Journal of Neural Engineering

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To cite this article: Finda Putri *et al* 2022 *J. Neural Eng.* **19** 046037

IOP Publishing J. Neural Eng. 19 (2022) 046037 https://doi.org/10.1088/1741-2552/ac8451

Journal of Neural Engineering

OPEN ACCESS

RECEIVED
1 April 2022

REVISED
12 July 2022

ACCEPTED FOR PUBLICATION
26 July 2022

PUBLISHED
11 August 2022

PAPER

Winners and losers in brain computer interface competitive gaming: directional connectivity analysis

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Keywords: brain computer interface, EEG, multiuser, competitive gaming, interbrain connectivity

Supplementary material for this article is available online

Abstract

Objective. To characterize the direction within and between brain connectivity in winning and losing players in a competitive brain-computer interface game. *Approach.* Ten dyads (26.9 ± 4.7 yr old, eight females and 12 males) participated in the study. In a competitive game based on neurofeedback, they used their relative alpha (RA) band power from the electrode location Pz, to control a virtual seesaw. The players in each pair were separated into winners (W) and losers (L) based on their scores. Intrabrain connectivity was analyzed using multivariate Granger causality (GC) and directed transfer function, while interbrain connectivity was analyzed using bivariate GC. *Main results.* Linear regression analysis revealed a significant relationship ($p < 0.05$) between RA and individual scores. During the game, W players maintained a higher RA than L players, although it was not higher than their baseline RA. The analysis of intrabrain GC indicated that both groups engaged in general social interactions, but only the W group succeeded in controlling their brain activity at Pz. Group L applied an inappropriate metal strategy, characterized by strong activity in the left frontal cortex, indicative of collaborative gaming. Interbrain GC showed a larger flow of information from the L to the W group, suggesting a higher capability of the W group to monitor the activity of their opponent. *Significance.* Both innate neurological indices and gaming mental strategies contribute to game outcomes. Future studies should investigate whether there is a causal relationship between these two factors.

1. Introduction

A recent trend in brain-computer interface (BCI) and neurofeedback (NF) applications is the use of games and game-like feedback scenarios with the aim of increasing training motivation and engagement. Early BCI games were developed for single users. More advanced BCI technology has initiated a new line of research–the development of BCI gaming based on recording brain activity from multiple users simultaneously (Nijholt 2015). Multiuser BCI is possible due to hyperscanning, a method that was originally introduced to explore the neural mechanisms that occur during social interaction (Montague *et al* 2002).

For single-user BCIs, it is estimated that up to 30% of people cannot achieve control of their brain signals, and the number of training sessions required to master the BCI strategy and obtain a significant effect from training varies from 1 to 100 (McFarland *et al* 2010, Arns *et al* 2014, Gruzelier 2014, Vučković *et al* 2018). Multiuser BCI has shown the potential to improve the performance of single user BCI for people with disabilities (Li and Nam 2016, Short *et al* 2021), as well as augment the performance of healthy people (Wang and Jung 2011).

Brain activity during multiuser BCI involves two components: neural activity due to social interaction and game planning and neural activity used to control the game. However, most previous studies on multiuser BCI games focused on the performance aspect (e.g. classification accuracy and mental effort) and users' preferences (for a review see Valeriani and Matran-Fernandez 2018). The available information related to the underlying neural mechanisms during active multiuser BCI gaming is still relatively limited.

Interaction between BCI players includes working towards a common goal (collaboration) or working individually to assert dominance (competition). Collaborative gaming has been based on different BCI modalities, such as steady-state visual evoked potential (Li and Nam 2016), event-related potential (Poli *et al* 2014), P300 (Korczowski *et al* 2015), motor imagery (MI) (Bonnet *et al* 2013), and operant conditioning (Hjelm and Browall 2000, Susnoschi Luca *et al* 2021). Collaboratively performing a task has the potential to improve players' performance (Li and Nam 2016) and fusing information from multiple participants (Poli *et al* 2014, Zheng *et al* 2020) reduces BCI training time and improves classification accuracy.

Competitive gaming has been mostly based on MI or operant conditioning (Li *et al* 2013, Novak *et al* 2017, Daeglau *et al* 2020) and some studies have used these two paradigms for both collaborative and competitive tasks (Hjelm and Browall 2000, Bonnet *et al* 2013, Cho *et al* 2020, Susnoschi Luca *et al* 2021). Bonnet *et al* (2013) found that competitive and collaborative conditions may lead to similar levels of performance and motivation. It is not well known how a competitive game might affect players' brain activity during a BCI game or over time. Players who practiced MI for Cybathlon 2016 (Novak *et al* 2017) reportedly improved control of their brainwaves and increased the activation of sensory-motor cortex over several months of practice (Perdikis *et al* 2018). However, they were solely focused on completing the task, and during the competition, they were unaware of the performance of other players.

Most studies that compared intra and interbrain connectivity between collaborative and competitive gaming were based on physical gaming, either between players or between a player and a computer (De Vico Fallani *et al* 2010, Balconi and Vanutelli 2016, 2017, Sinha *et al* 2016). Sinha *et al* (2016) found a decrease in frontal alpha and beta synchrony between dyads when they competed in a ping-pong-type game compared to when they played cooperatively against a computer. However, studies based on 'prisoners' dilemma' and 'chicken game' found increased spectral power in the theta and beta bands in competitive compared to collaborative mode (Astolfi *et al* 2009, 2010). Balconi and Vanutelli (2018) analyzed the interbrain connectivity between competing dyads based on partial correlation coefficient. The dyads tried to outplay each other in a selective attention task using a keyboard. They found a decrease in interbrain coupling, particularly in bilateral prefrontal areas. This confirmed the results of previous functional Magnetic Resonance Imaging (fMRI) studies (Decety *et al* 2004) showing that competitive dynamics involve fewer inclusion mechanisms than cooperative ones, as well as a clear separation between the self and the other. A recent study comparing dyads' interbrain connectivity during joystick competitive and collaborative tasks found increased lower beta band synchrony in the frontal area (Cho *et al* 2020).

Apart from the gaming strategy, it is believed that some innate gamer features may influence BCI performance. Several studies have reported on the relationship between neurophysiological parameters or brain volumetry and BCI gaming performance, while others have provided evidence that more subjective psychological factors such as control belief, mood, motivation, or the chosen mental strategy correlate with the BCI success rate (Kober *et al* 2013, 2020).

Single-user games have found that resting-state alpha activity is the most reliable prognostic marker in gaming paradigms based on MI (Blankertz *et al* 2010), covert attention (Treder *et al* 2011) or operant conditioning (Wan *et al* 2014). In single-user games, a user has a fixed target or one that is set with respect to own brain activity. In multiuser gaming, the task is more challenging because the target is set externally and changes dynamically; therefore, a higher level of control is required.

In our previous study, we investigated the differences in intra- and interbrain synchrony between competitive and collaborative dyads in a BCI game based on relative alpha (RA) operant conditioning (Susnoschi Luca *et al* 2021). As phase-locking value (PLV) has to be calculated over short time periods, we compared only 0.5 s epochs during scoring. The analysis of the PLV showed that interbrain synchrony was the strongest between homologous structures of dyads in a collaborative task, as opposed to asymmetrically distributed areas of winning and losing players in a competitive task. In the collaborative task dyads had the strongest synchrony between frontal cortices in the theta band and between occipital and right centro parietal cortices in both players in the alpha band. In the competitive tasks, the occipital cortex of winning players was in synchrony with the frontal cortex of losing players in the theta band and the centro-parietal-occipital region of winning players was in synchrony with frontocentral region of the losing players in the alpha band.

In this study, we focus on the competitive task only and look at the direction of the intra and interbrain information flow within the entire gaming session, rather than just at the moment of scoring. While synchrony is best observed over short periods of time, directional connectivity is typically observed over longer time periods, such as several minutes of a NF game. The latter allows the analysis of the intra and interbrain information flow as a result of an ongoing strategy rather than just at the moment of scoring, providing complementary information to the previous study.

We aim to answer the following questions:

- How does a dynamic, externally driven target affect the gaming performance?
- Does the baseline alpha power relate to players' ability to modulate RA during gaming?
- What is the difference between the intrabrain connectivity of the winning and losing players?
- What is the direction of the information flow between gamers during neurofeedback?

2. Methods

2.1. Experimental paradigm

Ten dyads of able-bodied individuals (26.9 ± 4.7 yr old, eight females and 12 males) participated in the study. There were four dyads with both males, two dyads with both females, and four dyads of both sexes. The eight dyads were new to each other prior to the experiment. None of the participants were couples or close friends, so as to avoid additional influence on their non-verbal communication. The participants were not allowed to talk during the experiment. A researcher sitting behind the dyads, outside of their visual field, observed them to ensure that there was no verbal communication and that participants sat still during gaming, and any sub-session in which communication occurred was repeated.

All the participants signed an informed consent form. This study was approved by the University of Glasgow's College of Science and Engineering Ethical Committee.

The experimental session consisted of baseline electroencephalography (EEG) recordings (2 min eyes open, EO; 2 min eyes closed, EC), 30 min of gaming (six sub-sessions of 5 min each), and a final EO EEG recording. The first EO recording prior to NF served as the baseline EEG recording. Each pair took part in three daily sessions because NF requires some experience (Gruzelier 2014 or Vučković *et al* 2019). EEG power and regression analyses were performed based on data from all three sessions. Analysis of information flow was performed on third session data only, when the multichannel EEG was recorded.

Participants sat close to each other, looking at a computer screen approximately 50 cm in front of them. Their EEG was recorded using the same EEG device to avoid synchronization issues. The BCI interface was presented as two bars on either side of the screen, with a seesaw located between the bars, as shown in figure 1. Bars were primarily used during the first two sessions, while the participants learned the NF strategy, to provide players with a more intuitive visualization of their own brainwaves. During gaming, players were instructed to focus on the seesaw and attempt to 'lower' it, as if being 'heavier' in a physical world.

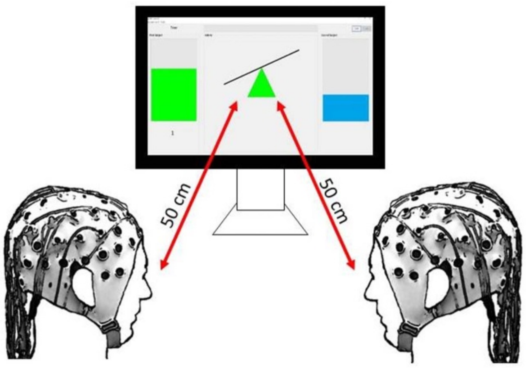

Figure 1. Experimental paradigm. Players sit close to each other facing the computer screen. Their task was to 'lower' their side of a virtual seesaw for at least 1 s in order to score a point. Participants were not allowed to talk with each other during the game.

The control signal for the seesaw was the RA power recorded at electrode location Pz. The RA represents the alpha band power (8–13 Hz) with respect to the power of a wide-band EEG signal (2–30 Hz):

$$\mathrm{RA}\,(\%) = (P_{\mathrm{alpha}}/P_{\mathrm{wide}}) \cdot 100\%. \qquad (1)$$

It was noted that some players had naturally higher baseline alpha power and would therefore win the game, irrespective of their effort. Therefore, their gaming RA ($\mathrm{RA}_{\mathrm{G\_higher}}$) was scaled by the ratio of the two players' RA during the baseline, that is, $k = \mathrm{RA}_{\mathrm{B\_lower}}/\mathrm{RA}_{\mathrm{B\_higher}}$. Thus, a player with a higher RA controlled the game with $k{\cdot}\mathrm{RA}_{\mathrm{G\_higher}}$, whereas a player with a lower RA controlled the game with their original $\mathrm{RA}_{\mathrm{G\_lower}}$, and both were presented with scaled scores on screen.

The player who managed to keep the control signal 10% higher than that of their opponent for 1 s scored a point. The bars presented on the left and right sides of the screen changed in size in real time, in proportion to the control signal. Upon scoring a point, the color of the respective bar changed from blue to green and remained that color as long as the RA was more than 10% above the current RA of their opponent. Each player's score was presented under their corresponding bar. No additional instructions were given to the players, apart from general instructions to relax.

For the purpose of analysis, players were grouped into winning players (W) and losing players (L) based on their average overall score across the three daily sessions.

2.2. EEG recording

The EEG signal was recorded using a g.USBamp amplifier (g.tec Medical Engineering GmbH). During the first two training sessions, EEG was recorded from the electrode location Pz, and in the third session, it was recorded from 16 locations (AF3, AF4, FC3, FC4, C3,Cz, C4, P3, Pz, P4, O1, Oz and O2), following the standard 10–10 EEG electrode placement system (Nuwer *et al* 1999), with linked ear reference and ground at FCz. Impedance was maintained below 5 kΩ. The sampling frequency was 256 Hz. The amplified EEG was bandpass-filtered using a hardware analog filter between 0.5 and 40 Hz. A notch filter was used to suppress the 50 Hz power line noise.

2.3. NF online EEG analysis

During the NF game, the data were analyzed in real time and presented on a graphical user interface (GUI). EEG analysis was performed using MATLAB (R2015a, The Mathworks, Inc., USA) and Simulink, and the GUI was developed in Java (version 1.8.0). A 5th order infinite impulse response (IIR) digital Butterworth filter (g.USBamp biosignal processing blocks, Simulink) was used to bandpass the signal in the 8–13 Hz and 2–30 Hz ranges over 0.5 s moving average windows updated for every eight samples. The RA, i.e. the ratio of alpha to broadband power (equation (1)), was calculated in Simulink and sent as a control signal to the GUI.

2.4. Offline EEG analysis

For offline analysis, all raw EEG data were bandpass filtered in the frequency band of 2–30 Hz using 5th order IIR digital Butterworth filter. Noise removal for single-channel data (sessions I and II) was performed manually based on visual inspection, whereas for multichannel data (session III), it was performed using independent component analysis with the Infomax algorithm implemented in EEGLAB v14.1.2b (Delorme and Makeig 2004). Independent components containing eye blinking were removed (typically 1–2 components) and portions of the signal with excessively high amplitude (higher than 100 μV) present on most electrodes were manually removed.

2.4.1. Dominant frequency and power spectral density

Prior to the analysis, each continuous time series was segmented into 4 s epochs with a 50% overlap. Statistical analyses for individual RA at Pz and individual alpha (IA) peak frequency at Pz from all sessions were performed using SPSS (version 25.0; IBM Corp., USA). The IA peak frequency at Pz was determined from the 6 to 16 Hz band (Bazanova and Aftanas 2008). EEG was recorded at EO and EC baselines. A frequency corresponding to a decrease in spectral power of more than 20% in the EO condition compared to the EC condition was defined as the dominant alpha frequency (Bazanova and Aftanas 2008). Two-way ANOVA with factors groups and sessions was performed. Prior to statistical analysis, the Shapiro–Wilk normality test was performed to confirm the normal distribution of the data. Non-parametric statistical analyses were performed for RA and score data using the Kruskal–Wallis H and Wilcoxon signed-rank tests.

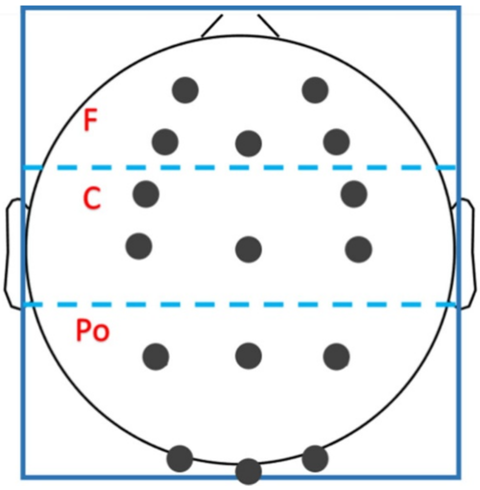

Figure 2. Three zones in which brain activity was analysed: frontal F, central C and parieto-occipital Po.

All multichannel EEG data were uploaded into a STUDY structure in EEGLAB for power spectral group analysis. The data were divided into groups (W and L) and conditions (baseline and gaming). In a STUDY structure, the spatial distribution of power for all conditions was calculated in four predefined frequency bands (theta, 4–7 Hz; alpha, 8–13 Hz; lower beta, 14–20 Hz; higher beta, 21–30 Hz). A non-parametric unpaired permutation test with 800 repetitions ($p < 0.05$) was performed to test the statistical significance of the absolute power difference between groups or conditions in each frequency band, and the false discovery rate (FDR) statistical correction method (Benjamini and Yekutieli 2001) was applied to account for multiple comparisons.

2.4.2. Intra and interbrain connectivity

Brain connectivity can be measured by quantifying the interrelations between EEG channels. Granger causality was used to estimate intra (within a player) and interbrain (between two players) connectivity in the wide band of 2–30 Hz, while the directed transfer function (DTF) (Kaminski and Blinowska 1991) was used to estimate intrabrain connectivity in selected frequency bands. The analysis was performed on data from the sub-session with the largest score difference between the players in the third session.

Both methods are based on the parametric representation of EEG time series. Akaike's information criterion (Akaike 1974) was used to estimate the order of the autoregressive model, with the maximum order set to 30. Permutation analysis with correction for multiple comparisons (FDR) was applied to determine the statistical significance between conditions (baseline/gaming, winning vs. losing players).

As the algorithms implemented in the study have high computational complexity, the cortex was divided into zones (figure 2) prior to analyzing intra and interbrain connectivity, and ten representative

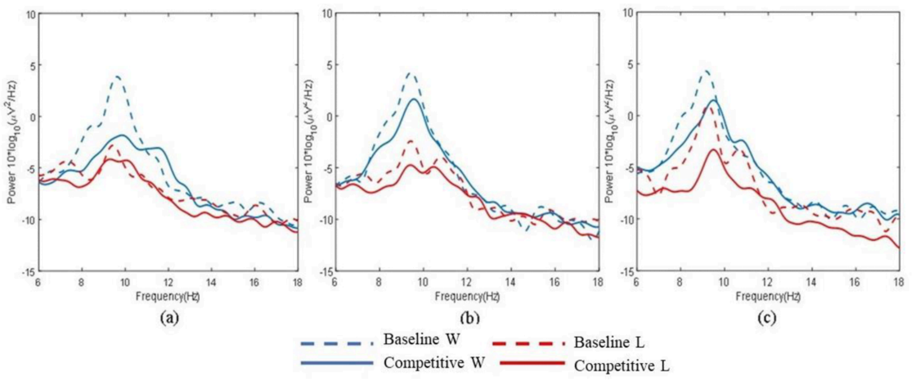

Figure 3. (a)–(c) Power spectrum density at Pz during baseline (dashed line) and NF session (solid line) in W group (blue) and L group (red) in first, second and third sessions respectively.

channels were selected for the analysis. The following zones were defined: frontal (F3, Fz, F4), central (C3, Cz, C4), and parieto-occipital (P3, Pz, P4, Oz), with sensors distributed in both hemispheres and over midline areas. Individual channel connections are presented for the 25% strongest connections.

2.4.2.1. Granger causality (GC)

Figures 3(a)–(c) power spectrum density at Pz during baseline (dashed line) and NF session (solid line) in W group (blue) and L group (red) in first, second and third sessions respectively. Bivariate GC was applied to analyze inter-subject connectivity, allowing the computation of 10 × 10 interconnectivity on the representative channels mentioned above. Multivariate GC was used to calculate intrabrain connectivity. Bivariate GC analysis was performed using the MATLAB toolbox Brainstorm 3.4 (University of Southern California and McGill University, USA) (Tadel *et al* 2011), and multivariate GC analysis was performed using the MVGC v1.0 MATLAB toolbox (the Sackler Center for Consciousness Science (SCCS), University of Sussex) (Barnett and Seth 2014).

GC is an estimation of the causal influence of two time series, $X(t)$ and $Y(t)$, implying that the past measurement of the second time series, $Y(t)$, will help predict the future measurement of the first time series, $X(\mathrm{t})$ (Nijboer *et al* 2010, Nan *et al* 2012). The two-directional GC from the two time series can be described by equation (2):

$$\begin{aligned} X'(t) &= \sum_{i=1}^{p} A_{11}(i)\, X(t-i) \\ &\quad + \sum_{i=1}^{p} B_{12}(i)\, Y(t-i) + E_x(t) \\ Y'(t) &= \sum_{i=1}^{p} B_{21}(i)\, X(t-i) \\ &\quad + \sum_{i=1}^{p} A_{22}(i)\, Y(y-i) + E_y(t). \end{aligned} \tag{2}$$

where time series $X(t-i)$ and $Y(t-\mathrm{i})$ are the past values of time series $X(t)$ and $Y(t)$, respectively, with order p and prediction error E.

2.4.2.2. Directed transfer function (DTF)

DTF describes the ratio between the information inflow from channel j to i relative to all inflows to i, thus focusing on sources of activity. Sources rather than sinks were selected because of the nature of the NF task applied in the experiment, with Pz as the control channel being 'source' of the NF control. In this study, DTF was estimated using a custom-written MATLAB algorithm for asymptotic DTF (Baccalá *et al* 2015). Four frequency bands were extracted for the DTF analysis: theta (4–7 Hz), alpha (8–13 Hz), lower beta (14–20 Hz), and higher beta (21–30 Hz) bands. DTF from j to i at frequency f, with the transfer matrix H can be defined as (Kaminski and Blinowska 1991):

$$\gamma^2_{j\to i}(f) = \frac{\left|H_{ij}(f)\right|^2}{\sum_{m=1}^{k} \left|H_{im}(f)\right|^2}. \tag{3}$$

2.5. Questionnaires

The NASA Task Load Index (TLX) questionnaire was administered to all participants after every experimental session to provide insight into whether the behavioral aspects affect gaming performance. The questionnaire consisted of six aspects representing perceived workload: mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart and Staveland 1988).

3. Results

3.1. Power spectral density and game score

Figure 3 shows group average PSD at electrode location Pz during the baseline and during gaming for all three sessions, averaged over six sub-sessions, for both W and L groups. In both groups the alpha power was always smaller during gaming than during baseline, although gaming RA increased in second

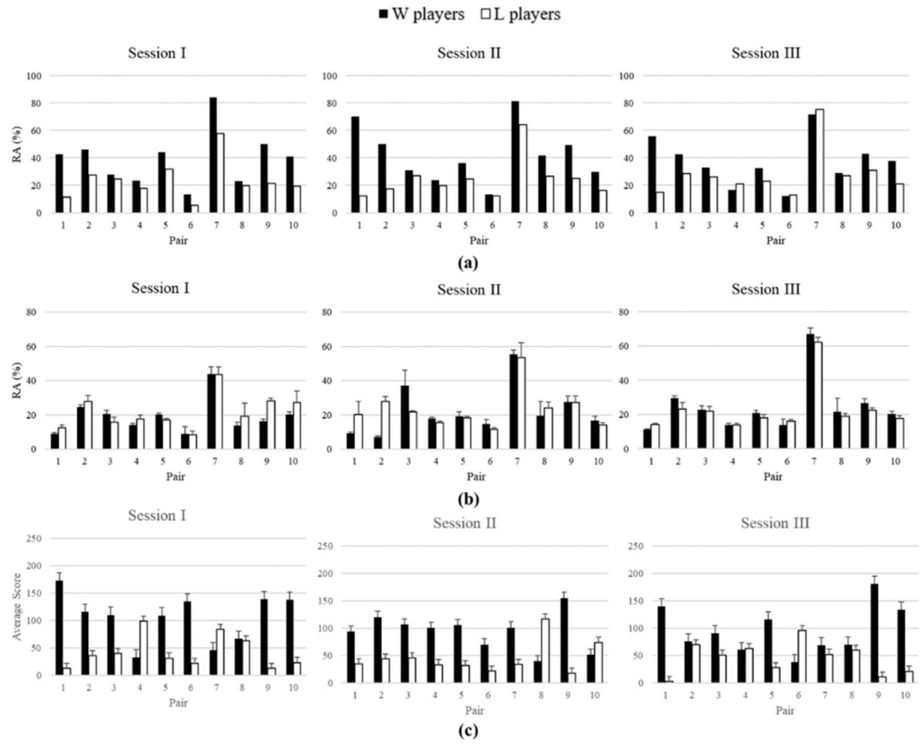

Figure 4. (a) Baseline RA power of each player in W and L groups for each experimental session; (b) RA during gaming and (c) average unscaled gaming score of all six sub-sessions. Theoretical maximal score was 1800. Note that while in each gaming session, a person with higher baseline alpha power received a scaled visual feedback, figure 3(b) shows unscaled, real values.

and third sessions as compared to the first gaming session (group W session I vs session III $p = 0.049$ and group L session I vs session II, $p = 0.033$, Wilcoxon rank sum test). In group L, baseline alpha power also increased in the third session. However, Kruskal–Wallis H-test failed to show a significant increase of baseline RA over time. On average, W group had consistently higher RA power over all three gaming sessions as compared to L group ($p = 0.02 \times 10^{-2}$, Friedman's test) as well as in every single session (Wilcoxon's signed-rank test, $p_{\mathrm{I}} = 0.0117$; $p_{\mathrm{II}} = 0.0117$; $p_{\mathrm{III}} = 0.0215$, for sessions I, II and III, respectively).

A two-way ANOVA of IA peak frequency with group (W, L) and session number (I, II, III) as factors showed no significant difference between groups ($p = 0.969$) or between sessions ($p = 0.878$), session-group interaction ($p = 0.739$), with both groups having a stable average IA peak frequency around 10 Hz (W:10.3 Hz; L: 10.2 Hz). Thus, while NF gaming did affect alpha power, it did not affect IA peak frequency.

Figure 4 shows for each session, the baseline RA power, average RA power over all six gaming sub-sessions, and the unscaled average score. Note that for each 300 s long sub-session, a player scored a point when their RA power was 10% higher than the opponent's for 1 s, thus the maximum number of points is 300. Figure 4(a) shows that, during the first two sessions, all W players had a consistently higher baseline than L players, while in the third session, L players in dyads 4, 6, and 7 achieved higher baseline power than W players, which is consistent with the increase in the baseline alpha power in the L group shown in figure 3(c). In most cases, players with a higher baseline alpha power also sustained a higher alpha power during gaming. However, in some cases, like dyad 1 in session I, the player with higher baseline RA power had lower RA power during gaming but achieved a higher score. This is because players gained scores for managing to sustain the RA power for 1 s which is not always the same as having the overall higher alpha power throughout the session. Scaled scores significantly increased in the W group only (session I vs. II, $p = 0.51 \times 10^{-4}$ and session I vs. III, $p = 0.23 \times 10^{-3}$, Wilcoxon rank-sum test). These results further confirm that people with a higher baseline alpha power performed better during the game.

Figure 5 shows the linear regression analysis for cumulative scoring in the W and L groups as a function of RA in the three sessions separately. In each session, there was a significant relationship between players' scores and their RA (session I $p = 0.031$, $R^2 = 0.233$; session II $p = 0.021 \times 10^{-2}$, $R^2 = 0.544$; session III $p = 0.008$, $R^2 = 0.328$). With or without scaling, the average scores of most players with higher baseline alpha remain higher than those of their counterparts'. This indicates that scaling allows players to control and perceive the game as being easier, yet to win, the ability to maintain alpha power for a certain duration is crucial.

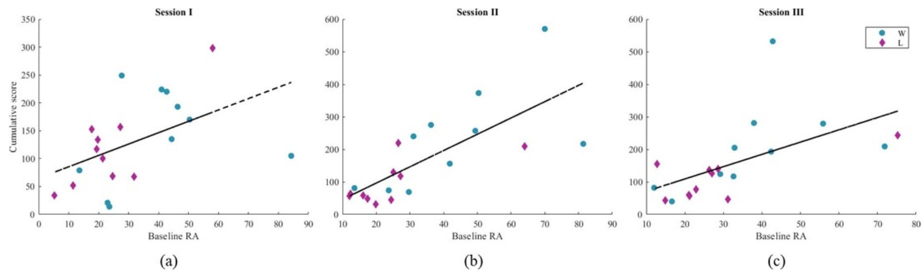

Figure 5. Scatter plot diagrams and linear regression results predicting the cumulative scaled gaming scores for each session based on baseline RA of all players (both groups) for (a) session I, (b) session II, and (c) session III. W group—blue circle, L group—violet.

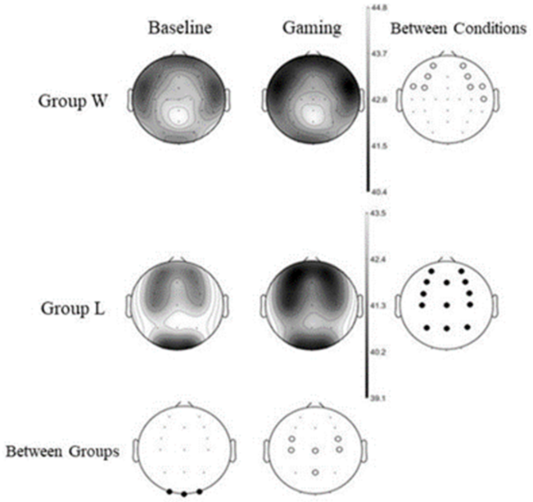

Figure 6. Scalp maps of the RA power (8–13 Hz) during baseline and the biggest scoring sub-sessions (game) in session III. Black circles show significant locations after FDR correction for multiple comparison, while open circles show significant values before correction.

Cumulative analysis of scores during all three sessions for the W and L groups separately also showed a significant weak relationship for the W group ($p = 0.007$, $R^2 = 0.232$) and medium strength relationship for the L group ($p = 0.06 \times 10^{-4}$, $R^2 = 0.525$).

Figure 6 shows the average scalp maps for the baseline alpha power and the largest scoring sub-session in session III. Group W had a significantly higher alpha band power in the occipital area than group L ($p < 0.05$), permutation test with FDR correction) at baseline. Although a significant increase in alpha power was found during gaming in W compared with L at Cz, C3, C4, FC3, FC4, and Pz, no significant difference remained after FDR correction for multiple comparisons.

No significant difference between groups was found in any other frequency band during gaming, indicating that players in group W selectively modulated only alpha band power. Although no electrode location remained significant after FDR correction, it should be noted that FDR is prone to type II error (false negative), and that significant locations in figure 6 show clustering around the centro-parietal cortex, including electrode Pz. Additionally, figure 6 shows the average RA over a whole sub-session, while gaming scores reflect only instances of 1 s sustained RA activity. During gaming, both groups reduced their alpha power with respect to the baseline, although this was more pronounced in L, where all electrode locations showed significant differences after FDR. Significant differences after FDR were also noticed in the frontal area, in the lower beta band in group L, reflecting a reduction in power during gaming due to increased cognitive engagement.

This shows that the rules of the game did not necessarily encourage the winning player to increase the alpha power above their baseline.

3.2. Intrabrain connectivity

3.2.1. Granger causality

Figure 7 shows GC within and between the three scalp zones for W and L groups in the baseline state and during the best gaming sub-session from session III. Significant differences between these two conditions are marked by an asterisk (permutation test, $p < 0.01$ after FDR). In W group, a decrease of connectivity during gaming as compared to baseline can be noticed within the central (CC) and from the central to parieto-occipital region (CPo). The parieto-occipital region (the region containing electrode Pz used to control the NF game) shows increased connectivity with frontal, central areas (PoF, PoC), as well as increased connectivity within the parieto-occipital area (PoPo).

Figures 7(c) and (d) shows the 75 percentile (or 25% strongest connections) from the averaged GC values during the baseline and gaming for the W and L groups. During gaming, there is a decrease in connections in group W. In group L, central-to-frontal connections persisted from baseline to gaming, but the frontal-to-central or parietal connections decreased.

3.2.2. Directed transfer function

In the W group, DTF decreased from the frontal to central and parieto-occipital regions, and from parieto-occipital to central regions in all frequency

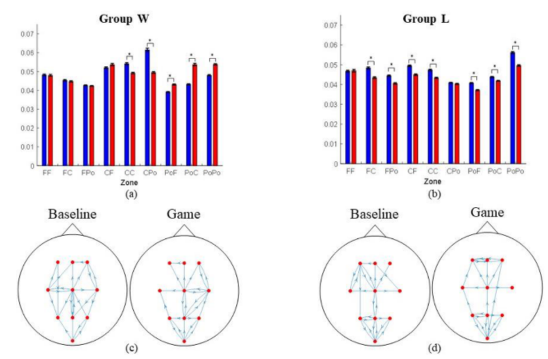

Figure 7. GC (a) between zones in group W (b) between zones in group L. Blue shows cumulative GC during baseline; red shows cumulative GC during the sub-session with biggest scoring difference in session III. Cumulative GC was calculated by summing averaged GC between each pair of electrodes in the corresponding zones (c) the 75 percentile from the averaged GC in group W (d) the 75 percentile from the averaged GC in group L.

bands; it increased from the parieto-occipital to the frontal region in all frequency bands. Furthermore, DTF increased from the CPo region in the lower beta band and remained unchanged in other frequency bands.

Similarly, in the L group, intraregional connectivity increased in the frontal region and decreased in the central and parieto-occipital regions during the game; it also decreased from the frontal to the central and parieto-occipital regions in all frequency bands (figure 8(b)). The DTF increased from the parieto-occipital region to the frontal region in all frequency bands. The largest difference between the W and L groups was a decrease from the CPo region in all frequency bands in the L group. Overall, changes in DTF between baseline and gaming conditions within a group, are similar across different frequency bands.

The scalp maps in figure 9 show the 75 percentile (or 25% strongest connections) from the averaged alpha-band DTF values during baseline and gaming for the W and L groups. In the W group, a strong bidirectional connection along the midline and parietal to central flow (Fz, Cz, Pz) was evident in both conditions. The main difference between baseline and gaming was stronger central (Cz) to parietal (P3, P4) connectivity at baseline, as opposed to stronger frontal (Fz) to parietal (P3, P4) connectivity during gaming. The baseline DTF results of the L group appear to be very similar to the W-group gaming results. However, during gaming, there is a marked reduction in connectivity between the central and parietal regions, and the left frontal area (F3) becomes the main source of information for the bilateral central, parietal, and occipital regions. The DTF connectivity distribution in the other frequency bands (theta, lower beta, and higher beta) appears similar to the alpha band. The figures are available in the supplementary material (figures S1–S3).

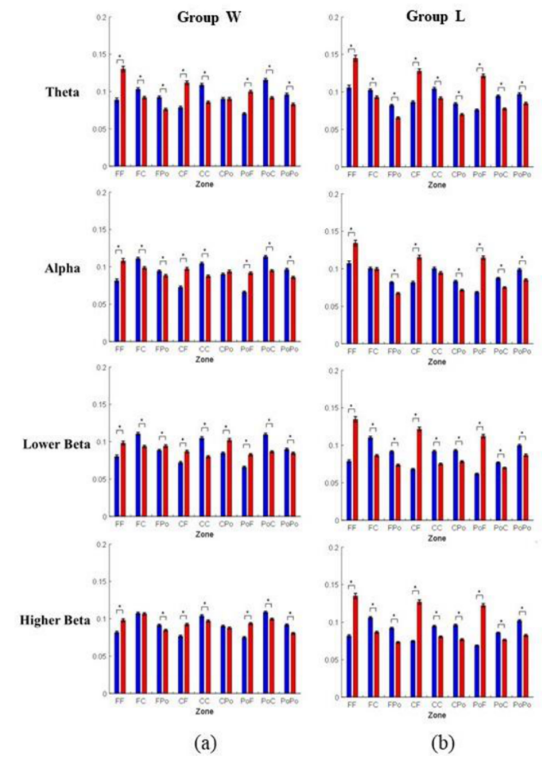

Figure 8. DTF in different frequency bands within and between zones for (a) group W and (b) group L. Blue is for baseline and red is for gaming. Asterisks show statistically significant differences in means ($p < 0.05$) between baseline and gaming.

In summary, both GC and DTF showed a decrease in connectivity from the parietal region during gaming in the L group, whereas in the W group, wideband connectivity increased (GC) and frequency-specific connectivity remained unchanged (DTF). In the W group, GC did not show any significant changes in connectivity from the frontal region, in contrast to DTF, which showed an increase. In the L group, both GC and DTF showed a decrease in connectivity from the frontal region, although 75 percentile DTF indicated strong dominance of the left frontal area as a source of alpha activity.

3.3. Interbrain connectivity

Figure 10 shows interbrain connectivity during gaming (a) from W to L and (b) from L to W ($p < 0.001$ with FDR). No direct communication between two brains is expected, therefore these results reflect indirect interbrain communication through the common GUI. Information flow is considerably larger in L to W direction compared to W to L direction. This occurs from nearly all L locations towards occipital and central-left parietal cortex, and towards the right frontal and central cortex of W. From W, information flows from the left central and parietal cortex towards L frontal cortex, and from W occipital and right central cortex towards L left parietal and occipital ortex.

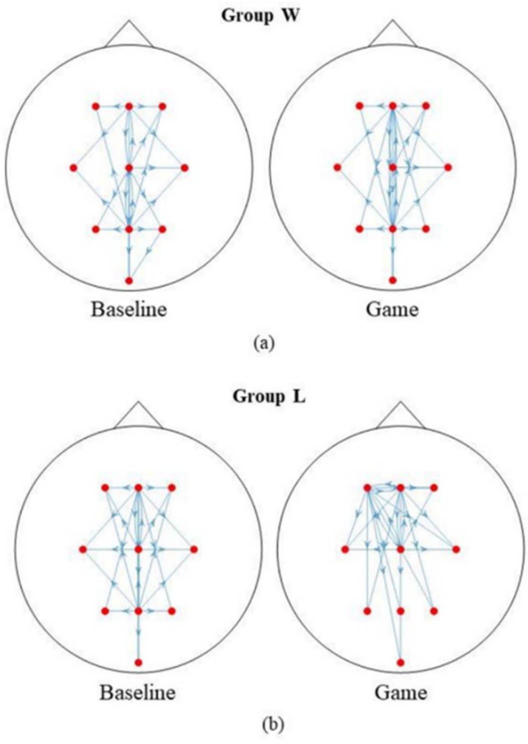

Figure 9. The 75 percentile from the averaged DTF in the alpha band in W group and L group during baseline and gaming.

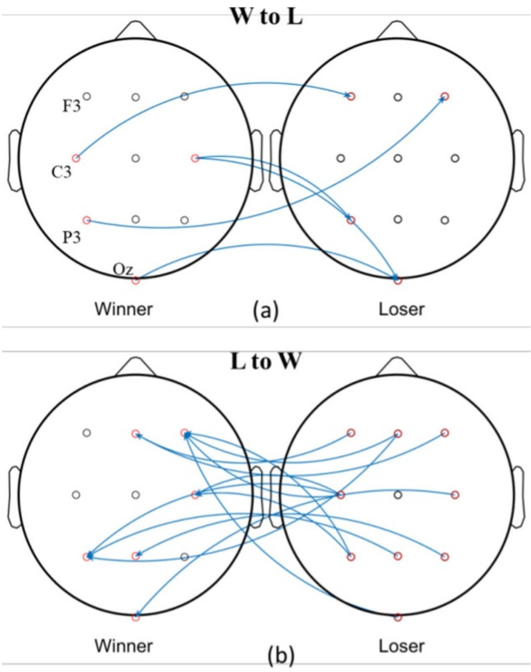

Figure 10. Interbrain GC during gaming in session III (a) from W to L, (b) from L to W. Left hemisphere electrode labels shown.

3.4. Perceived experimental workload

The perceived experimental workload was measured using the NASA TLX questionnaire. Friedman's test ($p < 0.05$) showed no statistically significant differences across the three sessions for any category in any of the groups. Likewise, no significant difference was found between the three sessions across any of the scores (Kruskal–Wallis test, $p < 0.05$). Finally, no significant differences were found between the W and L groups for any category (Wilcoxon signed-rank test, $p < 0.05$) (figure 11).

Although not statistically significant, the highest score was achieved for the effort category in both groups, indicating that both groups experienced increased effort during gaming. The W and L groups experienced similar levels of task load.

4. Discussion

This study aimed to understand the information flow within and between winning and losing players and to explore neural indices that might predict gaming performance. In contrast to most previously published studies, which focused on non-directional measures such as intra and interbrain synchrony, connectivity, or power analysis (Astolfi *et al* 2009, Li *et al* 2013, Sinha *et al* 2016, Cho *et al* 2020, Susnoschi Luca *et al* 2021), we analyzed the direction of the information flow and based the competitive task on non-muscular activity.

The competitive task in this study was based on the upregulation of alpha activity at the electrode location Pz. This electrode lies over the somatosensory association cortex and alpha upregulation over Pz has been implemented for improving spatial awareness (Zoefel *et al* 2011) and improvement of cognitive performance in general (for a review see Marzbani *et al* 2016). A recent meta-analysis on alpha NF on healthy people showed that upregulating alpha power over Pz improves working and episodic memory (Yeh *et al* 2021). Thus, this protocol is quite appealing to the healthy population who would likely be the main initial users of multiuser neurofeedback. Alternatively, the frontal cortex has also been used for improving cognitive performances (Farnia *et al* 2017). While frontal locations have the advantage of better contact between the electrode and skin as typically this area has no hair, they are more prone to artifacts due to eye movement, blinking, and facial muscle activity. That would increase both theta and beta activity and would affect the RA power, requiring online artifact removal.

Unlike single-user NF games, in a competitive game, users had to adapt to a variable externally controlled target (competitor's RA) and sustain their alpha activity above that threshold for 1 s. For that reason, the winning players did not necessarily have to upregulate the alpha power above their own baseline. Thus, a multiuser BCI based on operant conditioning, although engaging, might not be a good strategy to train a person to upregulate their brain waves above resting state activity. Therefore, the answer to the first research question regarding the influence of an externally driven dynamic target on individual RA is

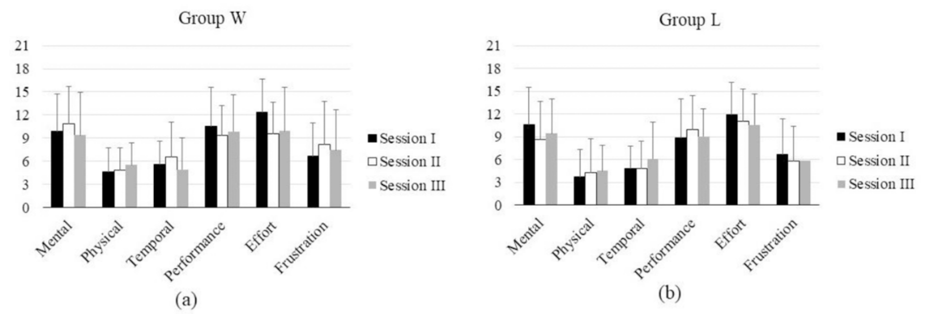

Figure 11. Group average values (mean ± std) of different components NASA TLX in each session for (a) group W (b) group L.

that neither winning nor losing players increased their alpha power above their baseline values.

The second research question relates to the prognostic EEG markers of gaming performance. Previous single-player studies have suggested that higher resting-state alpha predicts better learning ability in alpha NF (Blankertz *et al* 2010, Treder *et al* 2011, Wan *et al* 2014). The results of the current study support this finding, although with a much more complex task that includes an externally driven target. There was a significant mild-to-moderate correlation between RA and scoring in both groups across all three sessions. This relationship was stronger in the L group. Increased RA power reflects the inhibition of non-essential activities, which in turn may facilitate task performance (Klimesch *et al* 2007). Therefore, a higher resting-state RA amplitude may lead to stronger inhibition of irrelevant processes during NF, allowing more cognitive resources for learning, in this case, to regulate the alpha amplitude during gaming. This finding is significant for future developers of multiuser BCI games, indicating that a more sophisticated strategy, rather than simple leveraging of alpha power, is necessary to provide a fair playground for players. Fusing control signals from multiple users is a well-known challenge in multiuser BCI (Valeriani and Matran-Fernandez 2018). The complexity of this issue would increase if more than two players are involved in the game. One solution to this problem might be to leverage the RA of each player during NF with respect to their own baseline RA, which may be adequate for a game with more than two players. This might also solve the problem of upregulating RA above one's baseline value during gaming.

However, we need to emphasize that while the resting state RA has been a good prognostic marker for this particular gaming strategy, which requires upregulation of the alpha band power, it might not be a good performance predictor for a NF game based on different rules, for example, increasing beta or frontal theta band power. It also implies that if paired differently, W and L players might change their roles. Ideally, shuffling players in new dyads would reveal the relevance of RA in successful brain wave regulation during NF.

4.1. Intrabrain connectivity

Although neither winning nor losing players increased RA above their own baseline, winning players had a significantly stronger RA during the second and third sessions compared to the first session, indicating that they were improving their strategy over time. It is known from literature that alpha enhancement NF leads to higher outgoing connectivity in the neighboring region of the training area (Hartmann *et al* 2014). The NF strategy of the winning group was characterized by increased connectivity from the parieto-occipital region towards the frontal and central regions, as well as stronger interregional connectivity (GC results), and by a frequency-specific information outflow from Pz (based on DTF results). These results suggest that, despite no significant RA changes at Pz, winning players managed to increase control of the Pz channel by increasing its activity as a source, sending information to other channels, compared to its activity as a sink, receiving information from other channels.

Activation of the frontoparietal network (frontal areas being sources of activity) in the winning group might reflect the level of task engagement during gaming. The frontoparietal network is known to be activated during cognitive control, and it has been proposed that its role is to regulate the activities of antagonistic networks of the default mode network (DMN) and the dorsal attention network (Gao and Lin 2012, Marek and Dosenbach 2018). Intrabrain GC analysis revealed decreased connections from the frontal to central and parietal area in both groups, indicating switching off DMN during gaming.

Losing players had a lower baseline RA and maintained a lower RA during the game. Another reason why losing players were less successful might be that they applied the wrong mental strategy, that is, concentration, as indicated by the significant decrease in alpha and lower beta power frontally during gaming. Moreover, DTF analysis revealed that the dominant source of alpha activity during gaming was located in the left frontal cortex, rather than around Pz. In contrast to the W results, the overall GC intrabrain connectivity decreased in the L group.

Evidence from the literature suggests that cooperative tasks activate the left, but not the right, prefrontal cortex (PFC), whereas competitive tasks activate both sides (Balconi *et al* 2017) and induce players' separation from their competitors (Decety *et al* 2004). Furthermore, both GC and DTF analyses indicated increased connectivity in the frontal cortex of the L group, an area adjacent to the PFC that is associated with social interaction. Thus, a bidirectional increase in interhemispheric prefrontal connectivity and activation of the left frontal cortex during gaming (with the frontal cortex serving as a source) might indicate the wrong strategy–a failure of the losing player to separate from their opponents. Nonetheless, we must emphasize that this strategy was unsuitable for this particular NF task, as increased prefrontal connectivity is related to cognitive control and reinforcement learning (Cavanagh *et al* 2010, van Driel *et al* 2015) which is desirable in conventional games.

To reflect again on the third research question, a competitive task based on NF is based on social interaction, as evident from interbrain activity. The difference between winning and losing players lies in the individual's ability to modulate brain activity and form intrabrain connections.

4.2. Interbrain connectivity

Our final research question concerns the existence of interbrain connectivity. In our previous study, we showed that during competitive gaming, the PLV was asymmetrical—almost all cortical areas in W players were in synchrony with the parietal area of L players in the alpha band (Susnoschi Luca *et al* 2021). Because PLV is non-directional, the method could not reveal the direction of information flow. The interbrain GC analysis in this study confirms that interbrain connectivity is asymmetric and in addition reveals the direction of interbrain connectivity. More successful players had a more significant inflow of information from their opponents, indicating their ability to follow the opponent's performance (visual cortex) and make decisions accordingly (frontal and parietal cortices). This indicates that L players were less capable of monitoring their opponent's behavior, which might be related to their lower ability to dynamically adjust the level of RA with respect to their opponent. This also indicates that the W strategy was not a simple disengaged relaxation, which would have also resulted in an increase in RA.

In summary, the results of this study show the importance of both engagement in the social aspect of a game and the ability to self-regulate one's brain activity. This shows that, although L players had a lower ability to follow and predict opponents' moves, they might perform better in games that require conventional communication (verbal and physical), rather than self-regulation of the brain activity.

The main limitation of this study is the small number of EEG channels, which require sensors rather than source analysis. Therefore, connectivity analysis was performed by grouping the electrodes into three main domains. We distributed EEG electrodes over the whole cortex rather than focusing on one area because adjacent EEG electrodes would inevitably pick up the activity from similar sources, which would be counterproductive for connectivity analysis. The GC and DTF methods are insensitive to volume conduction and have previously been used to analyze EEG signals at the sensor level (Blinowska 2011). In particular, the DTF is often used to analyze the connectivity of a smaller number of channels owing to its computational cost.

Another limitation of the study is the small number of NF sessions because NF is a technique that requires training (Gruzelier 2014). However, our previous experience with operant conditioning (Vučković *et al* 2019) indicates that 2–4 training sessions are sufficient for alpha upregulation. Ideally, all players would have been initially tested with a single-user NF to identify people who are naturally unable to self-regulate their brain waves. However, the W group showed a trend of increased alpha power over repeated NF sessions and a significant increase in gaming scores in the second and third sessions, indicating that they successfully learned the NF strategy.

In this study, the participants shared the same screen and EEG device to avoid synchronization issues, but this might have led to additional nonverbal communication. We attempted to minimize interbrain coupling from sources outside of those induced by the experimental paradigm, as proposed by Dikker *et al* (2021). For example, the impact of social behavior was minimized as dyads were not closely related and were not allowed to communicate during the experiment, either verbally or non-verbally. They faced the same screen and did not make eye contact during gaming. In addition, in Susnoschi Luca *et al* (2021) we tested phase-based connectivity during the baseline and during scoring and found no significant interbrain synchronization during the baseline. Personality traits and mental states were not specifically tested, but the NASA TLX did not show significant differences between W and L players.

5. Conclusions

The unique feature of NF gaming is the requirement to simultaneously engage in social interaction and self-regulate brain activity with respect to the brain activity of the opponent. While previous studies have mainly focused on game design and scoring, this study aims to understand the gaming strategy of winning and losing players and to explore any natural predisposition towards winning for this particular

NF task. The results of this study should inform the design of BCI games to counterbalance the players' innate advantages and put all players on an even playfield.

The ability to adjust one's brain activity with respect to the opponent's, at least for this gaming rule, is related to players' innate baseline RA activity. Another neural correlate of successful gaming is a higher level of directional interbrain connectivity, from losing to winning players, indicating the ability of the winning player to follow the performance of their opponent. An additional factor, probably not directly related to innate neural indices, was the inadequate gaming strategy of losing players, which would be more appropriate for a collaborative task.

Multiuser gaming might not be the best strategy to increase EEG power beyond the baseline power owing to the externally driven target.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

Acknowledgments

This work was supported by the Indonesian Endowment Fund for Education PhD scholarship and the RCUK EPSRC PhD scholarship EP/R513222/1ENG.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Author contributions

F P contributed to data acquisition, methodology, and investigation, and substantially contributed to drafting the manuscript; I S L contributed to the investigation and drafting of the manuscript; J A G P contributed to the conceptualization, methodology, and drafting of the manuscript; H W contributed to the methodology and drafting of the manuscript; A V contributed to the conceptualization, methodology, investigation, and substantially contributed to drafting the manuscript.

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