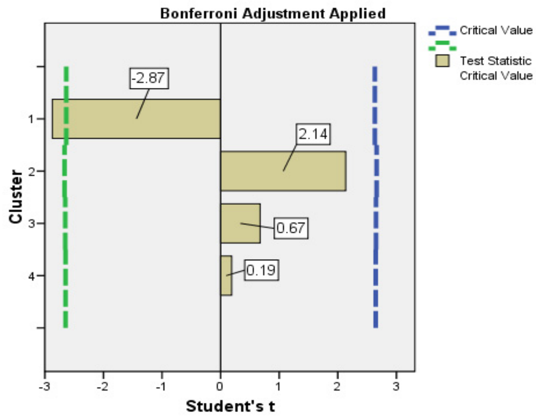

Fig. 3(b) : Cluster importance for Beta summative PSD mean for closed eyes at right scalp frontal location

4. Conclusion

The research findings showed that convergers and assimilators were significantly related to Openness. The relation of the former to Openness was found based on the Beta Summative PSD mean in closed eyes condition at the left scalp frontal location. On the other hand, the relation of the latter to Openness was detected based on the Beta Summative PSD mean in closed eyes condition at right scalp frontal location. More importantly, the cluster wise importance checking on both LS found that the assimilator group was better in distinguishing the appropriate cluster that links to Openness. Being an important personality trait, Openness serves as a marker for individual differences in intellectual curiosity, needs for cognition, and cognitive ability [24]. Accordingly, persons with high Openness prefer deep learning that fosters better knowledge and skill acquisition [16] and are more receptive to new ideas [14]. On the other hand, the assimilators, who prefer abstract conceptualization and reflective observation, will react differently compared to convergers. In other words, assimilators will find fundamental ideas to be logically sound than practical aspects of the learning process. More precisely, assimilators prefer inductive reasoning, more concerned with ideas and abstract concepts rather than with people, thus having the proclivity in creating theoretical models [25]. Hence, having an efficient method to determine the relations of Openness with LS, notably convergers and assimilators will be important to the practitioners in planning their teaching activities. Thus, the main finding of this research strongly suggests that the summative EEG-based assessment provides a practical avenue for researchers and educational practitioners to better understand the cognitive and affective aspects of learning in the future.

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