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Extended Interaction with a BCI Video Game Changes Resting-State Brain Activity

Avinash Kumar Singh, *Member, IEEE*, Yu-Kai Wang, Jung-Tai King, and Chin-Teng Lin, *Fellow Member, IEEE*

Abstract— Video games are a widespread leisure activity and essential for a substantial field of research. In several kinds of research, video games show positive effects on cognition. Video games' ability to change the brain in a way that improves cognition is already evident in the research world. The underlying brain dynamics assessed by coherence (Coh) and partial-directed coherence (PDC) can shed light on the effect of video game playing. Here, resting-state brain dynamics have been analyzed before and after four weeks of video game playing. Fifteen participants took part in this study, which ran for one consecutive month. Participants played a gem-swapping game with a brain-computer interface (BCI) paradigm for five days per week for approximately 90 minutes for four continuous weeks. Significant ($p < 0.05$) changes in information flow and connectivity measures for Coh and PDC were found in the fronto-central, fronto-parietal, and centro-parietal network due to extended interaction with BCI. The results suggest that BCI is a potential facilitator of such resting-state network changes and may help to develop new strategies for improving cognition, but we also cannot deny the possible effects of such an effort on the disruption of a player's sense of engagement and increased mental fatigue.

Index Terms— EEG, Resting-State, Brain Connectivity, Brain-Computer Interface, Video Game.

I. INTRODUCTION

VIDEO game playing has increased in today's society as a widespread leisure activity [1]. Young people commonly play video games every day for hours on end [2]. Therefore, it is worth considering the potential effects of playing video games on human brain dynamics. Despite many controversial debates on the positive and adverse effects, little has been done to understand the change in brain dynamics in the resting state of the human brain after playing video games for lengthy periods.

Recent advances in neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), and high-resolution electroencephalogram (EEG), have allowed game-related cognitive processing to be studied noninvasively in humans. Some of these non-invasive studies showed that games have the potential to change brain dynamics, strengthen information processing skills and motor skills, and decrease the time

required to process information about color [3]. However, other research (see the detailed review in [4]) has suggested that playing video games also allows neuroadaptation and structural changes in brain that are generally associated with addiction, which could possibly lead to a disorder. These findings indicate a mix of different game playing aspects, such as attention, cognitive control, visual-spatial skill, cognitive workload, reward processing, etc. (see the detailed review in [5]), due to multiple factors, such as the nature of the video game mechanics. For example, shooting games, in contrast to strategy games [6], require different cognitive demands [3, 7] and different strategies. Moreover, with game playing and tasks that require practice to dominate, the time-window of practice positively affects the brain [8], such as increased cognitive ability, improved reaction time, and mitigated user stress levels [9]. The physical structure of the brain also differs in video game playing groups compared to groups that do not play, and this is shown to change the brain's gray and white matter, which correlates with the general intelligence of participants [10]. Importantly, it is evident that any cognition-training-related task, such as video games with a purpose (GWAP), also modulates the resting-state [11] derived from the functional connectivity of the central executive network and the default mode salience, which is also shown to impact other cognitive functions – for example, mitigating the aging-related dysfunction in the high cognitive network [12]. Efforts have been underway to use fMRI to examine different brain regions involved in gaming and to explore the relative effect of gaming on the cognitive aspects of decision making, cognitive improvement, memory, learning, and addiction [13-15]. Moreover, fNIRS has been shown to be an effective tool to measure functional connectivity in the resting-state brain [16] and in cognitive control in gaming-related research [17].

An EEG is known to be effective tool to study human brain dynamics with high temporal resolution. In an EEG study of video game playing on young participants with epilepsy, which required attention to be placed on the orientation and color of objects, showed that there were changes in oscillatory cortical activity in the theta and alpha spectral power among the control group compared to those with epilepsy [18, 19]. These results can be seen as the first evidence that video games influence the brain dynamics of the user using EEG. In other studies [9, 20], it was also shown that video games impacted cognitive functionality when played continuously for long periods and improved memory consolidation and cognitive processing [21,

22], which is thought to be an essential part of learning. Some studies [23, 24] of action video games have debated whether different games may have different effects on cognition when played for long periods. An example of this is whether action video games are beneficial for improving the visual attention of the user since they require a fast response time to search for a target. Such an improvement would have a positive impact on daily activities and especially sports, such as boxing, tennis, baseball, and cricket, which require a high level of hand-eye coordination while visually attending to a target [25, 26]. Motor-practice-related changes in sensory-motor tasks could also increase connectivity within the primary cortex, as demonstrated in previous studies [27, 28]. It has been shown that there is a change in cortical activity during training that requires higher-order cognition [29, 30], such as visual attention, working memory, or planning. It has also been shown that the learning effect of one task can be transferred to another task [31]. In general, these findings suggest that the predominant pattern of change involves a change in cortical activation across the brain network, including the brain areas underlying the associated task's performance.

There is recent literature [32] that suggests that playing a multitasking video game can significantly improve performance among older adults (60 to 85 years old), allowing them to perform at an almost equivalent skill level to that of untrained 20-year-old participants. Such results further prompt a discussion about how playing video games might affect everyday performance. However, some EEG methods of functional connectivity [33, 34] have allowed the extraction of more information on how these changes interact with different brain regions during the resting state. The resting-state brain correlates with different aspects of the brain, such as motor learning [35], cognitive training [12], memory consolidation [22], drug addiction [36], and cognitive impairment [37].

Recently, some works started experimenting with BCI-based game intervention for rehabilitation [38]. For example, in one study [39], the author showed a correlation between behavioral improvement (arm test, nine-peg hold test) and resting-state functional connectivity after playing a BCI-based video game three times per week for a month. Similarly, another study [40] showed an increase in the clustering coefficient of the resting-state functional connectivity network in the motor region of the brain after playing three times per week for six weeks. Some work [41] has also suggested that the use of BCI-based video games can re-normalize the functional network, particularly the attention network, the task positive network, and the subcortical regions in children with attention deficit hyperactivity disorder (ADHD). These children played a BCI-based game three times per week for eight weeks. These studies are very encouraging about the potential of extended interaction with video games, particularly those with BCI. However, these studies of extended use of video games with BCI have so far always focused on non-healthy people; there is no known study to extend the knowledge of similar effects in healthy people. Importantly, video gaming is already an important leisure activity among people, and more and more BCI-based video games are appearing in the mainstream market [42] than ever. It is critical to understand the impact of such extended interaction with BCI

video games on healthy people to see if the effects persist as they do with non-healthy people.

In line with this previous research, the goal of the present study is to investigate the changes in resting-state brain dynamics in healthy participants caused by extended interaction with a BCI video playing.

II. METHODS

A. Ethics statement

This study was approved and carried out under strict guidelines set out by the National Chiao Tung University's human research ethics committee. Each participant read and signed an informed consent form before participating in the experiment.

B. Participants

Thirty EEG datasets were recorded from two groups of participants, composed of 10 participants in the experimental group and five participants in the control group. One participant from the experimental group was excluded from the study due to malfunctioning in the EEG device, which results in corrupted data. The data were recorded at two-time points – the start and the end of the four weeks of video gaming, with BCI for the experimental group and without BCI for the control group. The median age of the participants was 21.1 years (with a range of 20-26 years), and the participants had no prior experience with similar experiments. Participants were asked to refrain from consuming caffeine, tea, or highly calorific food one hour before the experiment.

C. Procedure

Three minutes of resting-state EEG data with the eyes opened were recorded before participants started playing the game, and this was followed by recording EEG data during the first session of game playing and after four weeks of gameplay. The game played was a visual match-three puzzle game that was controlled using BCI [43] and a pointing device (i.e., a mouse). There were five BCI paradigms (see Supplementary Figure 2) used to control the game: steady-state visual evoked potential (SSVEP), motor imagery (MI), attention, event-related negativity (ERN), and rapid serial visual representation (RSVP) [43]. The participants scored in the game by using the mouse to move a square block to match the colors of three or more blocks. While playing the video game, every participant was exposed to all of the above mentioned BCI paradigms to obtain extra points while continuing to play the video game for approximately 90 minutes. The presented work in this manuscript is focused on resting-state data only.

All these BCI paradigms appeared with a warning screen lasting for almost 2 seconds, followed by one of five paradigms at a time. There were six consecutive stages in the video game, and the participants reached the next stage after receiving a fixed score (predefined). The participants were required to play this game five days per week for four weeks in the lab environment, with EEG recordings during the first day's and

the last day's session. (see Figure 1; Supplementary Figure 2).

In the control group, participants followed the same experimental protocol, but without any BCI paradigms. The control group participants played the game using only a pointing device. Three minutes of resting-state EEG data with eyes open was recorded before participants started playing the game in the first and last week of game playing.

D. Data Acquisition

EEG activity was recorded with a Scan SynAmps2 Express system built by Compumedics Ltd., VIC, Australia, using 30 Ag/AgCl-based electrodes placed according to the modified international 10-20 system [44] and two reference channels. A digitizer was used for channel localization. The impedance at each scalp electrode was reduced to 5K Ω or below. EEG signals were recorded with a sampling rate of 1,000 by a Neuroscan NUamp and filtered online with a low-pass filter (DC to 60 HZ, 6-dB/octave attenuation). (see Supplementary Figure 1).

E. EEG data pre-processing

The EEG data were pre-processed using the EEGLAB [45] toolbox in MATLAB (R2016, Mathworks Inc., USA). The first step of data pre-processing was band-pass filtering, such that 1Hz high-pass and 40Hz low-pass finite impulse response filtering was followed by 250Hz down-sampling for data reduction. The second step involved identifying the artifact rejection for apparent noise contaminations in the EEG signals. These artifacts were removed manually by visual inspection. After the artifact removal, an independent component analysis (ICA) was applied, followed by component rejection for eye and muscle movement. The EEG signals without artifact-related components were reconstructed using the back-projection method [46]. The resultant data were subject to further inspection, and, therefore, automatic channel rejection was applied using Kurtosis measurement and the Z-score threshold to remove any noisy channels. After all the steps of artifact rejection, resting-state EEG signals were epoched as 2s chunks for further analysis. Resting-state data were used for spectral, coherence (Coh), and partial directed coherence (PDC) estimation. (see Figure 2(A) for the signal processing steps).

F. EEG power analysis for resting-state data

The resting-state EEG data were analyzed for power analysis by converting the data into a frequency domain with a 250-point moving window, applying Welch's method [47] within each window with 50-point overlap to obtain the stationary power spectrum using fast Fourier transform (FFT). The number of frequency bins was increased by a factor of four by zero-padding the EEG data prior to applying the FFT, resulting in 160 frequency bins from 1 to 40Hz (frequency resolution of 0.25Hz). The mean data of four power bands - delta (1–3.5Hz), theta (4–7.5Hz), alpha (8–12.5Hz), and beta (13–30Hz) of 14 channels (F3, Fz, F4, C3, Cz, C4, FCz, CPz, P3, Pz, P4, O1, Oz, O2), were calculated and used for visualization and further analysis.

G. Source information flow analysis and measures

i. EEG source information flow analysis for resting-state data

Fourteen channels were selected, following [48], from different regions to cover the whole brain after artifact removal from the data preprocessing. Source Information Flow Toolbox (SIFT) [49, 50] was used to calculate the optimal multivariate autoregressive model within EEGLAB. All selected channels were grouped into four major areas of interest: frontal, central, parietal, and occipital. (see Figures 2(B) and 2(C))

ii. Coh measure

Coh [51] is defined as a squared correlation coefficient that provides information about the linear relationship between any two selected EEG electrodes at a given frequency. Coh measures the synchrony in neuronal oscillations between any two given EEG electrodes. Considering the two signals $x(t)$ and $y(t)$, Coh is expressed as follows:

$$Coh_{xy}(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f)S_{yy}(f)} \quad (1)$$

where $S_{xy}(f)$ represents the cross-spectral density between $x(t)$ and $y(t)$, and $S_{xx}(f)$ and $S_{yy}(f)$ represents the auto-spectral densities of $x(t)$ and $y(t)$, respectively.

iii. Granger causality measure

Granger causality [52] is a measure of causal influence between a signal X and a signal Y, possibly conditioned on a set of other measured signals. The Granger causality from X to Y is significantly non-zero if and only if past information in signal X improves the prediction of the present and future of signal Y, above and beyond the information contained in the past of Y and other variables included in the model. PDC [53] was applied based on the Granger causality principle to evaluate causality between a selected pair of electrodes.

Generally, a PDC estimation uses multivariate autoregressive (MVAR) modeling to estimate parameters. If we say that there are N channels of EEG signals of order p, then MVAR can be defined by:

$$x(t) = \sum_{r=1}^p A(r) X(t-r) + E(t) \quad (2)$$

where $X(t)$ and $A(r)$ are the matrix of N-EEG channels at a time t and matrix of the r^{th} order parameters, respectively. $E(t)$ represents the estimated error of an uncorrelated process with zero means. Further, the Akaike information criterion (AIC) was applied to evaluate the efficacy of the model order that was obtained using MVAR.

Once the parameters of Eq. (2) were estimated, the transfer function $A(f)$ at a frequency, f was be defined by:

$$A(f) = \sum_{r=1}^p A(r) e^{-i2\pi fr} \quad (3)$$

Similarly, Eq. (3) for N channels is:

$$\bar{A}(f) = I - A(f) = [\bar{a}_1(f) \bar{a}_2(f) \dots \bar{a}_N(f)]$$

where $A(f)$ is defined as Eq. (4) below:

$$\bar{A}_{ij}(f) = \begin{cases} 1 - \sum_{r=1}^p a_{ij}(r)e^{-i2\pi fr}, & \text{if } i = j \\ -\sum_{r=1}^p \hat{a}_{ij}(r)e^{-i2\pi fr}, & \text{otherwise} \end{cases} \quad (4)$$

Based on Eqs. (2), (3), and (4), the PDC at two given EEG channels j to i can be defined as:

$$PDC_{ij}(f) = \frac{\bar{A}_{ij}(f)}{\sqrt{\bar{a}_j^H(f) \bar{a}_j(f)}} \quad (5)$$

where $i, j = 1, 2, 3, \dots, N$ channels and $\bar{a}_i(f)$ is the i^{th} column of the matrix $\bar{A}(f)$. PDC_{ij} denotes the direction and intensity of the information flow from the EEG channel j to i at the frequency f .

iv. Graph connectivity measures

Different connectivity measures were applied using a Brain Connectivity Toolbox [54]. These measures were basic measures, the measures of integration, and the measure of centrality, as follows:

Basic measures. The number of all connected nodes to other nodes defines the degree of an individual node, while the mean of the network degree of all nodes represents graph density. If the graph is a directed graph, then the number of inward links of a node is known as in-degree, while the number of outward links of a node is known as out-degree. If the connectivity graph is weight-based, then the degree of such a graph is known as strength.

Measures of integration. This indicates how accessible communication is between nodes. It can be estimated by the average inverse shortest path length and is known as global efficiency. The measure of integration also provides the measurement of global efficiency that acts as a path between disconnected nodes – for example, a path between two disconnected nodes can imply zero global efficiencies.

Measures of segregation. This is the measure of the ability to process within densely interconnected groups of nodes and is known as the clustering coefficient. The clustering coefficient is defined as the number of node neighbors, which are also neighbors of each other. There is also another measure known as local efficiency, which is defined similarly to global efficiency but within the local group of nodes.

H. Statistical analysis

Statistical significance of Coh and PDC was assessed with respect to a null hypothesis using a non-parametric surrogate

statistical method [55] as follows. First, distribution was constructed using phase randomization with a sample size of 200. Then, the magnitude of two pairs of the null distribution was compared to obtain the p-value. All the obtained p-values were adjusted using a false discovery rate (FDR) for multiple comparisons procedure. Group differences before and after four weeks of video game playing were analyzed with paired t-tests (“X” week vs. “X+4” week) for continuous variables. EEG data for the power spectrum for the four bands (delta, theta, alpha, and beta), Coh, and PDC values were compared for the experimental and control group of participants.

III. RESULTS

A. Spectral power results for resting state

The dynamic changes in EEG power between “X” week of video game playing and “X+4” week of video game playing were compared in the experimental and control groups (see Figure 3 and 4). The EEG spectral power intensities in the alpha and beta frequency bands in the fronto-central and parietal regions were statistically significantly higher ($p < 0.05$) at the “X+4” week compared to “X” week for the experimental group (see Figure 5). The control group also showed a statistically significant increase ($p < 0.05$) in spectral power in delta, theta, alpha, and beta band in the frontal-central and parietal regions of the brain after “X+4” week compared to “X” week of game playing.

B. Source information flow results for resting state

The results from Coh and PDC showed a general increase in functional connectivity for all participants (experimental and control), but close inspection revealed more information and differences between experimental and control participants as follows. (see Figures 6-9).

Fronto-central. The fronto-central region showed a statistically significant increase in information flow ($p < 0.05$) in the delta, theta, alpha, and beta bands for both Coh analysis in the experimental group. On the other hand, the control group showed a statistically significant increase in information flow ($p < 0.05$) increase in connectivity only in the alpha band for Coh analysis. The increase of information flow in the fronto-central region was statistically significant ($p < 0.05$) for both the experimental group and the control group in the PDC analysis.

Centro-parietal. The centro-parietal region also showed a statistically significant increase ($p < 0.05$) in information flow in the alpha and beta bands for Coh analysis in the experimental group, while no statistically significant increase was found for the control group in any bands. Similarly, there was significant ($p < 0.05$) increase in information flow in the centro-parietal network in the PDC analysis for the delta, theta, alpha, and beta bands in the experimental group, while no statistically significant increase was found for the control group.

Parietal-occipital. The parietal-occipital region also showed a statistically significant increase ($p < 0.05$) in the information

flow in the alpha and beta bands for both the Coh and PDC analysis in the experimental group, but no such statistically significant increase was found in the control group.

C. Graph measures for source information flow in resting state

Different connectivity measures were calculated to understand the characteristics of connectivity and changes during “X” and “X+4” weeks of game playing for Coh and PDC analysis in the experimental and control groups.

Table 1 shows the change in degree, density, strength, global-local efficiency, and clustering coefficient for Coh and PDC analysis in the experimental and control groups after four weeks of game playing. The results clearly showed that there is no change in degree and density for Coh based on the analysis for the experimental and control groups after four weeks of game playing; on the other hand, the experimental group showed an increase in degree and density after four weeks of game playing for PDC, but again no change was found in the control group. When looking at global efficiency and local efficiency changes in the experimental and control groups, it was found that global and local efficiency decreased in the delta and theta band connectivity for Coh analysis in the experimental group, while alpha and beta showed an increase in the same group; on the other hand, the control group showed an increase in global and local efficiency in all four spectral bands (delta, theta, alpha, and beta) for Coh analysis after four weeks of game playing. Similarly, PDC analysis showed an increase in global efficiency in the experimental and control groups for all spectral bands after four weeks of game playing, while local efficiency showed an increase in the experimental group for all spectral bands, but the control group showed only an increase in the delta and alpha bands and no change in the theta and beta bands.

Another essential comparison is the clustering coefficient, which can also be seen in Table 1. It shows that all experimental group participants showed an increase in the clustering coefficient for all spectral bands, but that was not true for the control group of participants.

IV. DISCUSSION

In this study, we evaluated whether BCI based game playing affects the resting state network. For that, we conducted an experiment with the experimental and control group of participants. The experimental group played a BCI based game for four weeks, while the control group played the same game without any BCI paradigm for four weeks. Our results suggest that the resting-state network differed between the experimental group and the control group as hypothesized initially.

In [48], the author showed that EEG based resting-state information recorded before an MI task in two sessions which were on average three months apart was correlated with MI performance. Another study using EEG based MI task showed that, over the course of 12-sessions in a month, there were changes in the fMRI-based resting-state network compared to robotic rehabilitation [56]. These studies showed that EEG based MI task-based training improved motor rehabilitation in

stroke-patients and showed it be correlated with the fMRI based resting-state network [39]. In line with this, we also found improvement in BCI based MI performance shown in Supplementary Tables 2 and 3 in the experimental group of participants after five-days a week for four weeks, as shown in previous work [57]. More importantly, these effects are found in healthy participants.

Our results from the experimental group show changes in the resting-state brain network in the frontal, fronto-central, and centro-parietal networks during the resting state after four weeks of BCI-based game playing. These networks are assumed to be related to a wide variety of cognitive processes [58-61]. The fact that similar changes were not found in the control group suggests that changes in the frontal, fronto-central and centro-parietal networks are mainly caused by BCI based game playing. These results are in-line with a study on ADHD children, which also showed that BCI based training affects functional connectivity related to behavioral improvement, while a similar effect was not found in ADHD children without any BCI based training. [41]. The changes in the frontal, frontal-central, and centro-parietal regions are shown to be related to attention, working memory, memory retrieval and consolidation [62-64].

It is important to note that resting network changes in the control group represented in Coh (Figure 7) and PDC (Figure 9) appear to be highly connected compared to the experimental group (Figures 6 and 8). But, as shown in Table 1, degree, density, and cluster coefficient (for theta and beta) in connectivity measures for Coh and PDC stayed the same for the control group, which implies that non-BCI based video game playing does not affect the number of connection between fronto-central, centro-parietal, and parietal-occipital probably due to lack of effort required to learn and adapt toward BCI in video game. Interestingly, the experimental group also shows no changes in degree and density for Coh but only in the clustering coefficient. Even though there were no changes in degree and density, but cluster coefficient implies that certain groups (e.g., fronto-central, centro-parietal, and parietal-occipital) tends to cluster together after four weeks of game playing and also aligned with [40].

Interestingly, it was also found that resting-state spectral power in the delta and theta band does not change statistically significant from ‘X’ to week ‘X+4’ for experimental group but shows statistically significant alpha and beta. These findings might represent the phenomenon of the reorganization of brain network pathways [65, 66] to adapt the BCI component to play a video game that is not shown by the control group which happens in majorly lower bands power like theta [67, 68]. However, the control group still shows statistically significant changes in all the four spectral power probably due to lack of adaption due to non-BCI component during playing the video game.

In summary, our study relied on a cognitive process involving video game that required searching for a target, matching blocks of similar color, and acting as quickly as possible while also performing several active and reactive BCI tasks. The

complexity of the game continuously increased throughout the sessions. To successfully play this game, several complex cognitive processes and skills were required [69]. Our results suggested that this complex cognitive process is the result of the activity of different brain regions such as the frontal, central and parietal networks, and their interaction. We performed this study to elucidate how the brain dynamics at rest change in terms of the brain network and overall EEG power after playing a BCI-based involving video game for four continuous weeks.

This study looked at the effect of BCI based game playing on the resting state. The results are encouraging; however, there are some limitations to the current study and its interpretation.

Our results are encouraging and highlight the positive effect of gaming, but we also cannot deny the possibilities of any negative effects of cognitive involving game playing due to lack of behavioral data. For a well-defined gaming paradigm, such as a visual match-three puzzle based on Candy Crush Saga [70], using BCI to get additional score might be undesirable and required extra effort, independent of motor movements. Such an effort could disrupt and harm an individual's sense of engagement and induce mental fatigue. However, once the user learns BCI as one of the skills to control the game, the level of engagement might not always diminish [19, 71].

We collected EEG data from 15 participants only as an experimental and a control group. The results from these participants are very positive, but a higher number of participants with varying age groups could benefit more. This limitation arose due to the complexity of the experiment. The current study required participants' commitment to coming to the lab every weekday for four weeks and playing a cognitive-process-involving video game. In future experiments, we will systematically add different control groups with high statistical power using the current or similar experimental paradigm. In the future, we also plan to automate the whole process to involve more participants for the experiment with a setup such as Mobile Brain/Body Imaging (MoBI) [72] and also automate the analysis while processing the data in real-time [73, 74].

Another limitation is conducting Coh and PDC analysis based on EEG electrodes. The brain component extracted from the independent component analysis can be used for analysis, but due to the small size of the resting data (3 minutes) for each participant, it was not feasible to get enough components except for eye blinks for connectivity analysis. Therefore, an analysis was performed using EEG electrodes, but to avoid any false-positive results, we also performed cross-verification of results obtained from derived MVAR models using a SIFT.

V. CONCLUSION

The present study revealed resting-state network changes based on Coh and PDC analysis in the experimental group of participants who played a BCI-based video game for four weeks. However, similar changes were not found in the control group of participants who played the same video game without any BCI paradigm. The resting-state changes of Coh and PDC analysis were mainly in the frontal, fronto-central, fronto-

parietal, and centro-parietal networks. The brain network dynamics identified in this study may have implications for understanding the complex neurophysiology of playing BCI-based video games and the effects of playing video games in general.

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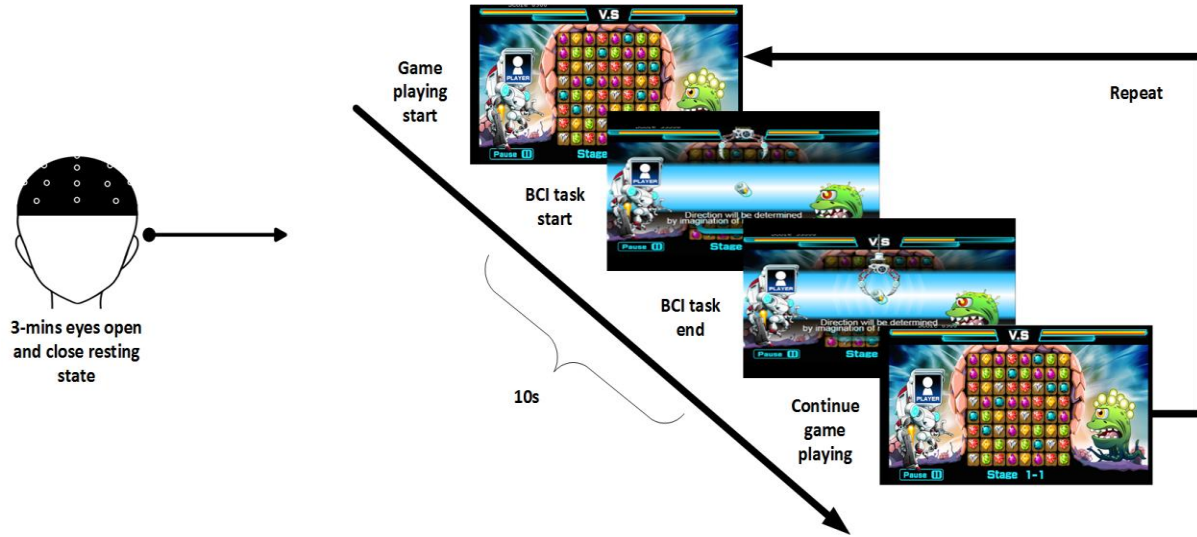


Figure 1. Experimental Paradigm: Participants played the BCI-Gem game for four continuous weeks (five days a week), and eyes-open and eyes-closed resting states were recorded for 3 min at the beginning and end of the four weeks.

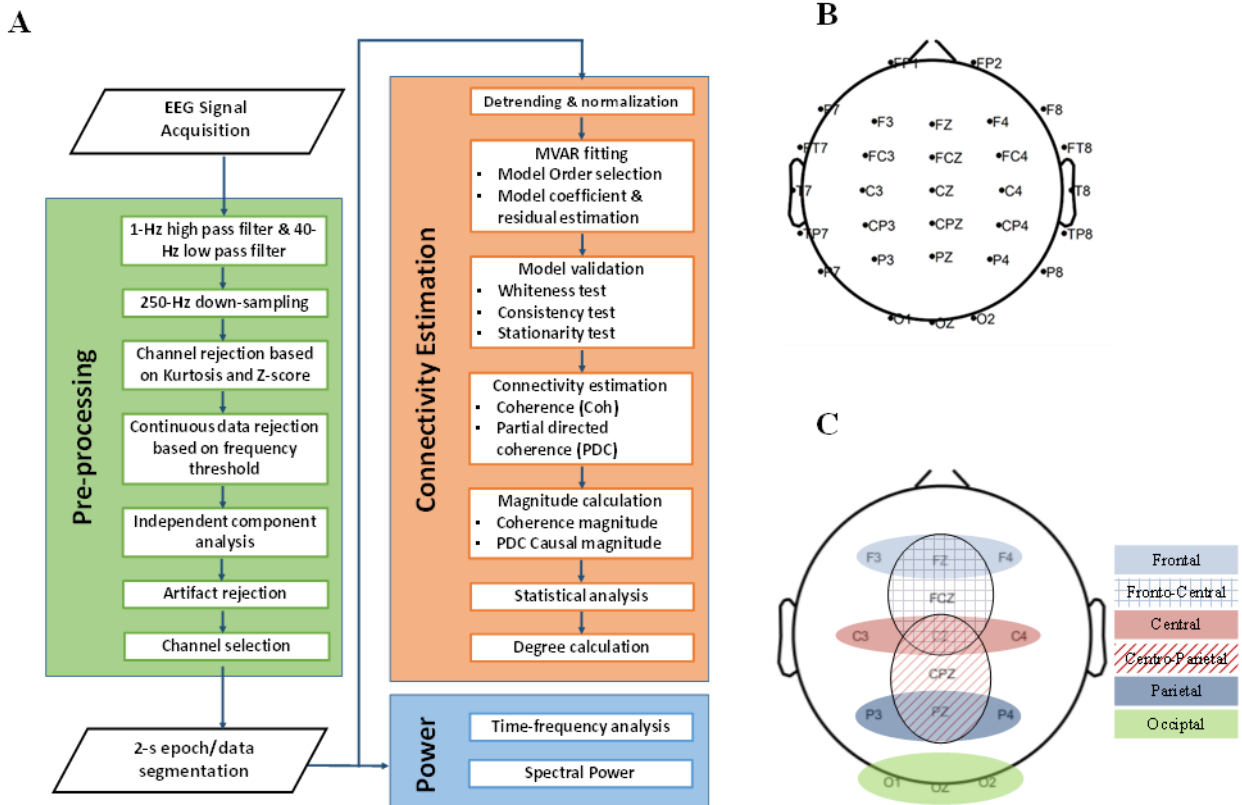


Figure 2. A. EEG Signal processing flow-chart; B. Placement of 30-channel EEG electrodes on the scalp; C. Chosen 14-electrode for analysis and their related location on brain

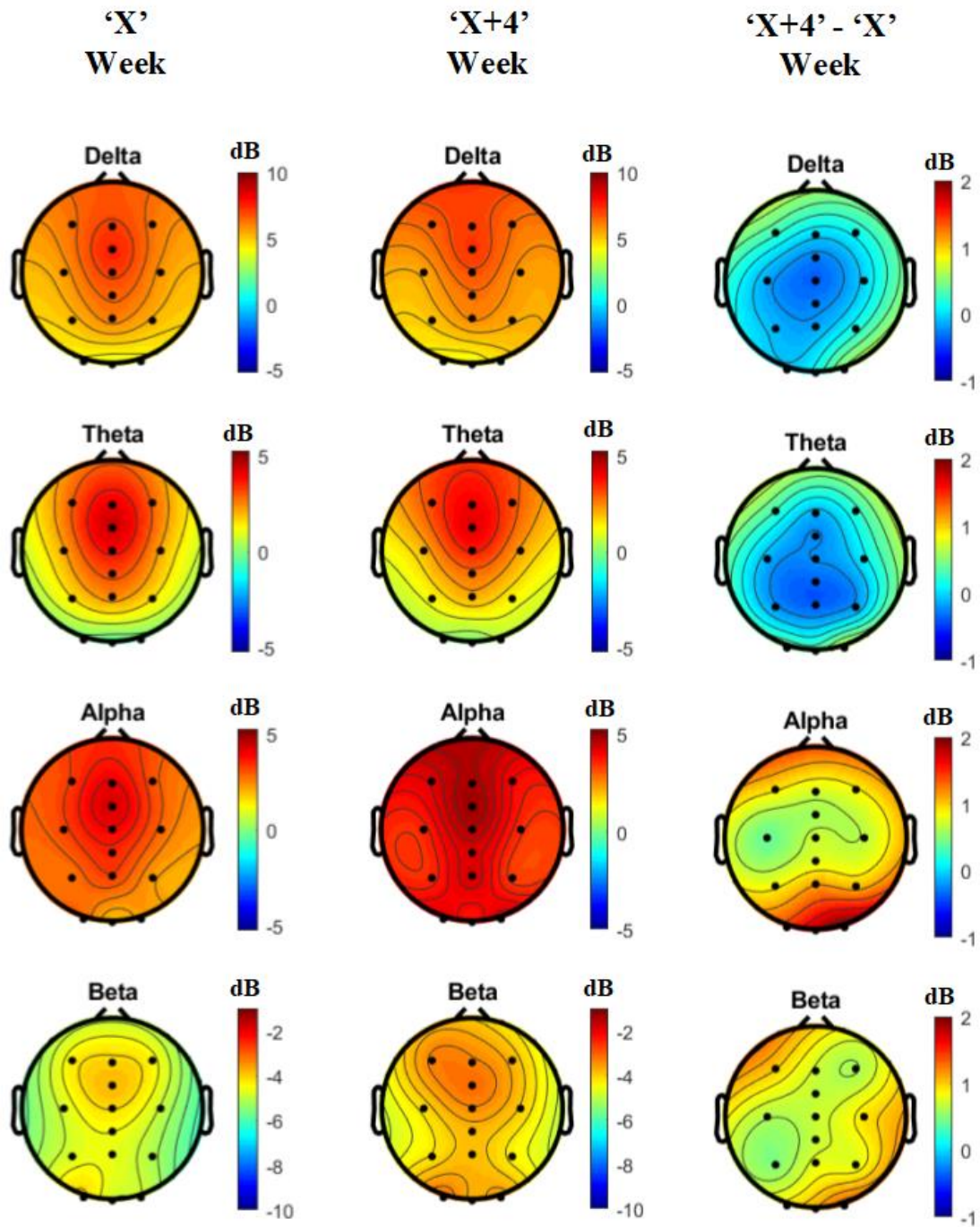


Figure 3. Comparisons of resting-state EEG power (in dB) across experimental group of participants in the 'X' (first column) and 'X+4' (second column) week of video game playing and power difference (third row) for the 'X+4'-'X' week. 'X' denotes the beginning of the four weeks; 'X+4' denotes the end of the four weeks.

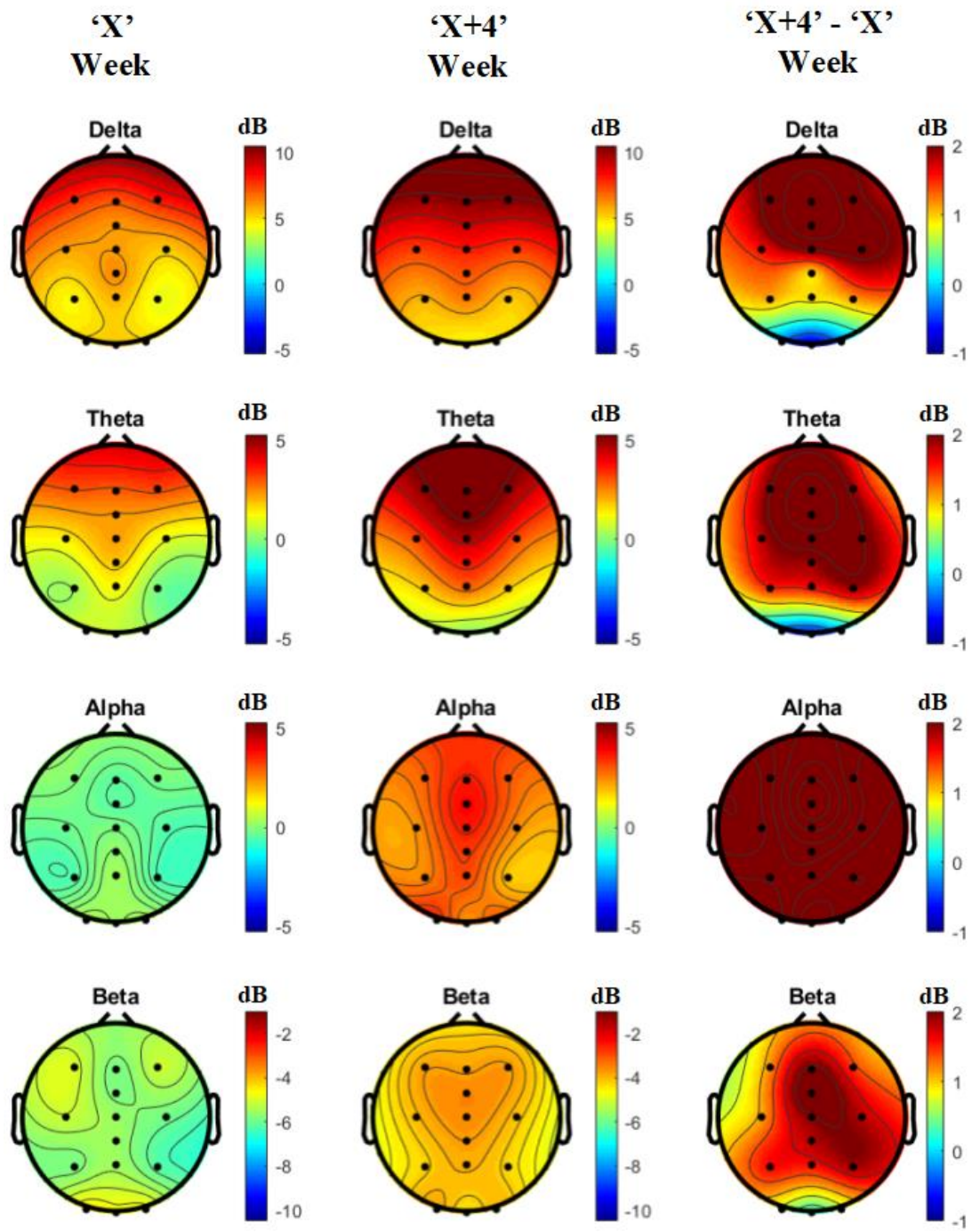


Figure 4. Comparisons of resting-state EEG power (in dB) across control group of participants in the 'X' (first column) and 'X+4' (second column) week of video game playing and power difference (third row) for the 'X+4'-'X' week. 'X' denotes the beginning of the four weeks; 'X+4' denotes the end of the four weeks.

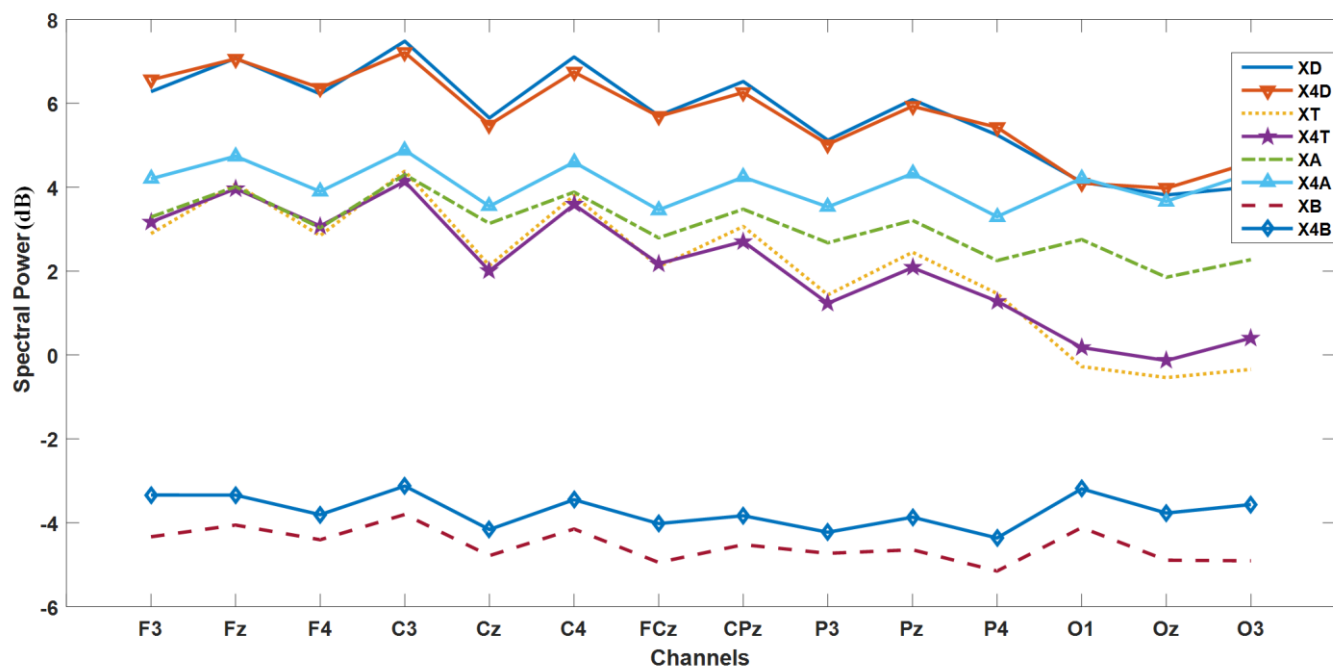


Figure 5. Resting-state EEG power (in dB) over all selected channels across experimental group of participants (XD=Delta power in week 'X'; X4D= Delta power in 'X+4' week; XT=Theta power in week 'X'; X4T= Theta power in 'X+4' week; XA=Alpha power in week 'X'; X4A=Alpha power in 'X+4' week; XB=Beta power in week 'X'; X4B= Beta power in 'X+4' week.

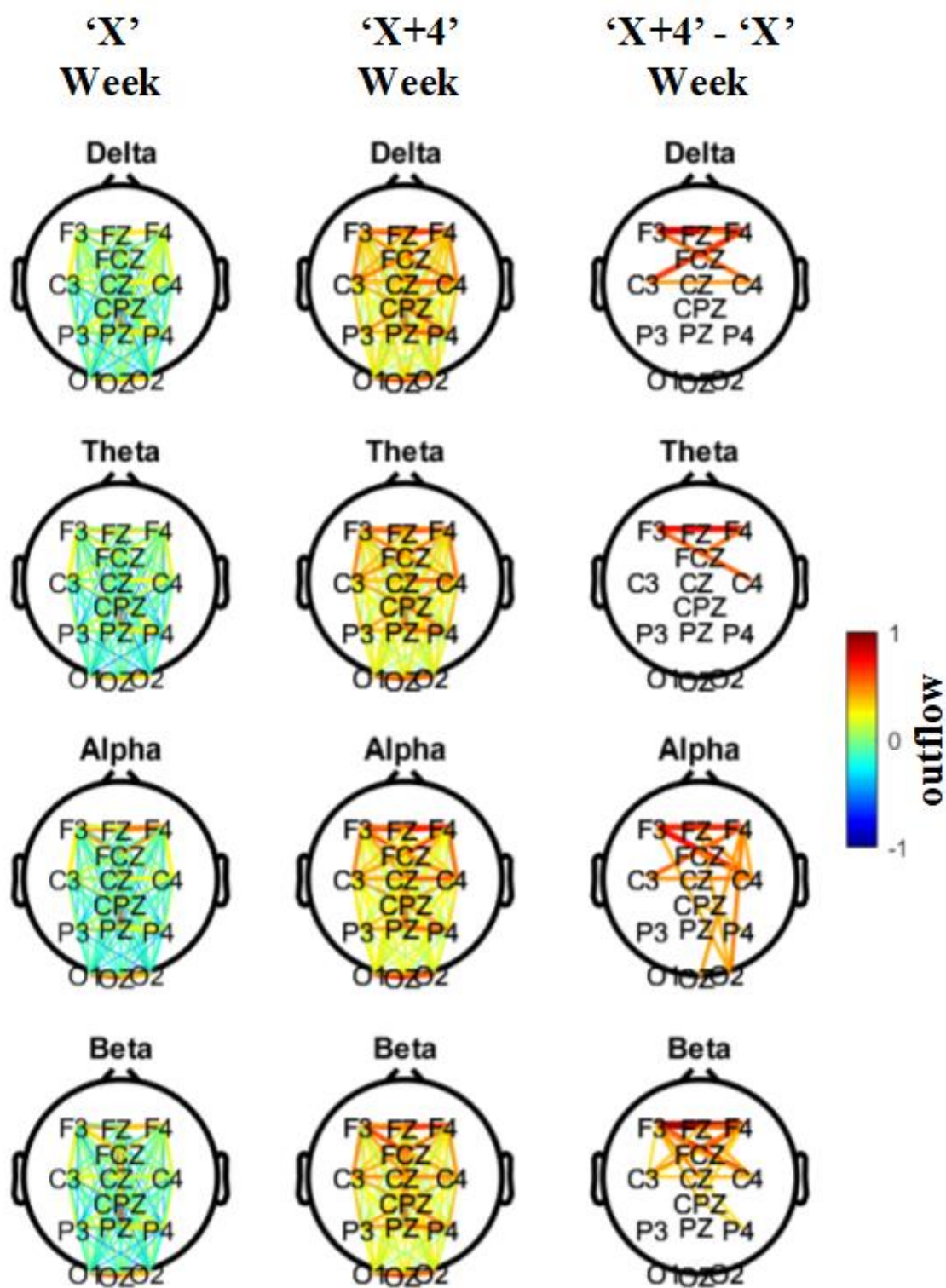


Figure 6. Comparisons of resting-state EEG Coh across experimental group of participants in the 'X' week (first column) and 'X+4' week (second column) of video game playing and their difference 'X+4' - 'X' week (third row). 'X' denotes the beginning of the four weeks; 'X+4' denotes the end of the four weeks.

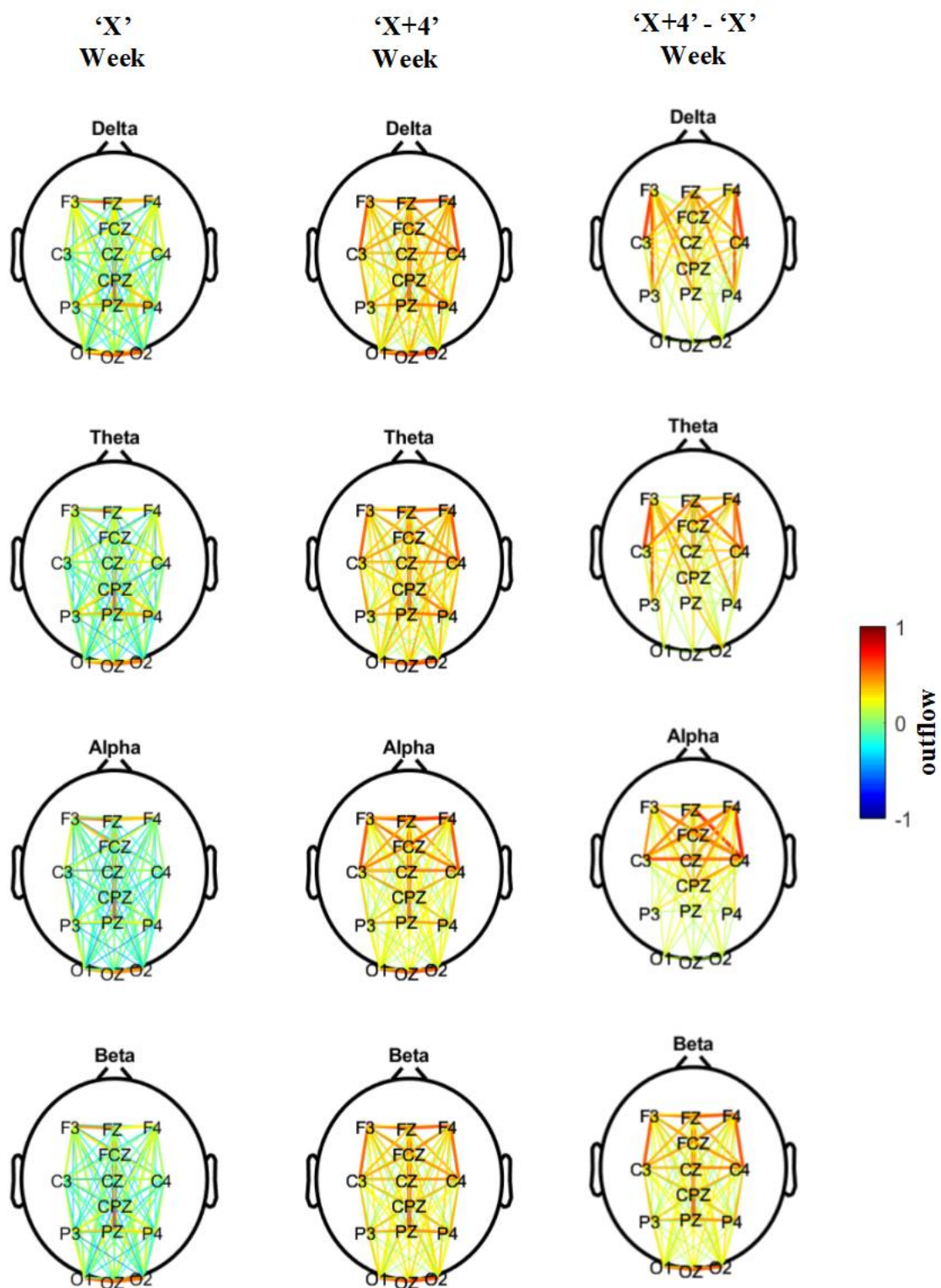


Figure 7. Comparisons of resting-state EEG Coh across control group of participants in the 'X' week (first column) and 'X+4' week (second column) of video game playing and their difference 'X+4' - 'X' week (third row). 'X' denotes the beginning of the four weeks; 'X+4' denotes the end of the four weeks.

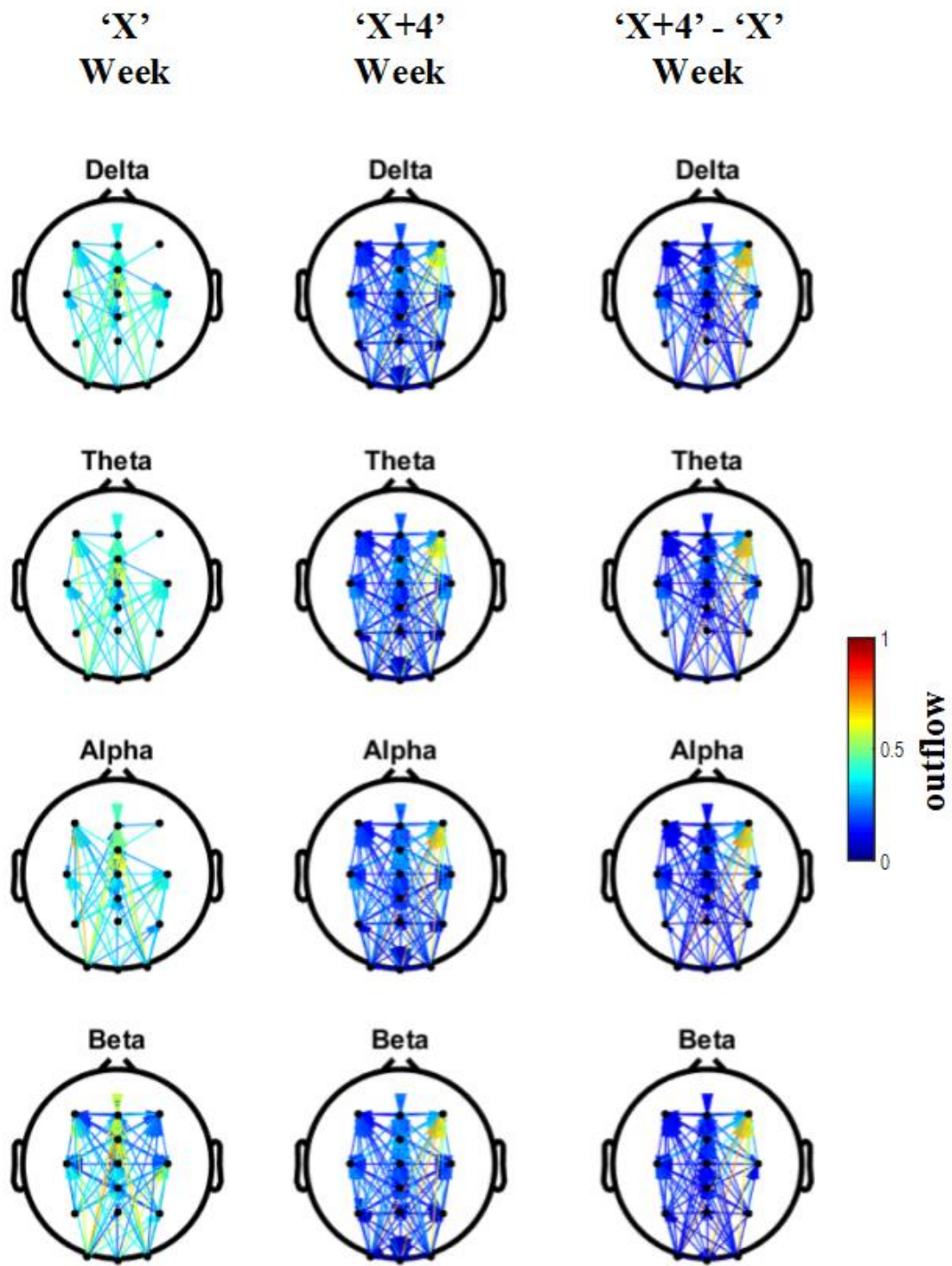


Figure 8. Comparisons of the resting-state EEG PDC across experimental group of participants in the 'X' (first column) and 'X+4' week (second column) of video game playing. 'X' denotes the beginning of the four weeks; 'X+4' denotes the end of the four weeks.

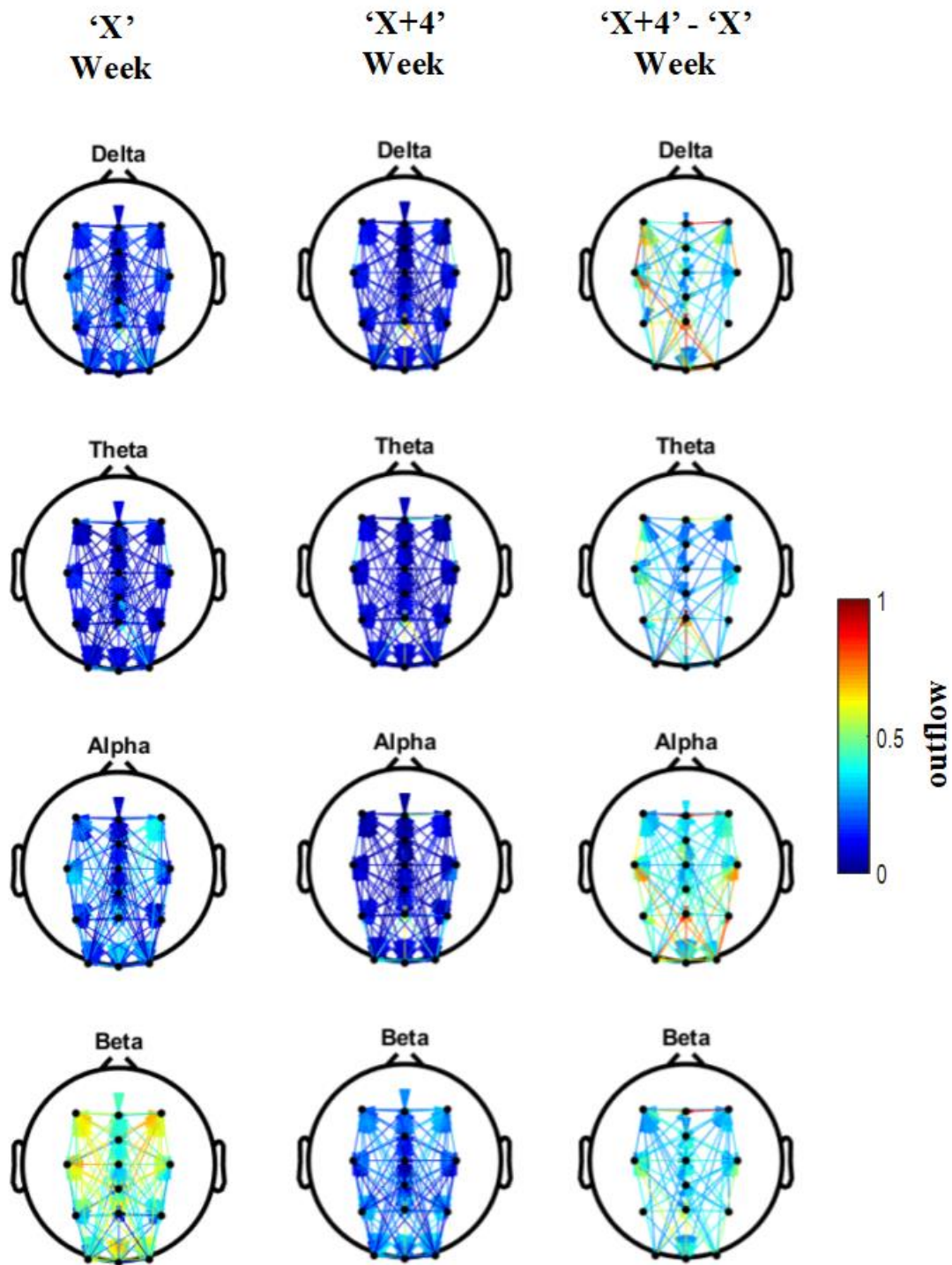


Figure 9. Comparisons of the resting-state EEG PDC across control group of participants in the 'X' (first column) and 'X+4' week (second column) of video game playing. 'X' denotes the beginning of the four weeks; 'X+4' denotes the end of the four weeks.

TABLE 1
CONNECTIVITY MEASURES FOR COH AND PDC OVER DELTA, THETA, ALPHA, AND BETA. UPWARD ARROW (↑) SIGNIFIES INCREASE WHILE DOWNWARD ARROW (↓) SIGNIFIES DECREASE IN ‘X+4’ WEEK COMPARE TO ‘X’ WEEK OF GAME PLAYING; NO CHANGE (NC).

Connectivity measure – Experimental Group								
Graph-based parameters	Coh with Cohen’s d > 0.40				Partial-Directed Coherence (PDC) with Cohen’s d > 1.2			
	Delta	Theta	Alpha	Beta	Delta	Theta	Alpha	Beta
Degree	NC	NC	NC	NC	↑	↑	↑	↑
Density	NC	NC	NC	NC	↑	↑	↑	↑
Strength	↓	↓	↑	↑	↑	↑	↑	↑
Global Efficiency	↓	↓	↑	↑	↑	↑	↑	↑
Local Efficiency	↓	↓	↑	↑	↑	↑	↑	↑
Cluster Coefficient	↑	↑	↑	↑	↑	↑	↑	↑
Connectivity Measures – Control Group								
Graph-based parameters	Coh with Cohen’s d < 0.20				Partial-Directed Coherence (PDC) with Cohen’s d < 0.10			
	Delta	Theta	Alpha	Beta	Delta	Theta	Alpha	Beta
Degree	NC	NC	NC	NC	NC	NC	NC	NC
Density	NC	NC	NC	NC	NC	NC	NC	NC
Strength	↑	↑	↑	↑	↑	↑	↓	↑
Global Efficiency	↑	↑	↑	↑	↑	↑	↑	↑
Local Efficiency	↑	↑	↑	↑	↑	NC	↑	NC
Cluster Coefficient	NC	NC	NC	NC	↑	NC	N	NC