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Emotional Testing on Facebook's User Experience

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ABSTRACT This study aims at understanding how a user's emotions fluctuate when undertaking certain tasks on a social media platform such as Facebook or other software products which may have emotional effects on its user. Specifically, we explored the difference in the usability aspect of Facebook concerning frequent and new Facebook users. The study involves a qualitative study on eighteen participants, nine of whom were Facebook users and nine non-Facebook users who had never used Facebook before participating in this study. During the testing procedure, users were asked to complete several tasks on Facebook, while the electrophysiological activity of their brain was recorded using an EEG (electroencephalogram) acquisition system. Certainly, this study can be applied to any software product, before its release, to improve its user interface by acquiring insight into how user-friendly it is for new users when compared to frequent users. Additionally, a correlation in user friendliness between new users and frequent users is investigated. Furthermore, the study will help us discern which parts of the brain had the most significant difference between groups and discuss the motives behind an individual's emotional state, concerning user experience. Based on the analysis of the power spectrum of the characteristic brain waves, this research establishes that there is a substantial statistical difference between new and frequent Facebook users. Also, it resulted that there is a significant difference between the central, temporal and occipital lobes of new and frequent users. These results will assist developers in creating optimal and user-friendly software products.

INDEX TERMS Social systems' behavior analysis, man-machine interaction, social systems design, emotion recognition, human-computer interaction, user experience, behavioral aspects in computational modeling, psychological factors in software design, usability testing, technology evaluation, modeling human emotions, neuroimaging, digital signal processing, EEG, testing tools, Facebook.

I. INTRODUCTION

With every single software that is being developed, there is always the need to test it out thoroughly and sufficiently. Software testing ranges from method testing to the testing of a whole system in its deployed environment. Through this study, it is hoped that a new trend takes on in testing software on new consumers to evaluate whether the user experience had a negative, positive or neutral effect on the new users. The study involves the usage of electroencephalogram (EEG) recorded the electrophysiological activity of the brain to quantitatively assess the user's real experience rather than relying solely on the users' opinions, which may be biased.

The study involves a qualitative study on eighteen participants, nine of whom were Facebook users and nine non-Facebook users who had never used Facebook before participating in this study. The participants were asked to provide their age, duration of computer usage, occupation, also if the participant is a Facebook user then the duration of Facebook usage in a week, since when, time of the day etc. Such details of the participants are provided in Appendix - A.

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II. AIMS AND OBJECTIVES

In this study, the relationship between recorded EEG data and the emotional experience felt by an individual was investigated. The main aim of this study was to enable software companies in recreating this study on potential end-users to see how they react to the software interface. Another objective is to see the correlation between new and frequent users, which might be an insightful result in understanding how users interact with a software product. Facebook is hugely connected to its contents, therefore the study was designed such that emotional response of a novice or non-experienced user can distinctly evaluate the ease of access of the Facebook as a software while excluding the effect of the content matters by providing similar resources to all the subjects.

The first hypothesis proposed is that there exists a substantial significant difference in brain activity between new and frequent Facebook user groups. It is because various groups perceive emotions differently [1]–[3].

The second hypothesis proposed is that the region near the temporal lobe has the most noticeable difference between groups. It should be due to the limbic system residing at the bottom of the temporal lobe, which is responsible for an individual's mood and emotions.

III. BACKGROUND

A. EEG EQUIPMENT AND DATA ACQUISITION

Every electrode records different types of waveforms, from a particular area of the brain. Having a cluster of these electrodes enables the research in acquiring electrical cortical brain activity from within the human brain. It will also help indicate the parts of the brain, which are more active, resulting in what frame of mind it is [4].

As suggested by [5], "Using the scalp electrodes, useful information about the emotional state may be obtained as long as stable EEG patterns on the scalp are produced" [5]. It demonstrates that through the use of EEG, one can determine the user's emotional state that can be analysed to understand the user's experience.

B. EMOTIONAL TESTING FOR SOFTWARE APPLICATIONS

Software testing is a significant phase in any methodology used, as this determines whether the software is at par with the client's requirements. Furthermore, it will depict whether the system will work efficiently, once it is deployed. User acceptance testing is one of the most challenging types of testing as this entails the end-user/client in testing the system out for the first time. Thus, such a test needs to be passed since failing would result in significant drawbacks in finalising the product. Usability is a notable factor in user acceptance testing as it classifies whether the interface is user-friendly. As stated in 'Usability Engineering,' by Nielson [6], it is imperative to have an efficient user interface in today's world as this results in the more proficient use of the product and puts less stress on the user.

IV. LITERARTURE REVIEW

The human brain is made up of four cerebral lobes, as can be seen in Table 1.

The lobe areas that are of interest in our research are the frontal, parietal and temporal lobes due to their responsibilities and functions. Moreover, the limbic system is a structure that is responsible for an individual's mood and emotion. The limbic system is located in the deep furrow between the two cerebral hemispheres, found between the brain's halves and at the base of the brain structure, towards the lower part of the temporal lobe, [7].

TABLE 1. Different lobes in the brain [7].

Cerebral Cortex / Lobes	Position	Brief Description
Frontal Lobe	Located in the frontal region of the brain.	Responsible for voluntary muscle movement, planning, making decisions, speech, smell and processing emotions. Controls our reactions and responses.
Parietal Lobe	Located behind the frontal lobe.	Closely responsible for the sense of touch
Temporal Lobe	Located underneath the parietal lobe.	Strongly associated with a person's emotions and also auditory processing of sound.
Occipital Lobe	Situated at the back of the brain, behind the temporal and parietal lobe.	Primary responsibility is for visual processing of the eyes, through the optic nerve, such as interpreting colour, light and movement. Processes other sensory input information, such as the sense of touch and memory, with the visuals.

The research was carried out on the detection of emotions from an individual, and the following are various methods that can be used to achieve this:

Facial Electromyography (EMG) - Where an EMG is used to measure an individual's negative and positive emotional valence while he/she is playing an interactive video game [8]. The method entails in placing electrodes on an individual's face to measure the electrical current from the individual's facial muscles. Through this approach, readings are being recorded from the individual's facial expression, which might not yield correct results. Hazlett [8], [9] stated the limitations of using EMG as follows: "*the conclusion about mental effort's effect on the corrugator (wrinkles which are formed due to skin muscle contraction) EMG is limited.*".

Eye Tracking Emotional Recognition - Where an eye tracker classifies emotions based on three eye characters of an individual, which are: blink characteristics, eye-gaze characteristics, and pupil change characteristics [10]. The accuracy of classifying emotions was more than 80%.

Heart Rate Emotional Recognition - where an individual's heart rate is recorded and later analysed to determine heart rate fluctuations to a negative emotion from neutral. This method was implemented by [9], [11], [12], where participants answered multiple polar questions (yes-no questions). This process produced satisfactory results as the study had an accuracy of 80%, yet they only classified negative and neutral emotional states.

EEG Emotional Recognition- Where an individual's brain activity is recorded using multiple electrodes placed on one's scalp. The data was recorded using an EEG recorder and later classified to a stimulus picture of emotion [13]. In [13], we observe promising results as they had a success rate of around 90%.

From the methods previously mentioned, we focused on EEG emotional recognition as this method had positive results with classifying emotions on a three-scale system, being positive, neutral and negative. This method appeared promising in the context of analysing and determining an individual's emotional state while using a software product.

Moreover, to come up with more robust conclusions, the respective participants filled a Self-Assessment Manikin (SAM) after completing each task. Here, the user was asked to give a rating from 1 to 5 for respectively how pleasing to stressful each of the tasks has felt to that user. This method was adopted by [9], [13]–[17] to get the personal opinions of the respective participants on whether the task at hand had a positive, neutral or negative emotional effect on them.

Various papers [5], [9], [13], [18]–[20] have stimulated participants with purposefully emotionally stimulating images to record the individual's mental state. These pictures were selected from the International Affective Picture System (IAPS) [9], [16], [17], which enabled the user looking at them to trigger certain areas of emotion in their brain unintentionally. Our study is based on furthering such research on user experience, such as Facebook.

Measuring emotions from electrical brain activity is a relatively new method. Additionally, the use of EEG data acquisition equipment is a cheap and easy-to-use measurement to record electrical brain activity [21]. It has been shown that emotional markers can be extracted through the use of EEG signals [13]. Furthermore, Bos [13] mentioned that achieving the result of recognising one's emotions could assist psychologists and therapists in their analysis. Moreover, other applications could include Human-Machine-Interaction (HMI), human communication through a computer and aiding physically challenged people with communicating their emotional state of mind. However, the disadvantage of using this method based on the analysis of brain signals is that the users are required to wear some form of measurement equipment.

V. DESIGN AND IMPLEMENTATION

A. STUDY DESIGN

Eighteen computer literate individuals participated in this research, nine of them being Facebook users and nine of them being non-Facebook users (who had never used Facebook before participating in the study). Potential participants were approached by word of mouth, a newspaper advertisement and through the use of Facebook groups. The study was approved by the University of Malta's Research Ethical Committee (UREC). The informed consent was collected from each participant through a consent form filled in by them and signed before the testing phase.

The EEG electrodes were placed through the scalp cap to ensure firm contact with the scalp, with the use of a water-based gel. Additionally, participants were instructed to have minimal body movements while using the computer as these muscle movements can interfere with the EEG data acquisition. The study required that all participants had to be in a calm state of mind before the testing phase. g.Recorder® software was used for EEG data acquisition.

B. SELF-ASSESSMENT MANIKIN (SAM) ANALYSIS

The self-assessment manikin (SAM) test is an indication, given by participants, on how difficult the task was to complete [22], [23]. It is a well-known assessment. However, it can have biased properties. Dunning *et al.* [24], stated that "*people overrate themselves.*", meaning that individuals think they are 'above average' and can do a better job when compared to others. Ultimately, this brings one to the conclusion that when people reflect on their performance, they tend to be biased with themselves, stating that the task was either easier or harder than experienced. As can be seen in Figure 1, the self-assessment manikin data was attained and later sectioned by the task.

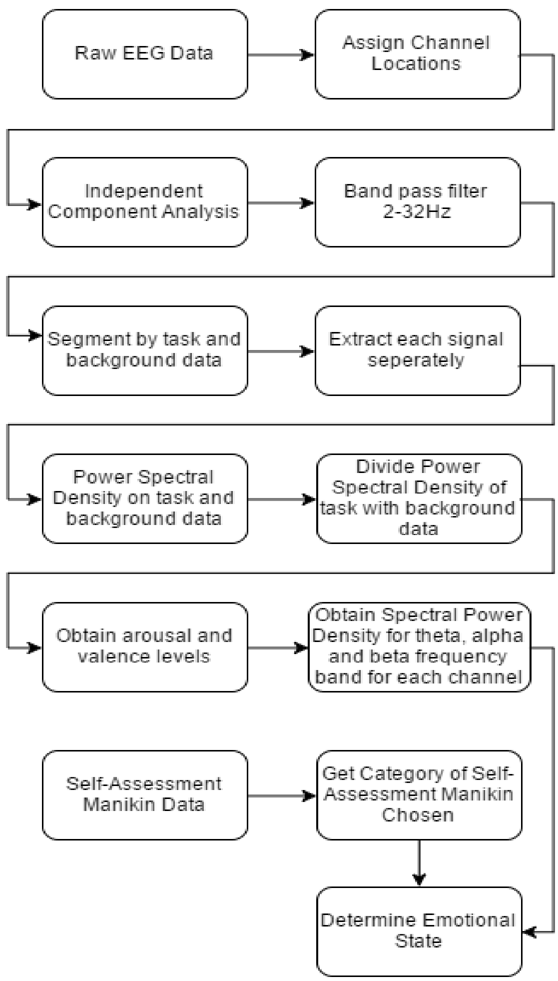

FIGURE 1. The structure of the experimental setup about the recordings used throughout the study.

C. THE EEG SYSTEM

Firstly, a gel-based EEG system following the 10-20 electrode placement system was used for this study. We set up all sixteen channels of EEG electrodes on the respective

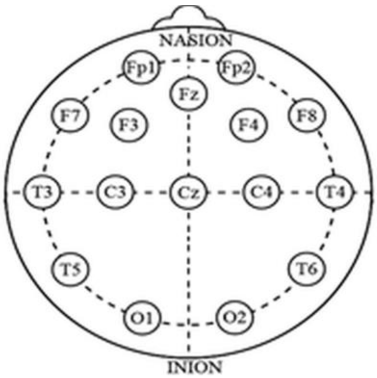

FIGURE 2. Channel locations for the selected scalp electrode placement system.

participant, through the use of the EEG cap and gel-based substance. The following electrode channels were used: Fp1, Fpz, Fp2, F7, F3, F4, F8, T7, C3, Cz, C4, T8, P7, O1, O2, P8, as can be seen in Figure 2. There were two additional channels aiding data acquisition, which were the ground and reference electrodes. The ground electrode was placed on the forehead and the reference electrodes were placed below each of the ears.

All the channels were connected to an electrode adapter, which passed the data to an EEG amplifier to take into account the reference and ground channels. The EEG signal amplifier was connected with the PC via Universal Serial Bus (USB). Furthermore, through the use of the g.Recorder® software [25], the EEG amplifier was set with the following settings:

1) Sampling frequency: 256Hz
2) Bandpass filter 0-100Hz; To record data between the specified frequencies.
3) Notch filter: 50Hz; To remove electricity background interference.

While the EEG electrodes were being placed on the scalp, we conversed with the respective participant ensuring that they are comfortable and started the testing phase in a calm state of mind.

D. EXPLANATION OF HOW EACH TASK WAS SANCTIONED

All the questions asked to all the participants are provided in Appendix - B. There were three types of questions;

1) The pre-testing phase – where participants were asked to give an overview of them.
2) The testing phase – where participants were asked to conduct the task questions of Facebook by using the computer provided.
3) The post-testing phase – where participants were asked to give feedback.

The testing phase was carried out in the manner, as illustrated in Figure 3. The experiment included twenty simple tasks to be conducted by the participants on Facebook.

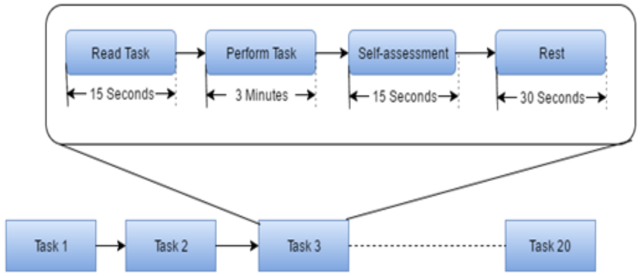

FIGURE 3. Segmentation of the experimental setup for each task.

These tasks are designed from the possible usage of a typical Facebook user profile. The tasks have suitable variability such that the first-time user would have to give more attention to perform these tasks than an experienced user. Each task was categorized into four sections. Firstly, the participants were asked to silently read the task for a maximum duration of fifteen seconds. After which, the participants were asked to perform the task on Facebook and advised that they had a maximum period of three minutes to complete the task. They were also asked to click the 'Home' page after completing the task. It was done to start each task on the same page. After completing the task, the participants were asked to mark the difficulty of the task on a 5-point self-assessment manikin (SAM) scale (one being easy and five being difficult). Lastly, the participants were asked to rest for an additional thirty seconds with their eyes closed.

E. FILES USED BY PARTICIPANTS

Three files used throughout the test were as shown in Table 2.

TABLE 2. Files used by participants through the study.

Files	Description of file
Display Picture to upload	A smiley face image file to be uploaded by the participant as a profile picture.
Picture to upload	A picture of a waterfall was used as a sample picture to be uploaded by the participant.
Video to upload	An educational nature video was used as a sample to be uploaded by the participant.

F. EEG DATA ANALYSIS

All data evaluation was completed offline using MATLAB 2017a with EEGLAB 14 toolbox [26]. EEG readings were used to analyse each task conducted by the individual, which were the task data, recorded while the individual was conducting the task on Facebook, and the background data where the participant was resting. Primarily, there are three main stages of analysing EEG data:

1) PRE-PROCESSING STAGE

The pre-processing stage is where the data is transformed from raw data to pre-processed data that is set to be processed and evaluated [27]. The following steps were carried out in the pre-processing stage:

TABLE 3. Channel number and corresponding location.

Channel Number	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16
Location	Fp1	Fz	Fp2	F7	F3	F4	F8	T3	C3	Cz	C4	T4	T5	O1	O2	T6

1. As a blind source separation technique, we used the Independent Component Analysis (ICA). It consists of identifying the source signal of a particular channel from a mixture of other interfering channels, as can be seen in Table 3 [18], [28].
2. A bandpass filter was chosen to be between 2-32Hz since theta, alpha and beta frequencies lie within this range [29]. It was implemented using the built-in EEGLAB 14 [26] feature 'Basic FIR Filter'. This eliminated power line and eye-movement interference, which oscillate at 50 and below 4Hz, respectively.

2) PROCESSING STAGE

Processing stage was a crucial stage, whereby it was essential to compute adequate analysis on the data. Power Spectrum Density (PSD) estimate analysis was used for feature extraction from the EEG data. It was due to multiple studies [27], [30]–[32] which have successfully established a correlation between the different frequency bands (theta, alpha, and beta) in EEG signals and emotions [29]. PSD transformed the EEG data from time-domain to frequency-domain [33]. Furthermore, this transformation assesses which frequencies were most prominent across the channels.

Firstly, we examined the periodogram power spectral density estimation algorithm. Periodogram computes the connotation of different frequencies in a time-domain signal [34]. It is similar to the Fast Fourier Transform (FFT) algorithm, yet more optimised for irregularly time-sampled data and different waveforms. The periodogram is an enhanced version of the FFT algorithm as it estimates the signal by averaging the square magnitude of the FFT with windowed sections of the signal [35].

Secondly, we investigated the Welch's power spectral density estimate (pwelch) algorithm [33] that is based on the periodogram function. Using Welch's overlapped segment to calculate the average power spectral density (PSD) [33]. The algorithm segments the signal into overlapped signals to accurately compute the PSD of each segment [33].

Welch's function was chosen over the FFT and periodogram function for the following reasons:

The signal was windowed, meaning each window is calculated separately [36].

Windowed signals were overlapped, meaning each windowed signal had traces of the previously windowed signal, which ultimately increased power spectral estimation [36].

Through this process, a power spectrum density estimate (in μV/Hz) of the tasks was obtained. One is required to obtain the power spectrum of the actual task through (1) as follows [37]:

$$PowerSpectrum\,(ActualTask) = \frac{PowerSpectrum\,(Task)}{PowerSpectrum\,(\mathrm{Re}st)} \tag{1}$$

Here, $PowerSpectrum\,(\text{Task})$ and $PowerSpectrum\,(\mathrm{Re}st)$ were calculated during the 'Perform Task' and 'Rest' state respectively as illustrated in Figure 3. about the experimental setup for each task. Asymmetrical power spectrum (in μV/Hz) differences was considered [38], to determine the difference between the left and right hemisphere, which was a significant factor when analysing the participant's valence levels. Thus, the band power was calculated for theta, alpha and beta, which have a frequency range of 4-8Hz, 9-13Hz and 14-30Hz, respectively. After that, the arousal and valence levels of an individual can be calculated [37].

One can determine the degree of arousal of a participant by defining the level of excitement a person was experiencing by calculating the ratio of beta and alpha brain waves. It was due to beta waves being associated with an excited state of mind and alpha waves are linked to a relaxed state of mind [37]. We consider four electrode channels, which are located on the prefrontal frontal region, labelled as Fp1, Fp2, F3, and F4 and calculated using (2) as follows [37].

$$Arousal = \frac{\alpha_{Fp1+Fp2+F3+F4}}{\beta_{Fp1+Fp2+F3+F4}} \tag{2}$$

We determined the level of the valence of each participant and this illustrates if an individual was in a positive or negative frame of mind. Ramirez and Vamvakousis [37] stated that comparing the difference in cortical hemispheres would indicate the individual's emotional state of mind. This was driven by R. J. Davidson, P. Ekman, C. D. Saron, J. A. Senulis, and W. V. Friesen's technique [39], where high alpha/beta left temporal ratio was linked to negative emotions, and whereas, the high alpha/beta right temporal ratio was linked to positive emotions. We consider the F4 and F3 temporal locations to calculate valence using (3) as follows [37], [54]:

$$Valence = \frac{\alpha_{F4}}{\beta_{F4}} - \frac{\alpha_{F3}}{\beta_{F3}} \tag{3}$$

3) COMPARISON OF STAGE

The new and frequent Facebook user's arousal and valence level results were compared using the previously mentioned formulas. It was conducted using an unpaired Student's t-test analysis, which would yield whether the means of both groups were statistically different from each other [40]. Further, it is illustrated in the literature that even a small sample size ($N1 = N2 \geq 5$) provides a significant hypothesis testing and statistical power for unpaired t-test for the within-pair correlation coefficient ≥ 0.8 [41]. Moreover, each group's theta, alpha and beta frequencies in each channel were examined to understand which frequencies were most prominent between groups. Lastly, the tasks that had the most statistically different frequencies between groups were inspected to analyse the possible reasons for the same.

VI. EVALUATION

The evaluation stage entails in analysing the results obtained through the research. Unpaired Student's t-test analysis [40] was chosen as it illustrates whether a statistically significant difference exists between new and frequency Facebook users. The processed data was evaluated in the following manner:

A. AROUSAL AND VALENCE LEVELS

After calculating the arousal and valence values for each participant by task, we compared both groups' arousal and valence levels [37]. It was revealed that there was no statistically significant difference between new and frequent Facebook user's valence levels, yet the least p-value for arousal levels were 0.0265 and 0.0224 for Task-5 and Task-21 respectively, where the within pair correlation coefficient (CC) were 0.8691 and 0.9861, and statistical power coefficient (SPC) were obtained as 0.9991 and 0.9999 respectively. This result steered us to investigate the power spectral density estimate between groups.

B. STATISTICAL POWER SPECTRAL DENSITY ESTIMATION

In the following test, we calculated the difference between both group's power spectral density difference, and the results in Table 4 were obtained. It was observed that there was a significant difference between both groups in task 12, 15, 16 and 21.

TABLE 4. A significant difference between new and frequent facebook users.

Task	p-value	CC	SPC	SAM scale difference
Task 12	0.0310	0.9957	0.9845	1.125
Task 15	0.0487	0.8272	0.9973	1.431
Task 16	0.0448	0.9428	0.8541	1
Task 21	0.0363	0.9673	0.9997	1.306

Task 12 returned a p-value of 0.0310, as this involved the user to go onto his newly created profile and change their privacy settings to public. The main reason for there to exist a significant difference between both groups was that frequent users would find this task easy, as they had performed this task multiple times while using Facebook. Furthermore, there was a 1.125 SAM scale difference between both groups.

Task 15 returned a p-value of 0.0487, as this entailed the user to upload a video to Facebook from the desktop wall and post it to his Facebook newsfeed. It was no easy task for new Facebook users as it required individuals to find the video upload box at Facebook web page and to select the specific video file to upload and post. Furthermore, there was a 1.43 SAM scale difference between both groups.

Task 16 returned a p-value of 0.0448, as this involved the user in finding the notification button and opening those notifications. The task involved the user in accessing his Facebook page and clicking the notification button at the top of the webpage. Additionally, there was the 1.00-scale difference on the SAM test.

Task 21 returned a p-value of 0.0363, as this comprised of the user to create a new private event with a scheduled date and time, then send the invitations to the Facebook friends asking them to join this event. The task had a 1.306-scale difference between both groups in the SAM test.

C. THETA, ALPHA AND BETA FREQUENCIES IN EACH CHANNEL

In the following test, we calculated each respective participant's theta, alpha, and beta spectral power bands and compared both groups [29]. Consequently, for every respective participant, we had twenty tasks multiplied by sixteen channels totalling three hundred thirty six features for each of the three frequency bands, i.e. totalling in one thousand eight features per user.

We evaluated each frequency band separately. It was done by calculating the substantial difference between new and frequent users by channel and tasks. The results obtained are provided in Table 5, 6 and 7.

TABLE 5. Theta frequency band's substantial difference by channel and task (based on unpaired student's t-test).

Theta frequency band					
Task	**Channel**	**p-value**	**CC**	**SPC**	**Total**
Task 9	6 **(F4)**	0.0481	0.9507	0.999	**2**
Task 10	14 **(O1)**	0.0152	0.9253	0.9720	

TABLE 6. Alpha frequency band's substantial difference by channel and task (based on unpaired student's t-test).

Alpha frequency band					
Task	**Channel**	**p-value**	**CC**	**SPC**	**Total**
Task 3	9 **(C3)**	0.0244	0.8817	0.9999	**10**
Task 3	13 **(T5)**	0.0034	0.9207	0.9997	
Task 3	14 **(O1)**	0.0281	0.8968	0.9999	
Task 4	7 **(F8)**	0.0307	0.9158	0.9999	
Task 8	4 **(F7)**	0.0370	0.9026	0.9999	
Task 8	9 **(C3)**	0.0491	0.8301	0.9997	
Task 8	14 **(O1)**	0.0278	0.8789	0.9999	
Task 10	14 **(O1)**	0.0377	0.8938	0.8462	
Task 14	5 **(F3)**	0.0410	0.8112	0.9999	
Task 17	14 **(O1)**	0.0277	0.8826	0.9999	

Through this feature extraction, it was shown once again that there was a statistically significant difference between new and frequent Facebook users on task 3, 4, 7, 10 and 15. As previously mentioned, these tasks were proved to be challenging for new Facebook users. It indicated that there was a statistically significant difference between both group's beta frequencies. Beta brainwaves are associated with an individual's alert state of mind while alpha brainwaves are linked with a relaxed state of mind. Additionally, we consider all three frequency bands independently, and the results are provided in Table 8 and Table 9.

Due to these results, our research delved into why there was such a substantial difference between both groups' theta, alpha and beta frequencies. Subsequently, we inspected the location of each of the electrodes. Thus, for every task,

TABLE 7. Beta frequency band's substantial difference by channel and task (based on unpaired student's t-test).

		Beta frequency band			
Task	**Channel**	**p-value**	**CC**	**SPC**	**Total**
Task 2	16 **(T6)**	0.0499	0.8582	0.8501	
Task 3	1 **(Fp1)**	0.0105	0.9316	0.9598	
Task 3	10 **(Cz)**	0.0190	0.9571	0.8823	
Task 4	2 **(Fz)**	0.0150	0.9581	0.9981	
Task 4	7 **(F8)**	0.0061	0.8688	0.9999	
Task 7	1 **(Fp1)**	0.0050	0.9777	0.9993	
Task 7	10 **(Cz)**	0.0195	0.9736	0.9148	
Task 8	5 **(F3)**	0.0388	0.9154	0.8791	
Task 10	5 **(F3)**	0.0254	0.9184	0.9990	**17**
Task 10	6 **(F4)**	0.0173	0.9409	0.9991	
Task 10	7 **(F8)**	0.0476	0.9275	0.9829	
Task 10	10 **(Cz)**	0.0070	0.8801	0.9999	
Task 10	16 **(T6)**	0.0049	0.8731	0.9992	
Task 15	4 **(F7)**	0.0050	0.9265	0.9995	
Task 15	14 **(O1)**	0.0006	0.9462	0.9999	
Task 17	4 **(F7)**	0.0208	0.9314	0.9999	
Task 18	2 **(Fz)**	0.0487	0.8046	0.9999	

TABLE 8. For each frequency band number of channels/features with a substantial difference between new and frequent users.

Total number of channels (features) = 16			
Task	Theta	Alpha	Beta
Task 2	0	0	1
Task 3	0	3	2
Task 4	0	1	2
Task 7	0	0	2
Task 8	0	3	1
Task 9	1	0	0
Task 10	1	1	5
Task 14	0	1	0
Task 15	0	0	2
Task 17	0	1	1
Task 18	0	0	1
Summation/total	2	10	17

TABLE 9. Frequency band's substantial difference between new and frequent users.

	Theta	Alpha	Beta
Total possible number of features for all tasks for each frequency band	16 channels * 21 tasks = 336 features	16 channels * 21 tasks = 336 features	16 channels * 21 tasks = 336 features
Summation of number of features for all tasks with a substantial difference on each frequency band (Table 8)	2 features	10 features	17 features
Total summation of features with a substantial difference over the total number of features	2/336	10/336	17/336
Percentage of features with a substantial difference	0.595%	2.976%	5.060%

the significant difference test results for theta, alpha and beta frequencies in each location were summed up, as can be seen in Figure 4. It was done to observe which channel locations had the highest difference, which would illustrate the most notable frequency difference between the groups.

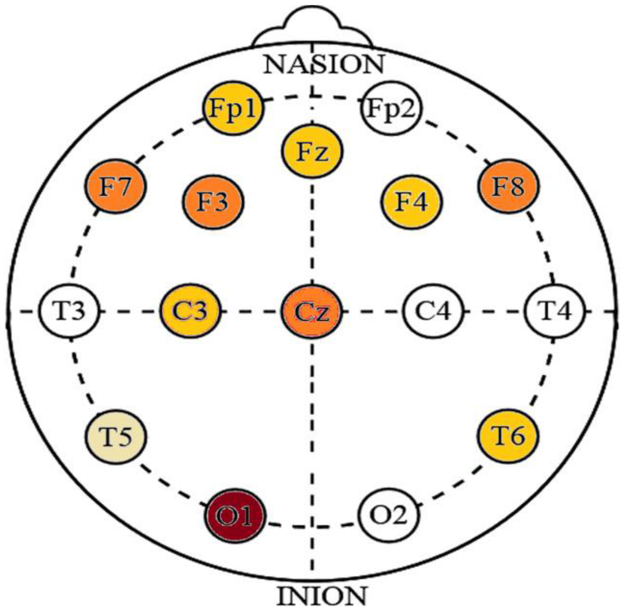

FIGURE 4. Summation of electrode locations of substantial difference results for theta, alpha and beta frequencies between new and frequent Facebook users for all twenty tasks based on Table 5, Table 6 and Table 7. Here, the channels of significant difference for the highest of 6 tasks are represented by dark-Red and lowest of 1 task is light-Yellow.

TABLE 10. Comparing the highest values of spectral power density in theta, alpha and beta frequency and the highest difference in the SAM tes.

Task	Total number of electrodes which are statistically different in theta, alpha and beta frequencies between new and frequent Facebook users	SAM test difference between groups
Task 3	5	0.833
Task 4	2	1.00
Task 7	2	0.89
Task 8	4	1.01
Task 10	6	1.76
Task 15	2	1.43

D. COMPARISON BETWEEN THE HIGHEST SAM SCALE DIFFERENCE

Additionally, our findings allowed us to compare the highest SAM scale difference with the highest statistical difference test results of spectral power density in theta, alpha and beta frequency bands between both groups as shown in Table 10.

Thus, through the results obtained in Table 10, it can be seen that there is a correlation between both group's highest spectral power density beta frequency difference and both group's highest SAM test difference.

We first illustrated the spectral power density of each task for theta, alpha and beta frequencies dependent on each location as can be seen in Figure 4 as well as Table 5, Table 6 and Table 7. The most difference between new and frequent users was primarily seen at the occipital, frontoparietal, frontal and the temporal locations.

Observing the theta, alpha and beta's spectral power density results (cf. Figure 4 and Table 5, Table 6 and Table 7), we could perceive that on channel locations O1: 6 tasks showed significant difference in EEG activity; then for F3, F7, F8 and Cz: 3 tasks showed the significant difference in the emotional response; similarly there was statistically significant emotional difference on channel locations of Fp1, Fz, F4, C3 and T6 for more than one task performed by the new and frequent Facebook users. These findings are supported by a recent study by *Song et al.* [9] for the emotional response of joy, anger, fear, disgust and sadness when watching movie clips related to such type of emotional content. Similarly, our results are also in-line with another study done for movie watching and consequent positive and negative emotions [17]. Electrode locations in the frontal lobe are responsible for emotional memory, while temporal lobe containing T5 and T6 electrodes are for logical thinking understanding, motivation and aspersion [9], [17], [42]. If one was to assume that frequent Facebook users found the tasks at ease and were tranquil while completing them, one could easily conclude that new Facebook users were in a significantly different emotional state of mind.

VII. FUTURE WORKS

Future works envisage the possibility of widening the study bearing in mind different factors coming in to play. In our opinion, these elements could be handled in the following ways to improve the results of this study.

Repetition of this study using a functional Magnetic Resonance Imaging (fMRI) system is highly recommended. An fMRI system uses a magnetic field and pulses to capture a three-dimensional image showing blood oxygen level dependent metabolic activity of an organ within the human body. The EEG and fMRI have been simultaneously used for more accurate localisation of the source of electrophysiological activity deep-down inside the 3D brain, which is otherwise not possible with the EEG being a 2D scalp modality. This system would accurately illustrate which areas of the brain are most electrically active while an individual is conducting a task. It could better assess the differences between frequent users and new users [43]–[45]. However, the main drawback of using such a system is its cost, as it is a high-end piece of equipment and incurs many maintenance costs. In particular, the electrodes made of conductive plastic or thin film of gold required to be used to limit the heating of electrodes inside the fMRI [45].

Another recommendation we deem fit to suggest is to create a user interface prototype and to reiterate the study with every upgrade to the prototype. Additionally, a comparative study can be drawn between a prototype and another, to understand better what the user is experiencing.

TABLE 11. Appendix - A: Demographic details of the participants.

User	*Age*	*Occupation?*	*Computer Hours/week?*	*Internet Hours/week?*
Facebook	20	Student	70	60
Facebook	21	Student	56	56
Facebook	21	Student	20	30
Facebook	20	Student	10	30
Facebook	21	Student	20	1
Facebook	19	Student	70	65
Facebook	20	Student	60	20
Facebook	21	Student	35	25
Facebook	20	Student	46	46
Non-Facebook	21	Student	20	15
Non-Facebook	20	Student	42	30
Non-Facebook	82	Pensioner	7	7
Non-Facebook	21	Student	42	41
Non-Facebook	24	Student	25	20
Non-Facebook	67	Lawyer	40	2
Non-Facebook	54	Judge	15	3.5
Non-Facebook	21	Student	70	65
Non-Facebook	21	Student	30	24
		Total		
Facebook	**20.33333**		**43**	**37**
Non-Facebook	**34.625**		**34.5**	**25.5**

Subsequently, we hope this research transcends itself into a steppingstone in creating an optimised framework for evaluating software between frequent and new users through the use of EEG data acquisition.

VIII. CONCLUSION

The hypothesis tackled was assessing whether a software package is user-friendly to new users. The research focused on Facebook, as it is one of the most used social media platforms these days. However, this study can be applied to any software product.

We adopted an approach by collecting data from frequent and new users to assess the difference between groups. The outcome of this research was on identifying the emotional differences between new and frequent Facebook users. We believe that through this study, software companies can scrutinise their software's user interface to ease users in their experience.

Our study found a statistically significant difference between new and frequent Facebook users in both their alpha and beta frequencies.

The second hypothesis was established through analysis of alpha and beta frequencies across sixteen channels, which leads to the discovery that some areas (i.e. central, temporal

TABLE 12. Appendix - B: Tasks performed by participants for the SAM and Facebook activity.

Task Number	Task Question	Description
Task 1	How old are you?	Pre-testing
Task 2	What is your occupation?	Pre-testing
Task 3	On average, how many hours do you spend using your computer each week?	Pre-testing
Task 4	On average, how many hours do you spend surfing the internet each week?	Pre-testing
Task 5	Do you have a Facebook account?	Pre-testing
Task 6	If yes, how long have you been using Facebook for?	Pre-testing
Task 7	If yes, how often do you log onto it?	Pre-testing
Task 8	If yes, at what time of the day do you usually log into Facebook? (morning, afternoon, evening)	Pre-testing
Task 9	If no, what are the reasons for not engaging in social media?	Pre-testing
Task 10	Register	Testing phase
Task 11	Go on your profile and upload a photo, with a description, as your display picture	Testing phase
Task 12	Click on 'Update Info' and enter information about yourself.	Testing phase
Task 13	Search for 'Roberto Mangion' and add him as a friend	Testing phase
Task 14	Check your new friend's about page	Testing phase
Task 15	Find your new friend's date of birth	Testing phase
Task 16	Find your new friend's email	Testing phase
Task 17	Find your new friend's current workplace	Testing phase
Task 18	Find the list of groups that your new friend is currently in	Testing phase
Task 19	Find your new friend's albums.	Testing phase
Task 20	Talk to your new friend on Facebook Messenger	Testing phase
Task 21	Change your privacy settings to public	Testing phase
Task 22	Post a sentence on your wall	Testing phase
Task 23	Post the picture from your desktop to your wall	Testing phase
Task 24	Post the video from your desktop to your wall	Testing phase
Task 25	Check your notifications	Testing phase
Task 26	Create a new group titled 'Facebook User Interface Testing' with privacy setting 'Secret' and add your new friend to the group	Testing phase
Task 27	Post something in the new group	Testing phase
Task 28	Search for the page titled 'Nelson Mandela.'	Testing phase
Task 29	Search a page of interest	Testing phase
Task 30	Create a new private event titled 'Testing' which will be on the 20th of June 2016 in Valletta at 16:00, and invite your new friend	Testing phase
Task 31	How would you rate the reading characters on the screen?	Post-testing
Task 32	How would you rate the layout of the interface?	Post-testing
Task 33	Is the screen too cluttered with information?	Post-testing
Task 34	Was it hard to learn to use Facebook?	Post-testing
Task 35	How would you rate your overall experience?	Post-testing
Task 36	Any suggestion to improve user interface?	Post-testing

and occipital lobes) were most distinctive between both groups. The temporal region, which consists of the limbic system that is responsible for an individual's mental state of mind, was the most notable finding.

APPENDIXES

APPENDIX A

See Table 11.

APPENDIX B

See Table 12.

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