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Pornography Addiction Detection based on Neurophysiological Computational Approach

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ABSTRACT

The rise of Internet access, social media and availability of smart phones intensify the epidemic of pornography addiction especially among younger teenagers. Such scenario may offer many side effects to the individual such as alteration of the behavior, changes in moral value and rejection to normal community convention. Hence, it is imperative to detect pornography addiction as early as possible. In this paper, a method of using brain signal from frontal area captured using EEG is proposed to detect whether the participant may have porn addiction or otherwise. It acts as a complementary approach to common psychological questionnaire. Experimental results show that the addicted participants had low alpha waves activity in the frontal brain region compared to non-addicted participants. It can be observed using power spectra computed using Low Resolution Electromagnetic Tomography (LORETA). The theta band also show there is disparity between addicted and non-addicted. However, the distinction is not as obvious as alpha band. Subsequently, more work need to be conducted to further test the validity of the hypothesis. It is envisaged that with more participants and further investigation, the proposed method will be the initial step to groundbreaking way of understanding the way porn addiction affects the brain.

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1. INTRODUCTION

People are constantly engaged with smartphone and communication devices. Based on the report released by Bank of America [1], 39% people age ranging from 18 to 34 years old (typically referred as Millennial) interacts more with their smartphone compared to other individuals. The second most frequently Millennial interacted with is their significant other (27%) followed by children (14%), parents (8%), friends (7%) and co-workers (4%). Such trend is interesting to observe as it indicates that 51% people of that age range are communicating more through Internet; namely, text and instant messaging (40%), social media (7%) and email (4%) as opposed to verbal conversation; that comprised of, in person (33%) and phone call (12%). Such finding is also in line with report published by Experian Marketing Services [2] stated that 77% Millennials own their smartphone and spend approximately 35 hours a week with digital media. The report also revealed that half of the Millennials need Internet connection constantly and 43% Millennials access Internet through smartphone than through a computer. Hence, it is no surprise if the younger age group can also have individual Internet accessibility to the internet contents as they are more technology savvy and very much into gadget and devices.

The individual Internet accessibility is one of the catalyst to Internet pornography addiction. It is almost impossible to detect the pornography access of an individual unless the log information of Internet navigation history is given. However, a violation of privacy may be an issue to gain such access to the data as one may just refuse to disclose such information. Furthermore, pornography contents are not limited to pay-by-view access. To date, free materials are widely available. The rise of social media applications such as Facebook, Instagram, Tumblr, WeChat and others offer a wide range of pornography stimuli ranging from soft pornography such as images depicting sexy and seductive individual to the more advance and hardcore contents. In the most recent publication, Lim et al. reported that the median age of first pornography viewing of 815 participants was 13 years for men and 16 years for women among young Australians [3]. 46% male participants admitted that they access pornography weekly compared to 19% female participants. As opposed to the Millennials, younger participants of the study tend to download or watch the pornography content online on computer (49% woman and 63% man). It is also reported that majority of the participants, 83% woman and 95% male participants access the pornography content when they are alone. It means that pornography exposure is common even at the young age regardless of the gender and such trend is getting more prominent and worrisome.

The trend is observed in the increased number of porn related website accessed by the Internet users. It was reported that one of the most popular porn website, Pornhub.com recorded 23 billion visits in 2016 and such statistic is equivalent to 729 visitors in a second by the total population of the United Kingdom (64.1 million) [4]. Moreover, it is also learnt that almost 4.6 billion of porn are watched in a year, making it equal to 5,245 years.Such trend is consistent with the statistic of Malaysian access time to PornHub website as presented in [4]. Figure 1 illustrates major cities in Malaysia and the time spend per day of accessing Pornhub website. It is observed that the longest usage (in term of time access) is from Kuala Terengganu with mean access time of approximately 13 minutes. It is closely followed by Kota Bharu and Miri with both access time is 12.27 minutes. However, information on the duration of access time may not give the overall picture of the situation. The number of population and access time are compared as presented in Table 1. It is found the highest visit frequency of 0.0078 is recorded by Putrajaya with population of 88,300. Melaka, with population of 872,900 yielded the second most frequently access city with frequency of 0.008. Although, Sabah is geographically large, the frequency of PornHub website access is only 0.0002. Hence, it can be hypothesized that Internet connection infrastructure may play an important role in porn accessibility. Urban area such as Putrajaya and Melaka have a better internet connection making it easier to access the website compared to rural area.

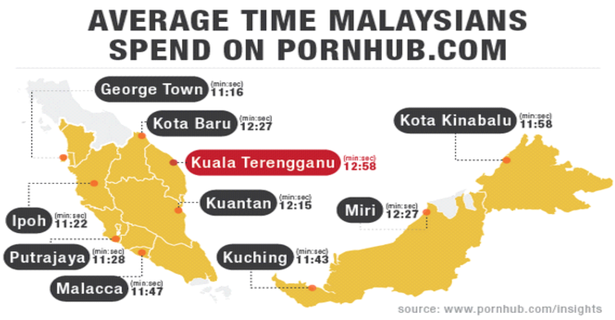


Figure 1. Average time Malaysian spent on Pornhub.com website [4]

Table 1. Number of Population for each State in Malaysia

State	Number of Population
Terengganu	1,254,000
Kelantan	1,718,000
Penang	1,719,000
Pahang	1,623,000
Perak	2,478,000
Putrajaya	88,300
Melaka	872,900
Sarawak	2,636,000
Sabah	3,544,000

The paper is organized in the following manner. Section 2 describes the literature review focusing on the definition of pornography addiction, the implication of the addiction and current psychological approach that is adopted to recognize teenagers who are addicted to porn. Section 3 presented the concept of employing electroencephalogram (EEG) and Low Resolution Electromagnetic Tomography (LORETA) to find disparity of the brain signals between addicted teenagers and non-addicted teenagers. Section 4 describes the results and discussion before concluded with Section 5 of summary, conclusion and future work.

2. LITERATURE REVIEW

Addiction such as pornography is very difficult to detect until the urges is no longer can be curbed and usually manifested by awkward behaviors that may not be accepted by community norm. Typically, when an individual is addicted, there will be no physical changes can be observed except alteration in the brain area making it difficult to spot. The brain's reward system is activated by pleasant or exciting stimuli. The dopamine will be released during porn use. It is a neurotransmitter that helps to carry nerve signals across a synapse. When it is activated, dopamine enables generalized feelings of well-being and satisfaction that can make porn users experience feelings similar to a drug user's high. An addicted brain is both physically and chemically vary from the normal brain that erodes the ability to feel pleasure to reach satisfaction. Consequently, it is hypothesized that the brain signal may also be affected by pornography addiction.

2.1. Adolescent Brain and Pornography Addiction

Teenagers who suffers from porn addiction and repeated use of pornographic materials may involve in sex abuse, have high tendency to be teen parents and develop social problem. In 2015, a total of 229,715 babies were born to women aged 15–19 years in the United States, for a birth rate of 22.3 per 1,000 women in this age group [5]. The report also stated that pregnancy and birth are significant contributors to high school dropout rates among girls. Only about 50% of teen mothers receive a high school diploma by 22 years of age, whereas approximately 90% of women who do not give birth during adolescence graduate from high school [5,6]. The statistics indicates that there is a strong need to detect the tendency of pornography addiction for teenagers because a teen's brain is at its peak of dopamine production and neuroplasticity, making it highly vulnerable to addiction.

Arain et. al stated that adolescent brain ranging from 10 to 25 years old are very much influenced by many factors such as heredity and environment, status inclusive of physical, mental, economical and psychological, hormones such as estrogen, progesterone and testosterone, sleep as well as nutritional intake [7]. Neurobehavioral, morphological, neurochemical, and pharmacological evidence suggests that the brain remains under construction during adolescence [8,9]. Hence, the best time to identify the porn addiction should be as early as possible to ensure that the brain is still in its high plasticity stage.

2.2. Current Approach in Detecting Porn Addiction

Psychologists typically construct an interview or questionnaire for the participants to honestly and truthfully answer. However, the taboo or bad perception/implication of having pornography addiction may result to exaggeration/suppression of the answer making it difficult to derive a consistent inference. Respondents have tendency to lie if they feel that their privacy and social desirability bias may be compromised. In addition, respondents may react negatively to the interviewer depending on the way the questions are being asked. This is especially obvious if the interviewer has bad rapport with the respondents making them feel uneasy and distrustful in such a way that it may affect the answer that is given by the respondent.

One of the way to eliminate embarrassment or discomfort by having individual interview is by answering online pornography test. For instance, Greenfield construct a brief 12-question test to determine whether an individual may have an issue with the use, abuse or addiction to online pornography [10]. Such instrument maybe beneficial for those who wants to remain anonymous and yet still have conscience to check their dependency to pornography whether it may be a concern or otherwise. However, Greenfield also remarked that the survey developed is only for educational and informational purposes. If the score is on the higher side, it is advised to seek for medical and psychiatric diagnosis.

2.3. Electroencephalogram (EEG)

EEG is a non-invasive medical imaging technique where small electrical signals of the brain are measured over the electrodes placed at the scalp of the head. EEG can capture between 0.5 and 500Hz of sampling data making it good for high temporal resolution data. The hardware cost for EEG is significantly cheap compared to other neuroimaging technology, namely; magnetoencephalography (MEG), Positron Emission Topography (PET), Single-Photon Emission Computer Tomography (SPECT), Magnetic

Resonance Imaging (MRI) and functional Magnetic Resonance Imaging (fMRI). Each frequency band of the EEG signal is associated with certain brain activities

Table 2. Association of Brain Signal Frequency Ranges and Mental Activities

Name	Frequency Range (Hz)	Mental Activities
Delta	0.5 – 3	Deep sleep
Theta	4 – 7	Drowsiness and fatigue due to monotonus task, control of working memory process
Alpha	8 – 13	Cognitive control, creative thinking
Beta	14 - 30	Alertness, phonological tasks

The EEG signal waves contain a lot of interesting information. It can be divided into four frequency band over time, namely; Delta, Theta, Alpha and Beta as in Table 2. Based Britton et. al [11], the normal background EEG during wakefulness contains posteriorly dominant, symmetrical, and reactive alpha rhythm. Alpha activity is more prominent in amplitude during relaxed, eyes-closed wakefulness and demonstrates reactivity by decreasing in amplitude and presence during eye opening and mental alerting. The theta (4–7 Hz) or even delta (1–3 Hz) frequencies transiently may be seen during normal wakefulness, but usually these slower activities only become prominent during drowsiness.

The brain signals are unique to each individual and can be a ‘pure’ source of information because one cannot control, emulate, replicate, manipulate or falsify. It is dynamic and represents the unaltered current state of mind as compared interview and questionnaire responses. Therefore, in this work, the brain signals captured from EEG are used as the input to see whether there is a disparity between porn addicted respondents or non-addicted respondents based on the hypotheses that, 1) addiction change the brain and the way its functions, 2) the brain’s function can be observed through brain signals, and 3) brain signals can be captured using EEG.

2.4. Low Resolution Electromagnetic Tomography (LORETA)

LORETA computes an instantaneous, three-dimensional, discrete linear solution consisting of the smoothest of all possible neural current density distribution [12, 13]. It is capable of determining the relative activity of regions in the brain using surface electrodes. The produced visualization helps further to understand the activated brain region when the stimuli is presented which may give some insight to the study.

3. DATA COLLECTION AND EXPERIMENTAL SETUP

3.1. Data Collection Protocol

There are six stages that need to be completed by the participants in the EEG data collection. The participants are comfortably seated in front of a computer that continuously shows the stimuli from one stage to another. It is conducted in a laboratory with minimal interference of noise and excessive background movements.

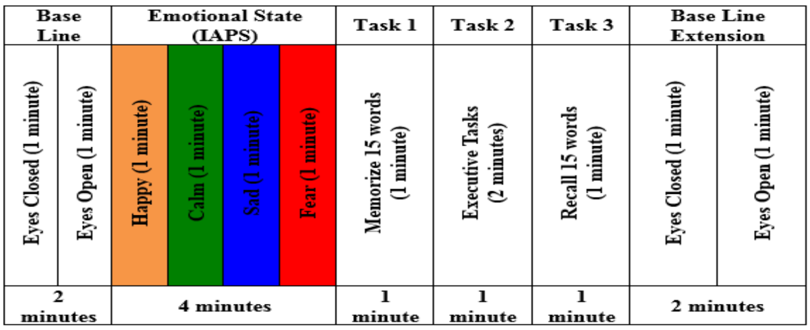


Figure 2. EEG Data Collection Protocol

Before participants start the tasks, they are asked to fill the consent form and be briefed of the overall experiment purpose. This is to ensure that the participants feel at ease and react as close to normal as possible. Prior to the EEG data collection, the participants undergo a psychological test conducted by the psychologists to determine whether the participants may suffer from porn addiction or not. Figure 2 summarizes the stages and time taken for each stage. The EEG signal data collection started with the recording of the EEG baseline signal. The participants had to close and open their eyes for a minute each. At this stage, participants are advised to keep calm and minimize their movement. This is because EEG is quite sensitive to movement including eye blinks, facial and muscle movement [20]. If these movements are executed, it may distort the actual EEG signal recording because the brain signal frequency is very much low as compared to the artifacts.

After that, four emotional stimuli were presented with each video lasting one minute. This is to gauge the way the brain reacts to the emotional stimuli. The selected emotion stimuli represent happiness, calm, sadness and fear emotions that can be represented in the different quadrant in the Affective Space Model [14,19]. Further works has been extended in [15,16] using emotion primitives' values of valence and arousal. Valence refers to the effect of the emotion to an individual. It is ranging from positive to negative effects. Moreover, the arousal is the degree of activation that can range between active or passive. Then, three tasks are introduced to the participants.

Task 1 comprises of memorization task [18] that needs the participants to memorize 15 unrelated and common words in their vocabulary for a minute. The selection of the word is constructed by the psychologists to ensure that the semantic of the word does not carry any emotional impact. It is also to observe the correlation between mood and the ability of word memorization. In Task 2, participants were then asked to watch executive function stimuli for two minutes. This is to be a distractor to the participants in such a way that the participants may forget the words that they have memorized earlier. The participants are asked to recall the memorized words again in Task 3. To conclude the experiment, the participants need to do both activities of eyes close and eyes open for one minute each.

3.2. Participants

Fourteen healthy participants (5 female and 9 male) are involved in the EEG data collection with age mean of ± 14.1 years old. The participants are the students from Yayasan Kita dan Buah Hati (YKBH), Jakarta, Indonesia. Prior to the EEG data collection, they are reported to be in calm mood and not under the influence of drug, alcohol or medication. The YKBH psychologists had identified the participants who are addicted or not and the psychologist's result is presented in Table 3. In order to respect and preserve the confidentiality and anonymity, participant's name is omitted. The psychologist's report is simplified in Table 3.

Table 3. Subject's Individual Pyschological Result

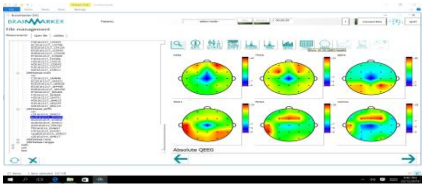
Gender	Addicted	Non-addicted
Male	S1, S5, S6, S14	S4, S7, S8, S12, S13
Female	S9, S10, S11	S2, S3

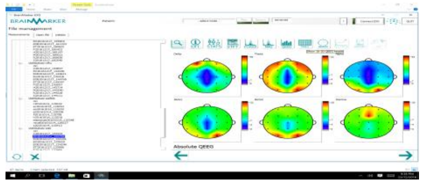
3.3. Memorized Words

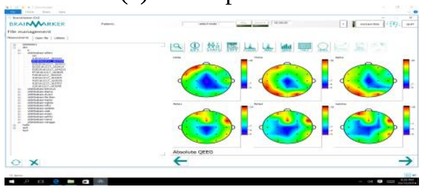
There are 15 carefully selected words that bear minimal emotional meaning. The words are in Bahasa Indonesia so that the language barrier factor can be eliminated. The words are *belajar* (study), *kertas* (paper), *ujian* (test), *sekolah menengah* (secondary school), *pekerjaan rumah* (homework), *pena* (pen), *pelajaran* (education), *guru* (teacher), *meja tulis* (desk), *murid* (pupil), *angka* (number), *penghapus* (eraser), *komputer* (computer), *kotak pensil* (pencil box) and *sekolah dasar* (primary school). There is no obligation for the participants to memorize the word in sequence and there is no restriction in the way they memorize the words.

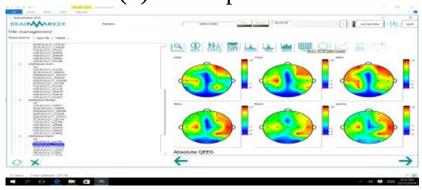
4. RESULT AND DISCUSSION

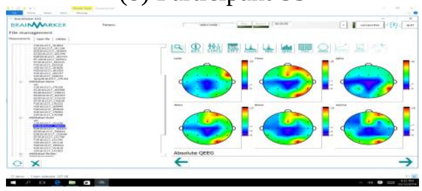
Once the EEG signal are captured, the raw signals are plotted using LORETA to see the level of brain activation at a specified region. In this work, we focused on the frontal region for eye-open and eye-close phases. This is because based on our prior knowledge, eye-open and eye-close session can distinguish between dyslexic and non-dyslexic children [17]. Hence, in this paper, such attention is also dedicated to study whether there is distinction between addicted and non-addicted. Figure 3 presented the brain activation diagram constructed using LORETA of EEG power spectra. The blue color indicates low brain activation compared to green-yellow-red that represent high activation. In the diagram, it is arranged that the right side is the brain mapping for the participants that have been identified by the psychologists as non-addicted. On the contrary, the left side is the brain mapping for addicted participants. It can be observed that participants that have been identified by the psychologists as addicted consistently show low alpha value as opposed to non-addicted participants that can be observed in S1, S6, S9, S10, S11, S14 for addicted participants and S2, S4 and S8 for non-addicted participants. However, there are cases that contradict to the psychologist's finding such as S5 for addicted participant. The alpha band distribution is high making it possible that the participant may not be addicted.

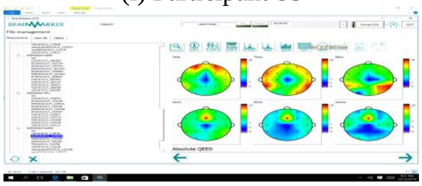

(a) Participant S1

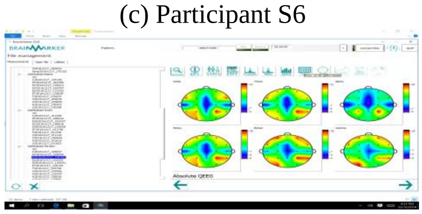

(h) Participant S2

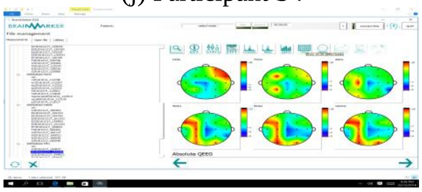

(b) Participant S5

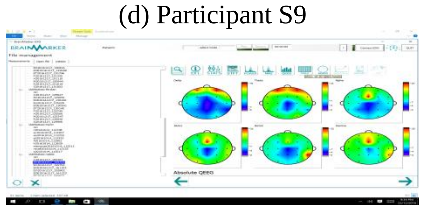

(i) Participant S3

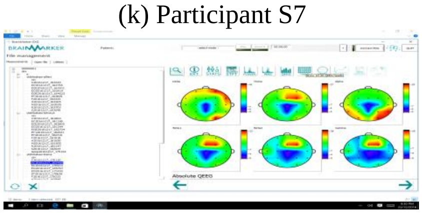

(c) Participant S6

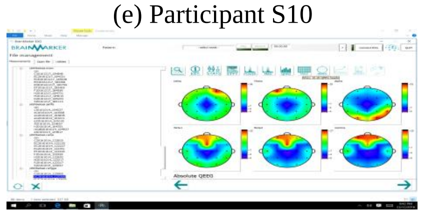

(j) Participant S4

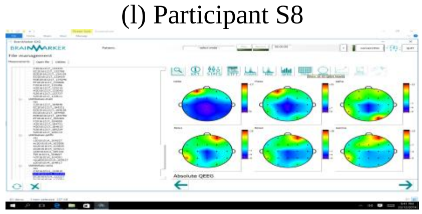

(d) Participant S9

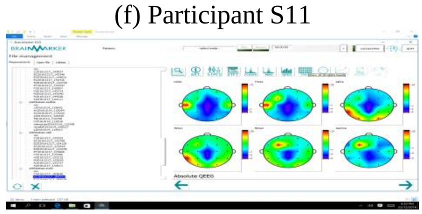

(k) Participant S7


(e) Participant S10


(l) Participant S8


(f) Participant S11


(m) Participant S12


(g) Participant S14

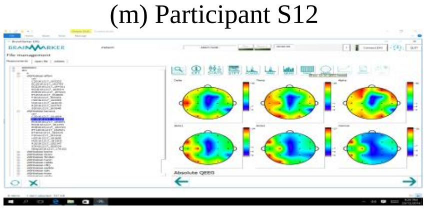

(n) Participant S13

Figure 3. Brain Mapping Topology using LORETA for Theta (Left) and Alpha (Right) Bands at Frontal Region

The experimental results for non-addicted participants also show an interesting observation. Participant S3, S12 and S13 show high power spectra in Alpha band as presented in Figure 3(i), 3(m) and

3(n). However, Participant S2 and S4 in Figure 3(h) and 3(j) show low Alpha band indicating they may suffer addiction. This is in-line with the psychological test that although the participants are identified as non-addicted, it is focusing on porn addiction that does not rule out other addiction.

Further analyses are conducted by constructing trapezoidal diagram in Figure 4 and 5 to show the difference between addicted and not addicted participants power using Alpha and Theta bands respectively. Based on the observation, the degree of separation is quite small for Alpha band in Figure 4 as opposed to Theta band in Figure 5. The gap or confusion region for Alpha band is between approximately 7000 to 7500 as opposed to 5000 to 9000 for Theta band. The experimental result show that it is possible for the proposed approach to give empirical evidence to complement the porn addiction questionnaire devised by the psychologists.

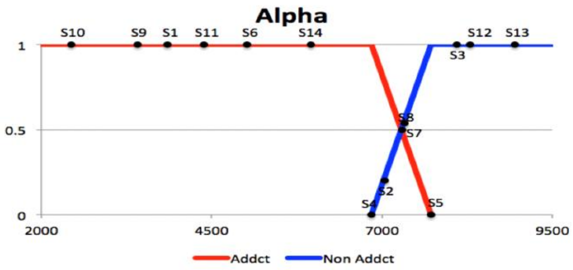


Figure 4. Trapezoidal Diagram for Alpha Band

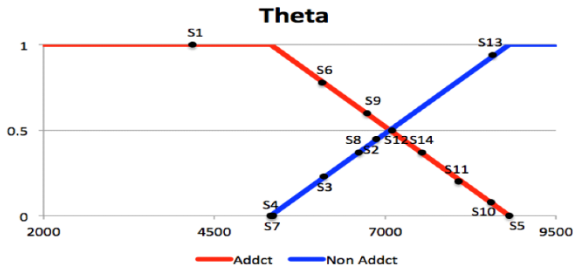


Figure 5.Trapezoidal Diagram for Theta Band

5. CONCLUSION AND FUTURE WORK

This paper proposes the use of EEG and LORETA to visualize the alpha band power spectra of frontal brain region to complement the questionnaire given by the psychologist to determine whether the participants may suffer from porn addiction. It can serve as an initial part for early intervention system to detect teenage porn addiction before the effect to the brain is permanent and recovery process may take longer time. It is envisaged that with more participants and further investigation, the proposed method will be the initial step to groundbreaking way of understanding the way porn addiction affects the brain.

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