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An Empirical Study on EEG Signals for Emotion Recognition Using SEED

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***Abstract*--Human emotions are too complex to be accurately recognized by others. In the era of Artificial Intelligence (AI), automatic emotion recognition has become an active field for research and applications. The technology of both AI could have a significant impact on public health. There are a variety of scientific methods that can precisely measure emotions even in the face of impassivity. Some of the most reliable methods include the electroencephalography (EEG) which depends on physiological signals. EEG-based emotion recognition has received much exploration in recent years. The SJTU Emotion EEG Dataset SEED is an open-source dataset that contains EEG signals used for emotion recognition. Most EEG-based emotion recognition research applies machine learning techniques for classifying emotions. In this paper, we conduct an empirical study on SEED dataset to investigate some characteristics of this dataset. We find that the recorded emotions among multiple sessions are the same for most participants. In addition, there is a difference in the detected emotions between participants from the same gender. Finally, the emotions between biologically male and female participants are distinctive.**

***Index Terms*—Empirical Study, EEG, SEED, Emotion Recognition.**

I. Introduction

Emotions play a significant role in human intelligence, perception, cognition, and supporting the decision-making processes [1]. There are various scientific methods that can accurately measure emotional stimuli precisely even in the face of impassivity. Emotional state can be measured by a model that harnesses both human participation and computer software. This model is provided by a research field called Affective Computing (AC) [2]. Automatic emotion recognition has become an active field for research and applications. Physiological signals reflect the most accurate measures of emotions because they are recorded by multichannel devices taken from the human nervous system [3]. Electroencephalography (EEG) can be used to measure the electrical activity of the brain which can be translated into different emotions. The process involves attaching electrodes to the scalp to identify the brain's cortex voltages. as each electrode collects EEG signals in their respective channels [4]. Nowadays, EEG devices are used for many purposes due to their commercial availability in different forms , cost, and practical functionality [5]. EEG is involved in online gaming, virtual reality, and e-health, and it support psychological analyses[1]. Majority of research papers have explored emotion recognition based on EEG signals using machine learning approaches [1, 6-17]. Some datasets are established for emotional recognition, such as the SJTU Emotion EEG Dataset (SEED) [7]. Authors of the SEED dataset [7] concluded that for a specific movie clips (which connote emotion), there is no difference between emotion data detected from a single participant for multiple sessions (Each session is a forthnight.). Also, they conclude that biological women and men have distinct emotions. The contribution of this study is to test these conclusions statistically and find out if they are satisfied or not. Thus, three focal research questions were addressed in this study:

RQ1: Is the subject (participating in many sessions) producing the same EEG signals?
RQ2a: Do EEG signals results vary between male participants?
RQ2b: Do EEG signal results vary between female participants?
RQ3: Is there a significant difference in EEG signal results between male and female participants?

The following section will cover a background of emotions and EEG signals. In section III, we presented the study's methodologies and results. A discussion takes place in section IV. Finally, in section V, we present conclusions.

II. Background

This section defines emotions and how EEG signals recognize these emotions.

A. Emotions

Emotions are complex psychological states composed of three components: a subjective experience, a physiological response, and a behavioral response [18]. Representation of emotions may be categorical or dimensional. The first approach (categorial) represents the eight basic emotions according to *Plutchik*, anger, fear, sadness, disgust, surprise, curiosity, acceptance, and joy [19]. The second approach (dimensional) is mapped into Valence, Arousal, and Dominance (VAD) dimensions [20]. The discrete emotion model is the most common emotion recognition model recognized by researchers [21]. This model, as shown in Fig. 1 [22] is defined as the Arousal–Valence space which denotes negativity to positivity ranges in the Valence axis, and the Arousal axis ranges from calmness to excitement.

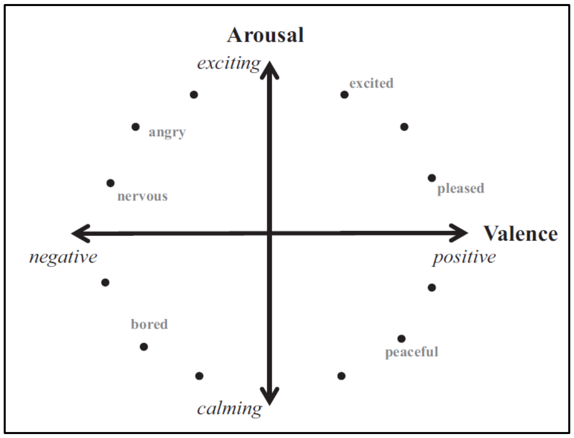

Fig. 1. Arousal–Valence Space

B. ECTROENCEPHALOGRAPHY (EEG)

EEG is defined as a medical imaging technique that reads scalp electrical activity generated by brain structures, i.e., it measures voltage fluctuations resulting from ionic current flows within the neurons of the brain [1]. The generated waves are divided into five waves, called delta, theta, alpha, beta, and gamma, to present the five types of signals taken from the scalp [23] as depicted in Fig. 2. The International 10/20 System (IS) provides a standard position for electrodes related to a certain location of the brain's cortex. Numbers 10 and 20 represent the distance between two electrodes. As depicted in Fig. 3, each site has letter and number to uniquely identify the location [7].

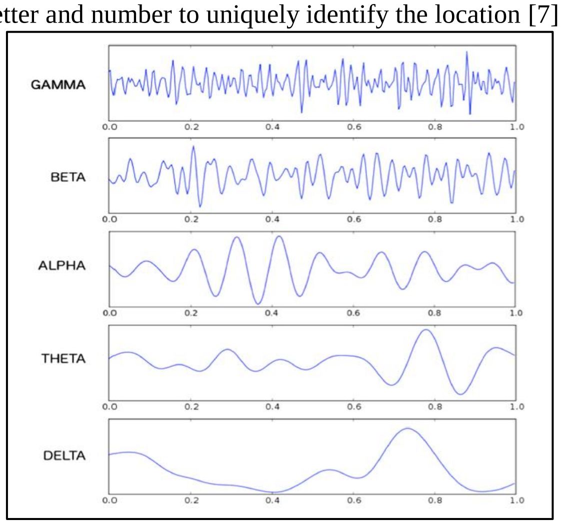

Fig. 2. Five brain waves, delta, theta, alpha, beta, and gamma

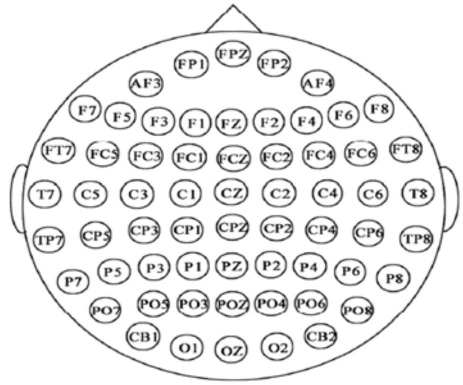

Fig. 3 The EEG cap layout for 62 electrodes

C. EEG Datasets

Few EEG datasets are established for emotional states examination [24]. There are two available datasets, DEAP [8] and SEED [7]. In many technical aspects, the two datasets are distinguishable:

- ***DEAP dataset (2012)***

The Database for Emotion Analysis using Physiological Signals (DEAP) is a benchmark affective EEG database for the analysis of emotions. In the DEAP dataset, 32 healthy participants (50% females), with a mean age 26.9, were involved in the study [8].

In order to stimulate the emotions of participants, all were exposed to 40 music videos. Each minute long videowas shown on a 17-inch screen (1280 X 1024, 60 Hz). To minimize eyes movements, all videos were presented at 800 X 600 resolution (about 2/3 of the screen) [8]. The physiological signals were then recorded. Biosemi ActiveTwo devices were used to record EEG signals at a sampling rate of 512 Hz and down sampled to 128 Hz. DEAP datasets constitute sectioned 32-channel EEG signals, 4-channel electrooculography, 4-channel electromyography, plethysmograph, galvanic skin response, respiration, and body temperature [24]. Each participant was then asked to rate their feeling immediately after watching each video. Participants' emotions are evaluated along the scales of arousal (associated with excitation level), valence (associated with pleasantness level), dominance (associated with control power), liking (associated with preference), and familiarity (associated with the knowledge of the stimulus). Each emotion ranged from one (weakest) to nine (strongest), except familiarity which ranged from one to five. [8].

- ***SEED dataset (2015)***

The SJTU Emotion EEG Dataset (SEED) is a free and publicly available EEG dataset for emotional analysis provided by Shanghai Jiao Tong University (SJTU) in 2015. A standard Fifteen, four-minute-long movie excerpts were selected to detect three emotions: positive, neutral, and negative. Five movies were assigned for each emotion [7].

Table. 1 present key contributions of previous studies that EEG signals are the main point. Table. 2 shows the key emphasis of these studies.

TABLE 1
Key Contributions of EEG Signals Studies

Ref #	Author(s)	Title of article	Key contribution
[25]	Liu Wei, Qiu Jie-Lin, Zheng Wei-Long Lu Bao-Liang. (2019)	Multimodal emotion recognition using deep canonical correlation analysis.	**Focus:** on deep canonical correlation analysis (DCCA) to multimodal emotion recognition.
[26]	Luo Yun, Zhang Si-Yang, Zheng Wei-Long, Lu Bao-Liang. (2018)	WGAN domain adaptation for EEG-based emotion recognition.	**Focus:** on building electroencephalography (EEG) emotion recognition models with the help of a Wasserstein generative adversarial network domain adaptation (WGANDA) framework.
[27]	Luo Yun, Zhu Li-Zhen, Wan Zi-Yu, Lu Bao-Liang. (2020)	Data augmentation for enhancing EEG-based emotion recognition with deep generative models.	**Focus**: on three methods for augmenting EEG training data to enhance the performance of emotion recognition models, based on two deep generative models, variational autoencoder (VAE) and generative adversarial network (GAN).
[28]	Chao Hao, Dong Liang, Liu Yongli, Lu Baoyun. (2019)	Emotion recognition from multiband EEG signals using CapsNet,Sensors.	**Focus**: on a deep learning framework based on a multiband feature matrix (MFM) and a capsule network (CapsNet).
[29]	Gupta Vipin, Chopda Mayur Dahyabhai, Pachori Ram Bilas. (2018)	Cross-subject emotion recognition using flexible analytic wavelet transform from EEG signals.	**Focus:** on EEG signals' channel specific nature and in creating an effective method of emotion recognition based on flexible analytic wavelet transform (FAWT) .
[30]	Liu Yong-Jin, Yu Minjing, Zhao Guozhen, Song Jinjing, Ge Yan, Shi Yuanchun. (2017)	Real-time movie-induced discrete emotion recognition from EEG signals.	**Focus:** on a real-time movie-induced emotion recognition system for identifying an individual's emotional states through the analysis of brain waves.
[31]	Zhuang Ning, Zeng Ying, Tong Li, Zhang Chi, Zhang Hanming, Yan Bin. (2017)	Emotion recognition from EEG signals using multidimensional information in EMD domain.	**Focus:** on a method for feature extraction and emotion recognition based on empirical mode decomposition (EMD).
[32]	Li Mi, Xu Hongpei, Liu Xingwang, Lu Shengfu. (2018)	Emotion recognition from multichannel EEG signals using K-nearest neighbor classification.	**Focus:** on the emotion recognition accuracy of EEG signals in different frequency bands and different number of channels.
[33]	Zhong Peixiang, Wang Di, Miao Chunyan. (2020)	EEG-based emotion recognition using regularized graph neural networks.	**Focus :** on a graph neural network (RGNN) for EEG-based emotion recognition.
[34]	Zhang Tong, Wang Xuehan, Xu Xiangmin, Chen CL Philip. (2019)	GCB-Net: Graph convolutional broad network and its application in emotion recognition.	**Focus:** on a GraphConvolutional Broad Network, designed for exploring the deeper-level information of graph-structured data.
[35]	Du Xiaobing, Ma Cuixia, Zhang Guanhua, Li Jinyao, Lai Yu-Kun, Zhao Guozhen, Deng Xiaoming, Liu Yong-Jin, Wang Hongan. (2020)	An efficient LSTM network for emotion recognition from multichannel EEG signals.	**Focus:** on a model called ATtention-based LSTM with Domain Discriminator (ATDD-LSTM) that can characterize nonlinear relations among EEG signals of different electrodes.
[36]	Rahman Md Asadur, Hossain Md Foisal, Hossain Mazhar, Ahmmed Rasel. (2020)	Employing PCA and t-statistical approach for feature extraction and classification of emotion	**Focus:** on a method that hybridizes the principal component analysis (PCA) and t-statistics for feature extraction.

		from multichannel EEG signal.	
[37]	Yang Fu, Zhao Xingcong, Jiang Wenge, Gao Pengfei, Liu Guangyuan. (2019)	Multi-method fusion of cross-subject emotion recognition based on high-dimensional EEG features.	**Focus**: on a method for cross-subject emotion recognition which integrated the significance test/sequential backward selection and the support vector machine (ST-SBSSVM).
[38]	Li Jingcong, Li Shuqi, Pan Jiahui, Wang Fei. (2021)	Cross-Subject EEG Emotion Recognition With Self-Organized Graph Neural Network,Frontiers in Neuroscience.	**Focus**: on a self-organized graph neural network (SOGNN) for cross-subject EEG emotion recognition.
[39]	Lu Yun, Wang Mingjiang, Wu Wanqing, Han Yufei, Zhang Qiquan, Chen Shixiong. (2020)	Dynamic entropy-based pattern learning to identify emotions from EEG signals across individuals.	**Focus:** on a new framework of dynamic entropy-based pattern learning to enable subject-independent emotion recognition from electroencephalogram (EEG) signals with good generalization.

TABLE 2
Key Emphasis of EEG Signals Studies

	Key emphasis					
Author	**Emotion recognition**	**EEG signals**	**Networks**	**Data**	**Artificial intelligence**	**Machine learning**
Liu Wei et al[25]	x	x		x		x
Luo Yun et al[26]	x	x	X GAN			X Domain adaption
Luo Yun et al[27]	x	x	X GAN VAE	X SEED DEAP		
Chao Hao et al[28]	x	x	X capsNET	X Feature extraction	X Deep learning	
Gupta Vipin et al[29]	x	x		X Feature extraction Databases Wavelet transforms		X Support vector machines
Liu Yong-Jin et al[30]	x	x			X Real time systems Brain models	X Support vector machines
Zhuang Ning et al[31]	x	x		X Feature extraction EMD DEEP		
Li Mi et al[32]	x	x		X DTW		
Zhong Peixiang et al[33]	x	x	X Graph neural network	X SEED	X Brain modeling	

				Feature extraction	Affective computing	
Zhang Tong et al[34]	x	X	X Convolutional neural network	X Feature extraction	X Brain modeling	
Du Xiaobing et al[35]	x	x		X Feature extraction Data modeling	X Brain modeling	X Domain adaption
Rahman Md Asadur et al[36]	x	x	X Artificial neural network	X SEED	X Brain computer interface	X Support vector machine
Yang Fu et al[37]	x	x		X SEED DEAP		X ST-SBSSVM
Li Jingcong et al[38]	x	x	X graph neural network	X SEED dataset		
Lu Yun et al[39]	x	x		X SEED dataset		x

Three sessions were conducted for each participant (forthnightly between every two consecutive sessions) to record EEG signals [7]. In the SEED dataset, 15 healthy participants (7 males and 8 females; age mean: 23.27) were involved in collecting EEG signals. ESI NeuroScan device were used to record EEG signals by 62-channel at a sampling rate of 1000 Hz and down sampled to 200 Hz [3].

III. METHODOLOGY AND RESULTS

In this section, an empirical study using the SEED dataset is applied to investigate if there is significant difference between participants (male/female) or between sessions within participants. The SEED dataset contains different methods to extract many features from EEG signals. One of these features is the Differential Entropy (DE) features from five frequency bands (Delta, Theta, Alpha, Beta, and Gamma) [40][41]. Our statistical analysis relies on the DE features for all experiments. All comparisons made use of the same one positive movie clip, (de_movingAve1.mat). Our argument stems that there is a significant differences in emotional stimuli between male and female according to previous studies [1, 7]. Nonetheless, we suppose that there is no difference in EEG signals between participants of the same gender.

For each participant, the standard session of 15 movie clips is repeated throughout the entire experiment, and we hypothesize that a single participant will produce the same results in all three sessions.

To answer the research questions RQ1, RQ2a, RQ2b, and RQ3 mentioned earlier in this study, we tested ourhypotheses using JMP software for statistical analysis.

A. HYPOTHESES

As all 15 participants in the SEED dataset are repeating the same session three times with a time interval of two weeks between one session and another, our first hypothesis is:

H1: The participant (male/female) records the same EEG results over the three sessions.

The null hypothesis will be:

1. $H_o : \mu_i - \mu_j = 0$

$for\ i, j\ \epsilon\ session 1,2, and\ 3$

Where μ_i is the average differential entropy of EEG result for session i.

H2a: The same EEG results are recorded for all male participants.

The null hypothesis will be:

2a. $H_o : \mu_i - \mu_j = 0$

$for\ i, j\ \epsilon\ male\ user\ 1,4,5,6,9,12, and 14$

Where μ_i, μ_j is the average differential entropy of EEG result for male subject i, j.

H2b: The same EEG results are recorded for all female participants.

So null hypothesis will be:

2b. $H_o : \mu_i - \mu_j = 0$

$for\ i, j\ \epsilon\ female\ user\ 2,3,7,8,10,11,13\ and\ 15$

Where μ_i, μ_j is the average EEG result for female subject i, j.

H3: There is a significat difference in the averege EEG results between male and female participant

So alternative hypothesis will be:

3. $H_1 : \mu_i - \mu_j \neq 0$

$for\ i\ \epsilon\ male\ user, j \epsilon\ female\ user$

Where μ_i is the average EEG result for male subject i and Where μ_j is the average EEG result for female subject j.

The next subsections aim to test these hypotheses and discuss the results.

B. Statistical Analysis Tests and Results

The first step in our study was data collection, and we chose the SEED dataset that is downloaded from:Brain-like Computing & Machine Intelliegence (BCMI) website from Shanghai Jiao Ton University (SJTU), China.

After submitting a license agreement, we downloaded the SEED folder and used the data by MATLAB R2021a. Then, all statistical analyses for our experiments weree done using JMP® Trial 16.0.0 software. JMP is a data analysis software with robust capabilities for statistics.

All experiments in this study is compared with the significance level set to 0.05.

- **Experiment 1**

This experiment was applied to all participants (15 participants). For each participant we compared the average of 62 channels for EEG signals between sessions 1, 2, and 3. We used ANOVA test (Analysis Of Variance) since the data are paired, and there are three sessions to be considered. The results are shown in detail in Table 3, which shows that most p-values are greater than alpha (set to 0.05). Only three participants had p-values less than 0.05. Fig. 4 shows the complete analysis of user 4 as an example.

TABLE 3
ANOVA Test Results for three sessions within participant

participant	P-Value			
	Sessions 1& 2	Sessions 1 & 3	Sessions 2 & 3	Sessions 1 & 2 & 3
1	0.9026	0.3999	0.6640	**0.4209**
2	0.6847	0.7334	0.2563	**0.2885**
3	0.2834	0.6984	0.7562	**0.3163**
4	0.9634	0.5137	0.3626	**0.3531**
5	0.9635	0. 2884	0.4250	**0.2738**
6	0.9759	0.9825	0.9995	**0.9745**
7	0.7218	0.8996	0.9411	**0.7424**
8	0.9518	0.9584	0.8325	**0.8467**
9	0.0034	0.5210	0.0729	**0.0042**
10	0.1319	0.2435	0.9439	**0.1196**
11	0.7797	0.8771	0.9814	**0.7856**
12	0.7327	0.8565	0.9733	**0.7421**
13	0.0127	0.2468	0.4161	**0.0175**
14	0.9669	0.0091	0.0187	**0.0049**
15	0.3179	0.1802	0.9426	**0.1701**

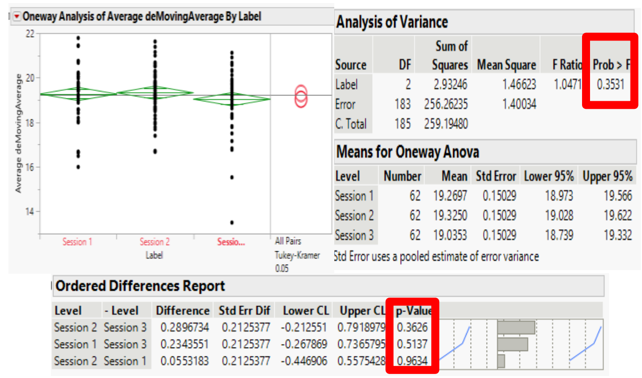

Fig. 4 ANOVA Test for participant 4

- **Experiment 2**

This experiment is composed of two sections, the first one is applied on male participants (7 participants), and the second is applied on female participants (8 participants). For all male participants, we compare the average differential entropy from 62 channels of EEG signals between users 1, 4, 5, 6, 9, 12, and 14. Then, the experiment is done for all female participants to compare the average differential entropy from 62 channels of EEG signals between users 2, 3, 7, 8, 10,11,13, and 15. This experiment comparison is repeated for sessions1, 2, and 3.

Experiment 2a:

In this experiment, we use ANOVA test since there are more than two participants to be considered. The overall p-value in three sessions for male participants is ($p<0.05$) and shown in table 4. The detailed results of average comparision between male participants in sessions 1, 2, and 3 are presented in Tables 5, 6, and 7 respectively. Fig. 5, 6, and 7 representing the ANOVA test by JMP software.

TABLE 4
ANOVA Test Results for three sessions between male participants

Session #	p-Value
Session 1	0.0037
Session 2	<0.0001
Session 3	<0.0001

TABLE 5
ANOVA Test Results for session1 between male participants

Male Participant		P-Value						
		User1	User4	User5	User6	User 9	User12	User 14
P-Value	User1		0.0298	0.6692	0.9442	0.4935	0.9870	0.9783
	User4			0.7340	0.3559	0.8712	0.0020	0.2561
	User5				0.9974	**1.0000**	0.2020	0.9883
	User6					0.9804	0.5365	**1.0000**
	User 9						0.1114	0.9484
	User12							0.5691
	User 14							

TABLE 6
ANOVA Test Results for session 2 between male participants

Male Participant		P-Value						
		User1	User4	User5	User6	User 9	User12	User 14
P-Value	User1		0.0043	0.3745	0.8904	<0.0001	0.9844	0.9750
	User4			0.6500	0.1593	0.4435	0.0002	0.0713
	User5				0.9784	0.0063	0.0642	0.9000
	User6					0.0002	0.4067	0.9999
	User 9						<0.0001	<0.0001
	User12							0.6241
	User 14							

TABLE 7
ANOVA Test Results for session 3 between male participants

Male Participant		P-Value						
		User1	User4	User5	User6	User 9	User12	User 14
P-Value	User1		0.0205	0.3895	**1.0000**	0.5638	0.4088	0.3689
	User4			0.8877	0.0164	0.7562	<0.0001	**1.0000**
	User5				0.3476	**1.0000**	0.0012	**1.0000**
	User6					0.5168	0.4536	0.3281
	User 9						0.0033	0.9999
	User12							0.0010
	User 14							

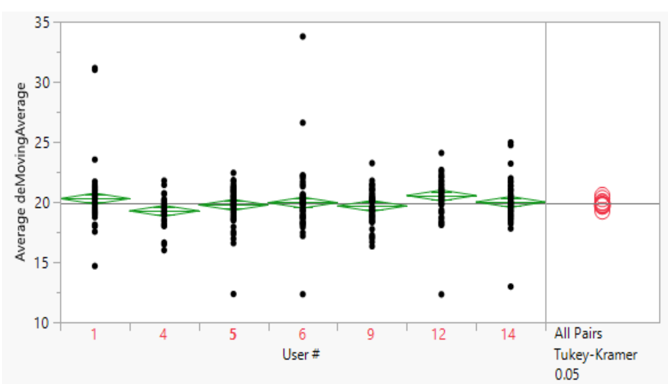

Fig. 5 ANOVA Test for session1 male participants comparison

Male Participant		P-Value							
		User2	User3	User7	User8	User10	User11	User13	User15
P-Value	User2		0.5589	0.1528	0.0104	0.1916	0.9999	0.0574	<0.0001
	User3			0.9962	0.7211	0.9985	0.8240	0.9553	0.0284
	User7				0.9840	**1.0000**	0.3569	0.9999	0.1952
	User8					0.9710	0.0405	0.9994	0.7594
	User10						0.4204	0.9997	0.1559
	User11							0.1676	<0.0001
	User13								0.3999
	User15								

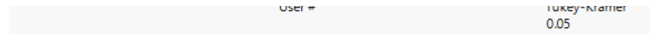

Fig. 6 ANOVA Test for session 2 male participants comparison

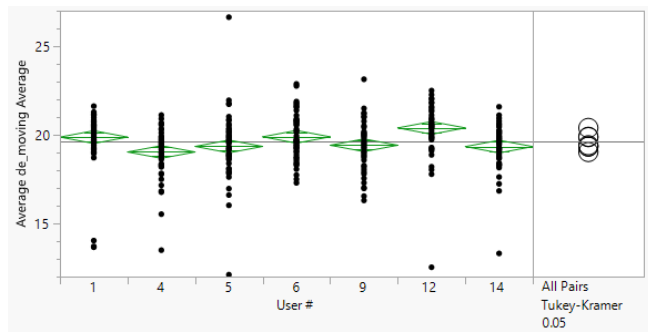

Fig. 7 ANOVA Test for session 3 male participants comparison

Experiment 2b:

In this experiment, we used ANOVA test since there were more than two Participants to be considered. The overall p-value in three sessions for female participants is (p<0.05) were shown in Table 8. The detailed results of average comparison between female participants in sessions 1, 2, and 3 are presented in Tables 9, 10 and 11 respectively. Fig. 8, 9, and 10 represent the ANOVA test by JMP software.

Table 8
ANOVA Test Results for three sessions between female participants

Session #	p-Value
Session 1	<0.0001
Session 2	<0.0001
Session 3	<0.0001

Table 9
ANOVA Test Results for session 1 between female Participants

Table 10
ANOVA Test Results for session 2 between female Participants

Male Participant		P-Value							
		User2	User3	User7	User8	User10	User11	User13	User15
P-Value	User2		**1.0000**	0.5638	0.0140	0.0010	0.9951	0.9968	0.0338
	User3			0.6216	0.0185	0.0014	0.9908	0.9986	0.0435
	User7				0.7689	0.3055	0.1451	0.9385	0.9011
	User8					0.9966	0.0008	0.1120	**1.0000**
	User10						<0.0001	0.0137	0.9759
	User11							0.8273	0.0024
	User13								0.2112
	User15								

Table 11
ANOVA Test Results for session 3 between female Participants

Male Participant		P-Value							
		User2	User3	User7	User8	User10	User11	User13	User15
P-Value	User2		0.9885	0.0015	<0.0001	<0.0001	0.9895	0.0100	0.0002
	User3			0.0331	<0.0001	<0.0001	**1.0000**	0.1315	0.0068
	User7				0.4135	0.5194	0.0318	0.9996	0.9998
	User8					**1.0000**	<0.0001	0.1554	0.7310
	User10						<0.0001	0.2197	0.8212
	User11							0.1273	0.0065
	User13								0.9775
	User15								

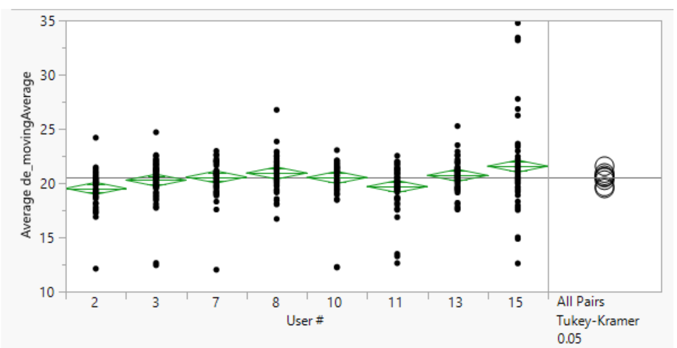

Fig. 8 ANOVA Test for session 1 female participants comparison

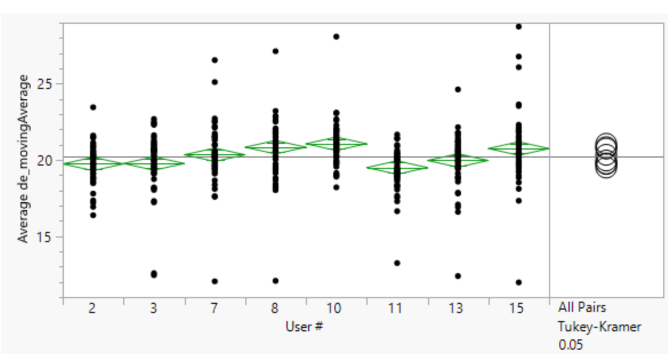

Fig. 9 ANOVA Test for session 2 female participants comparison

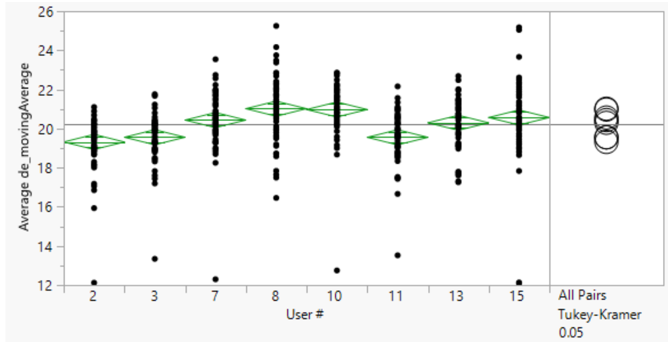

Fig. 10 ANOVA Test for session 3 female participants comparison

- **Experiment 3**

In the third experiment, we discovered if there was a variation between male and female emotions. We calculated the average DE from 62 channels of EEG signals for all male participants and for all female participants. By applying T-test for unpaired data (male/female), the p-values for this experiment are shown in Table 12 and the results for sessions 1, 2, and 3 are shown in Fig. 11, 12, and 13.

Table12
T-test Results for three sessions between male and female participants

Session #	p-Value
Session 1	0.0489
Session 2	0.0364
Session 3	0.0149

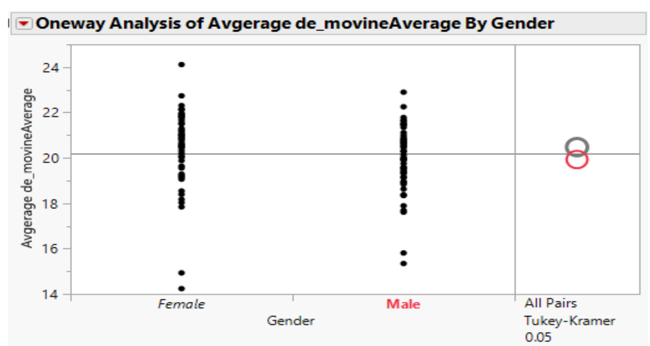

Fig. 11: T-test between male and female for session 1

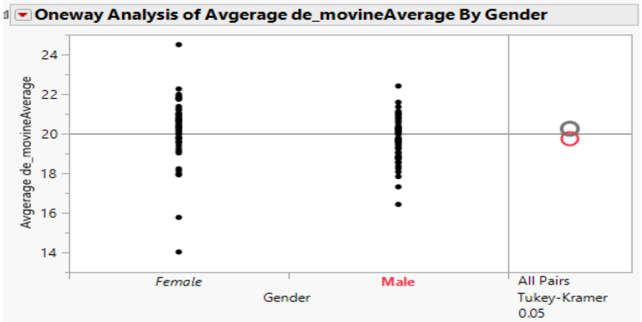

Fig. 12: T-test between male and female for session 2

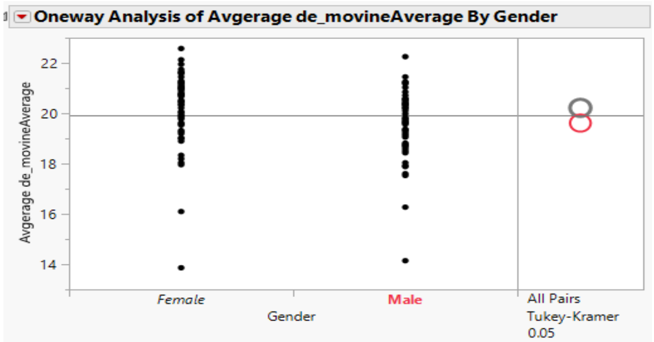

Fig. 13: T-test between male and female for session 3

IV. DISCUSSION

Conducting statistical analysis on the SEED dataset with some hypotheses will add significant facts to the SEED dataset. The first experiment studies if the three sessions for a single user will produce the same average DE of EEG signals or not. As the results are shown in Table 3, the p-value for 12 participants is greater than 0.05, but few participants (9, 13, and 14) have p-value less than 0.05 (indicated in orange). Therefore, hypothesis 1 (H1) was partially supported this means that the recorded sessions are the same for most participants.

In the second experiment, the first part tested the similarities of average DE of EEG signals between male individuals. From Table 4, for the three sessions, the p-value is less than 0.05. Thus, hypothesis 2a (H2a) was rejected because there is a significant difference between male participants' emotions. Nonetheless, when the p-value between male participants (tables 5, 6, and 7) were examined, it is noted that thereare some identical results among male participants as their p-value=1 (participants 5 &9 and 6 & 14 in session 1).

Regarding the second part of experiment 2, we studied the similarities of the average DE of EEG signals between female participants. The reults were the same as the male participants, for the three sessions the p-value is less than 0.05 as shown in Table 8. Therefore, we reject the hypothesis 2b (H2b) was rehected as there is a significant difference between female participants' emotions. by examining tables 9, 10, and 11, it was also noted some female participants had identical emotions (such as participants 2&3 and 8&15 in session 2).

Finally, in experiment 3, the average DE of EEG signals between male and female were compared. The p-value for the three sessions is less than 0.05 -as illustrated in Table 12- therefore, hypothesis 3 (H3) was supported. Accordingly, there is a significant difference between male and female emotions.

V. CONCLUSION

The study aims to use EEG signals for emotion recognition. SEED is a statistically accurate way to measure the similarities and differences in emotions. The empirical study with this method followed15 participants (7 males/8 females) who contributed to the SEED dataset. Three experiments were then conducted. The first was to compare the participant's emotions during three sessions. In the second experiment, descrepancies in the emotions participants of the same gender was noted. The last experiment aptly compared emotions between male and female participants. In most participants, there was no difference emotions results in each recorded session. However, when comparing the same gender emotions, some differences were noticeable in some participants and even identical results in others. The caterogery with the most distinct emtions remained that of the biological the male and female comparison.

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دراسة تجريبية لإشارات مخطط كهربية الدماغ EEG للتعرف على الانفعالات باستخدام SEED

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المستخلص. تمتاز العواطف البشرية بأنها معقدة للغاية ولا يمكن تحديدها أو تصنيفها بدقة من قبل الآخرين، وبما أننا في عصر الذكاء الاصطناعي (AI) ، أصبح التعرف الأوتوماتيكي على المشاعر مجالًا خصباً للبحث والتطبيقات مما يساهم في الرفع من كفاءة الصحة العامة. هناك مجموعة متنوعة من الأساليب العلمية التي يمكنها قياس العواطف بدقة من دون اشتراط وجود ملامح الوجه، ومن أكثر الطرق موثوقية تخطيط كهربية الدماغ (EEG) الذي يعتمد على الإشارات الفسيولوجية، لذلك أصبح موضوع التعرف على المشاعر استناداً على تخطيط كهربية الدماغ من الأبحاث النشطة في السنوات الأخيرة. SEED من جامعة SJTU هي مجموعة بيانات مفتوحة المصدر تحتوي على إشارات EEG المستخدمة للتعرف على المشاعر. معظم أبحاث التعرف على المشاعر بواسطة تخطيط كهربية الدماغ EEG تعتمد على استخدام تقنية تعليم الآلة لتصنيف المشاعر المختلفة. في هذا البحث نعتمد على تطبيق الدراسة التجريبية على SEED لاستكشاف بعض خصائص مجموعة البيانات هذه. خلصت الدراسة باستنتاج أن المشاعر المسجلة بين الجلسات المتعددة هي نفسها لمعظم المشاركين، بالإضافة إلى ذلك ، هناك اختلاف في المشاعر المكتشفة بين المشاركين من نفس الجنس، وأن هناك تمايز من الناحية البيولوجية في طبيعة المشاعر بين المشاركين من الذكور والإناث.