Increased Left Hemisphere Connectivity During Fine Finger Movements In Pianists

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Abstract

This paper is a new analysis of an existing dataset that aims to explore if previously observed behavioral differences between pianists and controls that an earlier ERP-related analysis could not explain can be explained with the help of EEG-Connectivity. In the dataset, pianists took significantly less time to perform fine finger movements and made fewer mistakes. The connectivity analysis focused on the alpha and beta bands, frequently described as the primary bandwidths that display changes during a movement's active part. The analysis found that pianists (n=12) had higher connectivity between the sensors FCz and C3 than controls (n=12) during the execution with both hands in the lower alpha band. Based on the behavioral differences that were previously found in this dataset and the connectivity pattern, it is suggested in this paper that pianists developed a left-hemispheric specialization that gives them an advantage in performing finger movements. Furthermore, since alpha waves are especially connected to inhibition, it seems likely that the specialization of the left hemisphere is for inhibiting unwanted finger movements. In conclusion, this paper found higher left-hemispheric connectivity (between FCz and C3) in pianists than in non-musicians, which is hypothesized to be showing a left-hemispheric specialization to inhibit unwanted finger movements in pianists. This specialization could explain the better performance since better inhibition could mean fewer wrong keys are pressed accidentally.

Introduction

Earlier research by Sobierajewicz et al. (2018) showed major differences in performance between pianists and non-musicians on a specific motor sequence learning task. These performance differences are likely related to changes in the pianists' brains compared to controls, but earlier ERP-related analyses did not demonstrate any group differences. In the current paper, the question will be explored whether the observed performance differences are possibly due to changes in the connections between the sensors above SMA (FCz) and M1(C3/C4); Additionally, between the sensors with the highest connectivity of the sample. The results of this analysis could be fascinating because they could give new insights into the functioning of brain plasticity. Brain plasticity refers to the brain's ability to adapt its organization and function to support environmental pressures, experiences, and challenges, including brain damage (Kolb et al., 2013; Johansson, 2010). Thus, brain plasticity is the basis for improving cognitive and motor functions in patients with impairment.

Organizational changes after a stroke or injury have been documented for a long time, so stroke therapy aims to enhance the organizational changes in the brain (Su & Xu, 2020). In the case of motor impairment, with active and motor imagery training, other brain regions can execute the functions of these impaired regions (Traversa et al., 1997). Another study describes this neural reorganizational process as the most critical driver for functional recovery (Grefkes & Fink, 2020). Additionally, it is highlighted that an improved understanding of the mechanisms that enable functional reorganization is critical to inventing new and improved stroke recovery methods. It is estimated that 88% of stroke patients experience motor impairment (Aqueveque et al., 2017). This makes understanding motor-related reorganization especially important, and it is crucial to future improved strategies for stroke recovery.

Experts frequently used to examine differences in motor execution and the corresponding changes in their brains are musicians because they belong to a group that consistently performs very specific and complex motor tasks, especially with their hands (Schlaug, 2001). In these tasks, musicians consistently perform better than controls. For example, Sobierajewicz et al. (2018) showed that pianists performed better at learning a specific motor skill than non-musicians. In addition, pianists showed faster response times and higher accuracy than novice controls. Hund-Georgiadis & von Cramon (1999) found that musicians learned new tapping sequences with higher tapping rates and fewer errors than non-musicians. Additionally, there are many studies about structural and functional changes in musicians' brains. These consistent findings make musicians an ideal group to study how their better performances are related to differences in their brains. Thus, musicians are ideal for better understanding motor-related brain plasticity.

Structural and functional differences in musicians' brains

Many studies have already investigated musicians regarding structural and functional changes in their brains. Structural changes have been found in the amount of grey or white matter and structural differences visible on the brain's surface (Gaser, & Schlaug, 2003; Basser & Pierpaoli, 2011). These changes occur predominantly in areas supposed to control hand movements. Grey matter contains many neurons, allowing it to process information and release new information through axons mainly located in white matter (Mercadante & Tadi, 2020). One example is Bangert & Schlaug's (2006) study, which found structural differences between different types of musicians. They observed visually different shapes in the precentral gyrus depending on the musicians' instruments using fMRI. Furthermore, hemispherical asymmetry has been observed between skilled movers and controls. One study found a high positive correlation between left hemisphere grey matter volume and right-hand tapping speed (Hervé et al., 2005). In contrast, right hemisphere grey matter volume at the hand region of M1 correlated negatively with tapping speed on the left hand. However, these results were only found in right-handers, and it was suggested that there might be a left hemispheric specialization for small, repeated movements. Thus, musicians' brains differ anatomically from controls in some areas, including essential areas for motor movements.

Functional changes to musicians' brains have been observed in literature in addition to the aforementioned structural changes. For example, one study investigated short-term motor learning and found that piano players recruited a larger area of the primary motor cortex (M1) during the beginning of learning a new and complex finger tapping task (Hund-Georgiadis & von Cramon, 1999). Additionally, the musicians showed increasing M1-activation throughout the learning session while tapping rates increased. Furthermore, it was discovered that the activation pattern during the play of a Mozart sequence on the violin is much more concentrated in specific brain areas in professional musicians than in amateurs (Watson, 2006). Thus, the anatomical differences in musicians' brains lead to different activation patterns in musically trained individuals compared to untrained individuals. Even though the earlier ERP-related analyses by Sobierajewicz et al. (2018) did not demonstrate any group differences, given the information above, it is still likely that there are differences in the tested pianists' brains compared to the brains of the non-musicians. Thus, a different method is needed to uncover these differences that could explain the performance differences.

Connectivity as a tool to find functional and structural differences

Another way of finding structural and functional differences between groups is to determine the connectivity between brain regions. There are two generally used connectivity types, namely functional and structural connectivity. Functional connectivity is a measure that is derived from the transient synchronization of brain area activations (Horwitz, 2003). These activations are hypothesized to be constructing unified and relatively stable neural states. These neural states represent specific mental and conscious states, meaning synchronized activations of brain areas are thought to resemble connectivity that underlies mental processes. In contrast, structural connectivity refers to the static anatomical structure of the brain independent of the specific state or currently active processes (Babaeeghazvini et al., 2021). Thus, connectivity patterns that are not linked to specific tasks or properties of tasks can be thought of as structural connectivity.

Functional connectivity was successfully used to highlight pre-and post-training changes in brain activity (Heitger et al., 2012). Functional connectivity was additionally able to highlight differences between motor imagery learning and control groups (Zhang et al., 2012). The study by Zhang et al. (2015) implies that the alteration in functional connectivity is due to the manipulation of motor imagery. Furthermore, a study using fMRI connectivity analysis found a connectivity pattern in the motor cortex of the left hemisphere that they hypothesized to be a specialization for complex actions (Verstynen et al., 2005). They came to this conclusion because they used chord and sequence tasks. In the chord task, participants had to tap chords in rhythm, and in the sequence task, participants had to reproduce sequences of keystrokes which is a more complex task. The left-hemispheric connectivity pattern was only visible in the sequence task. This research is particularly interesting because of the similarity of the movement to the movement in the study by Sobierajewicz et al. (2018). This information suggests that functional connectivity could be an excellent measure to differentiate the cognitive processing of separate groups. Additionally, a left-hemispheric specialization is highlighted on a similar task as in the study by Sobierajewicz et al. (2018).

Functional connectivity cannot only distinguish between groups; it can also be a predictor for differences in motor performance specifically. For example, Herszage et al. (2020) explained differences in the performance of individuals in a simple hand motor task with the help of functional connectivity. Specifically, they found that stronger resting-state functional connectivity between the contralateral M1 and SMA would predict an improved performance in an afterward performed tapping task. Furthermore, other studies found that older people, who tend to perform worse on an oddball task, show decreased connectivity in the same functional network (Geerligs et al., 2012). Thus, considering that functional connectivity can distinguish between groups and predict performance, it seems to be an excellent measure to explain the differences in performance of pianists compared to non-musicians in the study by Sobierajewicz et al. (2018), where traditional ERP related analysis did not give an explanation for the better performance by musicians.

EEG Bandwidths in relation to motor movements

Connectivity can be studied with many tools, and EEG is an excellent tool due to its high temporal resolution (Debener et al., 2006). Motor movements have been extensively studied with EEG in literature before. Two phenomena frequently observed in the analysis of EEG data are event-related synchronization (ERS) and event-related desynchronization (ERD). These two phenomena refer to the increase in power/amplitude (ERS) and the decrease in power/amplitude (ERD) in a specific frequency band (Klimesch, 2012). Most sources found that motor movements manifest themselves in the reduction of these ERD in the alpha and beta bands above relevant motor areas (Van der Lubbe et al., 2021). Thus, the alpha and beta bands are particularly interesting during motor events and are essential to analyze.

The alpha band was the frequency band with the most significant power changes during active movement in a study looking across all frequency bands (Ramos-Murguialday, & Birbaumer, 2015). These power changes were characterized as ERD. Above precentral electrodes, ERD occurred more pronounced and continuously ipsilateral. It was suggested that the ipsilateral precentral areas are integral for motor regulation. Therefore, the authors hypothesized that this decrease in alpha oscillatory power is a sign of inhibitory inputs, inhibition of movements, or the reception of an efference copy from the other hemisphere. Another possible interpretation of the observed ERD pattern (starting earlier in posterior sites than in anterior sites) in the study by Ramos-Murguialday, & Birbaumer (2015) was that observed decreases might indicate sensory information propagating from parietal to motor- and premotor areas. Thus, the alpha band seems associated with the inhibition of unwanted movements and sensory information. Inhibiting unwanted finger movements is especially relevant since more precise inhibition could explain trained musicians' improved task performance. Inhibition of finger movement is generally associated with the ipsilateral M1 area (Gerloff et al., 1998). Additionally, better processing of sensory information could lead to better movement results because of the more precise awareness of the position of the fingers.

In the beta band, Ramos-Murguialday, & Birbaumer (2015) found a significant power decrease during the initiation and beginning of the movement in medio-pre- and post-central areas. Therefore, it was hypothesized that the beta band is more related to the actual control of muscles, which could mean that pianists will be different from non-musicians, especially in the beta band, because they are better at controlling their fingers. Furthermore, a study that looked at

EEG connectivity during an isometric motor task found a strong coupling of SMA and M1 within the beta band (Herz et al., 2012). Therefore, suggesting that the beta band and the sensors above SMA and M1 could be particularly interesting to shed light on the performance differences between pianists and non-musicians that Sobierajewicz et al. (2018) found.

Sobierajewicz et al. (2018) reviewed how pianists and non-musician differ in performance and electrophysiologically during a fine finger movements sequence. Sobierajewicz et al. (2018) found significant behavioral group differences in their study. Musicians managed to complete sequences faster. The results indicated no significant difference between the reaction time to start the sequence. However, subsequent keypresses were executed significantly faster by pianists than non-musicians. Additionally, the pianists showed a significantly higher amount of correctly performed sequences than non-musicians. Thus, pianists performed sequences faster and more accurately than non-musicians in the study by Sobierajewicz et al. (2018). Electrophysiological results indicated that both groups showed increased negative lateralized activity above motor areas, but no significant differences were found. That the difference in performance could not be explained by the negative lateralized activity above motor areas suggests that more factors need to be included to explain the differences in performance. Thus, this paper will re-examine the dataset produced by Sobierajewicz et al. (2018) to possibly find an explanation for the significant behavioral differences that were observed. Since negative lateralized activity could not explain the behavioral differences, this paper will use functional connectivity as means to try to tackle the data from a different angle.

The current analysis

This paper is trying to answer whether functional connectivity can explain the behavioral performance differences between pianists and non-musicians found by Sobierajewicz et al.

(2018). An EEG connectivity analysis was performed on the existing dataset previously recorded by Sobierajewicz et al. (2018) to answer this question. The difference in reaction times between groups could have indicated a better preparation or less workload in the preparation time; however, the reaction time to start the sequence was similar. The differences were found in the error rate and time to press the subsequent buttons. Thus, the part of the active movement will be examined since the behavioral differences were found during the movement. The focus will be on the alpha and beta bands. The alpha bandwidth could show differences in the inhibition of unwanted movements. On the other hand, the beta bandwidth could show differences in the actual movement or the ability to move the fingers precisely. Hence, the focus will be on both bandwidths. There will be two different analyses. The first analysis will examine the connectivity between SMA and M1. The focus on these two areas was chosen because most studies indicated that connectivity differences between these two areas might explain differences in the ability to perform motor tasks (Herszage et al., 2020; Hund-Georgiadis & von Cramon, 1999). The second part of the analysis will first collapse the data across both groups and find the electrodes with the highest connectivity. Then, those electrode pairs with the highest connectivity will be compared between groups. This type of analysis will be done to investigate additional highly connected areas during the movement, which might contribute to the difference in the results of the execution of the movement.

Since most studies have focused on using fMRI to investigate resting-state connectivity differences in relation to motor movements, it is unclear how these relations will change when focusing on the execution of the movement with the higher temporal resolution that can be achieved by using EEG. Since pianists might be better at inhibiting unwanted movements, the first hypothesis is that in the alpha bandwidth, the connectivity between the SMA and ipsilateral

M1 will be higher in the pianist group than in the control group. Alternatively, two studies suggested a left-hemispheric specialization on a similar task (Hervé et al., 2005; Verstynen et al., 2005). Although they had different hypotheses about what this specialization is for, it is likely that it can also be seen in the current analysis. Thus, alternatively, connectivity between SMA and left M1 will be higher in the musician group during the execution of movements on both sides. Finally, considering collapsed data, it is hypothesized that the connectivity between electrode pairs with the highest connectivity will be higher in the pianist group than in the control group.

Methods

Participants

A sample of 24 healthy volunteers was recruited. The group of participants was of age 21 to 29 (M = 24.5, SD 2.41). The group consisted of four males and twenty females. All participants reported having no pre-existing mental or neurological disorders. The Ignacy Jan Paderewski Academy of Music in Poznan was used to recruit the participants of the musician group (n = 12, M age = 24.67, SD 1.56, 3 males, 9 females). The musicians reported an average playing time of 2-3 hours daily (SD 2.41). The musical training of the participants in this group started on average at the age of 10 (SD 3.9). The control group consisted of twelve people (1male, 11 females), mainly from the Adam Mickiewicz University (M age = 24.75, SD 2.9). Thus. Both groups were similarly old; however, the standard deviation of the control group was slightly higher (Table 1).

All control group participants reported not receiving any formal music education. Additionally, they indicated that they never learned to play any instrument. Annett's Handedness Inventory was used to assess the handedness of the participants. The results indicated that ten of the musicians were right-handed and two left-handed. In the control group, eleven participants were right-handed and one left-handed. All participants gave written consent.

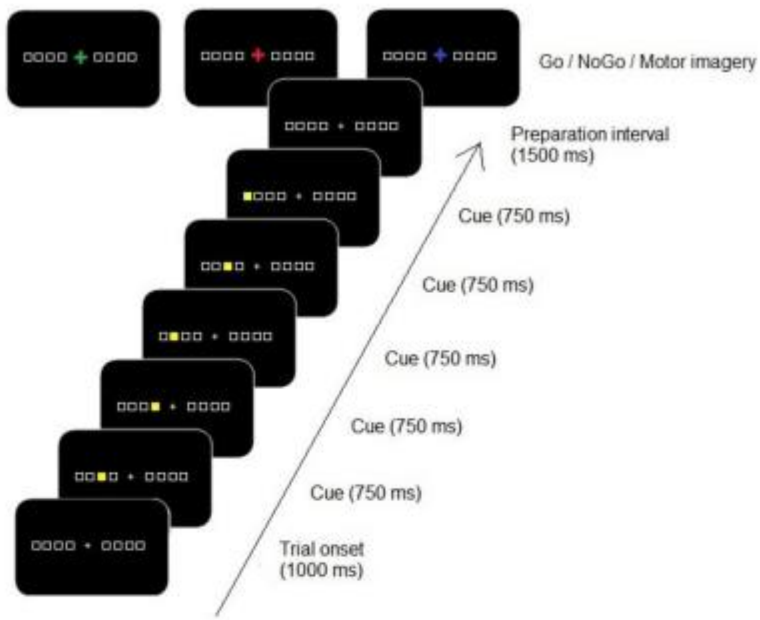
Table 1

This table shows the mean age and standard deviation of the sample.

	Mean Age	SD
Non-Musicians	24.75	2.9
Pianists	24.67	1.56

Figure 1

Screenshot of the task used in the original study with three possible information cues (Go/No-Go/Motor imagery) and the sequence that was presented before (Sobierajewicz et al., 2018)



Stimuli and Task

Every trial of the task used in this study started with a grey cross with four empty boxes to the right and left of the cross (Figure 1). Each of the boxes represented a button on the keyboard. The left side represented the keys' a',' s',' d',' f'. The right side represented the keys ';',' l', 'k', 'j'. Each trial started with a beep sound of 300 Hz that lasted for 300ms. Then, the sequence that the participant should recall later was displayed by filling the squares with yellow. The series of filled squares were presented either in the left four boxes or the right boxes. Each square of the sequence was filled for 750ms. The sequences consisted of five squares that were filled one after the other. Next, the participants were asked to remember the sequence that was displayed. After another 1500ms, the grey square turned green (Go-condition). In the Go-conditions, the participants reproduced the remembered sequence by pressing the corresponding keys on the QWERTY keyboard. The participants of both groups were asked to try to fixate the cross in the middle during the presentation and execution of the sequence. The imaginary and NOGO conditions were indicated with a yellow and red cross, respectively. This paper focuses only on the Go task.

Procedure

The task was executed in a dimly lit room. All participants were seated at 70 cm distance in front of the screen and were asked to sit relaxed. Then, the participants were asked to place the index, middle, ring, and little fingers of the right and left hand on the keyboard's buttons that were used to examine the sequence. The experiment contained five training blocks. Each training block consisted of 32 trials for each condition (Go, motor imagery, NoGO). After that, a final test block needed to be executed. In this test block, 32 sequences that were executed before were required to be performed. Also, 32 imagined and withheld sequences in the test blocks were now executed. Furthermore, 32 new sequences needed to be completed, which summed to 160 execution trials per participant. Twenty-four different sequences were used for each hand.

The participants were asked to reproduce as fast and accurately as possible. In the middle and at the end of each block, participants were given a pause. During the break, the participants got feedback about their performance. This feedback entailed their average reaction times and the error percentages. Additionally, with the press of a button before the Go signal, the participants could display feedback on incorrect responses after the subsequent trial. This feedback was also shown when a wrong button was pressed.

Data And Data-Analysis

The EEG data were recorded with an ActiCap (BrainProducts, GmbH) with 64 active channels. The electrodes were placed according to the extended International 10-20 system

(Böcker et al., 1994). The data (EEG, EOG, EMG) and markers that labeled the stimuli were registered and recorded with Vision Recorder software (Brain Products–version 2.0.3).

To analyze the data, MNE-Python was used, an open-source Python package to analyze EEG and other data. The data analysis was divided into four phases. In the first phase, the data was cleaned from disturbances like eye movement artifacts. In the second phase, the data was split into epochs. The third phase was the connectivity analysis, and the last stage contained the statistical analysis.

The data cleaning phase started with setting the montage to ensure the program knew where the data came from (Appendix A). In the second step of the data cleaning phase, an Independent Component Analysis (ICA) was performed. The ICA is an analysis that tries to separate all statistically independent components of the EEG Signal (Lee, 2011). The data was also scanned for any bad channels that are flatlined or have very high amplitudes. This process was done very conservatively, and no bad channels were found. Therefore, the decision was made to rely more on the ICA. Before the ICA, frequencies below 0.1 Hz and above 30 Hz were filtered out. The ICA was performed for every data file manually so that all components that are not EEG signals would be excluded. Fastica was the method that was chosen, and all other settings were also common (ica = mne.preprocessing.ICA()), which is common practice (Gramfort et al., 2018).

After the data was cleaned, the epoching phase began with selecting relevant stimuli (Go task start). The Go signal was chosen since the focus was on the active part of the movement. The other stimuli would be related to either an imaginary task or no task at all. Additionally, bad epochs were filtered out. The flat criterion for a bad epoch was 1µV. The reject criterion was defined as 150µV. Based on these criteria, the good epochs were saved for the next phase. The length of an epoch was set as one second before and two seconds after the start of motor execution. This interval was chosen to ensure enough baseline before the movement and that the whole trial is in the epoch. During the selection of bad epochs in most data files, below 7 percent of the epochs were dropped. Only in one data file, 24 percent of epochs were dropped. The criteria to drop a participant were set to 33 percent of the epochs, so the analysis included this participant.

After epochs were formed, the connectivity analysis was conducted (Appendix A). For the connectivity analysis, low alpha (8-10Hz), high alpha (10-12Hz), low beta (13-21Hz), and high beta (22-30Hz) bands were selected. The time frame used for the baseline was 1000 ms before the Go signal. The baseline time frame was used to get data from "normal" brain activity to compare to the changed activity from the stimulus. The time frame for the actual analysis started 0.25 seconds after the Go-signal to ensure that the focus was on the movement itself. The method used for the connectivity analysis is the phase lag index (PLI). PLI is a measure based on the assumption that a consistent phase lag that is not zero between two repeated activations cannot be explained by volume conduction from a strong common source (Stam et al., 2007). Thus, it is likely that these activities display true interactions. Furthermore, this method was chosen because it is not affected much by common sources and active reference electrodes. Because of the method PLIs' characteristics, there should be no problems due to volume conduction.

The final step of the data analysis was the statistical analysis done in R-Studio. First, the channels FCz and C3 and FCz and C4 were selected for analysis based on the literature (Herszage et al., 2020; Hund-Georgiadis & von Cramon, 1999; Hervé et al., 2005). This value was then used to compare the groups. Finally, statistical modeling was used because of its higher reliability than the traditional ANOVA (Hernandez, 2018). Several advantages are listed that statistical modeling has over the classical ANOVA. Two of these advantages are that no assumptions of the type of distribution are needed. Thus, the data does not need to be normally distributed. Additionally, many different factors, transformations, and combinations of factors can be considered simultaneously, independent of the sample size, which is a significant advantage considering that there are only 12 participants per group in this dataset.

In the present paper, a multi-factorial linear model approach was used. The connectivity values were used to compare between factors. The first factor considered was the Group, meaning if the participant was a pianist or non-musician. The second factor was the Sensor-Pair (FCz-C3/FCz-C4); the Sensor-Pair changed depending on the specific model's bandwidth. The last factor was the Hand that executed the task (right or left-hand). Since all connectivity values are between zero and one, it was determined that a Beta distribution would best fit the values. In addition to these predetermined factors, an analysis for the best model fit was performed. This analysis indicated that the model should include the interactions between factors. Thus, the final multi-factorial linear models included the three factors (Group, Hand, Sensor Pair) and the interactions between these factors (Group x Hand, Group x Sensor-Pair, Sensor Pair x Hand, Group x Sensor-Pair). Fixed effects were chosen for the model.

After the literature-based analysis, the statistical part, the sensors focused on in the group comparison were selected. This was done by choosing the collapsed localizers (Luck & Gaseplin, 2017). Thus, the connectivity was displayed for the whole dataset by collapsing the two groups to select the collapsed localizers. From this analysis, the two links with the highest connectivity were chosen. With the chosen sensor pairs for each frequency band, the same statistical models were made as in the literature-based analysis.

Results

The multi-factorial linear models' analysis showed that only the FCz-C3/FCz-C4 sample model in the low alpha band showed considerable differences between the groups. The location of the sensors FCz, C3, and C4 can be seen in Figure 2. The model for the FCz-C3/FCz C4 sensor pair in high beta waves also found differences between hand and sensor pairs in both groups, but that will not be examined further since this paper is about the differences between the groups. Thus, this section will focus mainly on the lower alpha band model. In all the other models, the differences between the variables and interactions from the intercept were only minor (maximum: 11.42%). The means and results of the statistical models of these bandwidths and sensor pairs can be found in Appendix C.

Figure 2

Visual representation of the location of the sensors FCz, C3, and C4

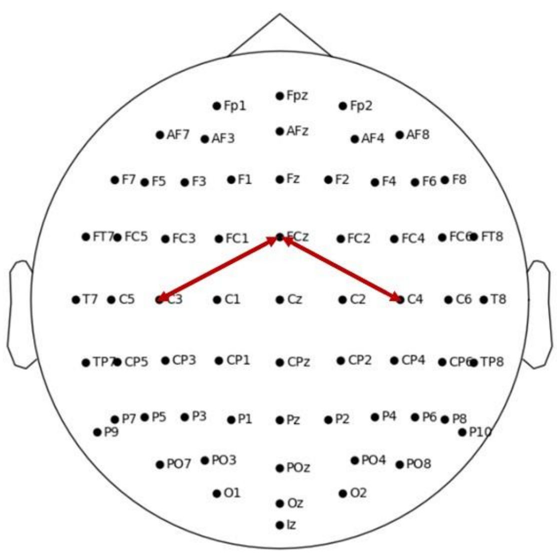
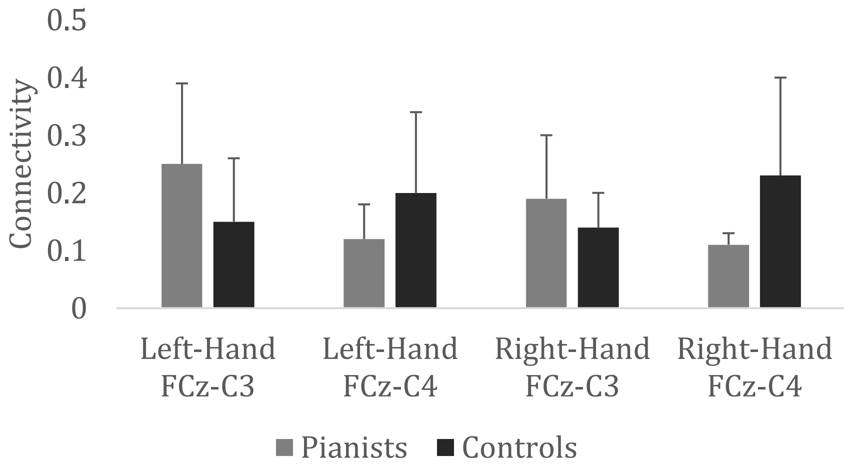


Figure 3

Visualization of the mean connectivity of each group and condition. The bars represent the mean connectivity, and the lines above the bars represent the standard deviations.



A first look at the mean values and standard deviations of the connectivity between FCz and C3/C4 in the lower alpha band (Figure 3) showed that there could be a difference between groups. A visual representation of the connectivity means can be seen in Figure 5. The statistical models' results showed that the intercept is with 95% certainty between -1.46 and -1.00, with a center of -1.38 on the logit scale (Table 2). This implies that the mean connectivity is -1.38 on the logit scale for the control group, left hand, FCz-C4 condition. In the following, the focus will be on relative differences on the logit scale rather than absolute differences on a regular scale because it makes interpreting easier and more.

A visual representation of this model can be seen in Figure 4. At first glance, the interaction between the musician group and sensor pair FCz and C3 differ the most from the intercept. When taking a closer look, it can be seen that there is almost no overlap between the ranges that the population connectivity means of the intercept and the interaction of musician group and the sensor pair FCz/C3 are estimated with 95% confidence—suggesting that the mean connectivity of the intercept is, in fact, different from that of the interaction musician group and sensor pair FCz/C3. In numbers, this means that with 95% certainty, the center estimation of the mean connectivity of the interaction between the musician group and FCz-C4 differs by 0.97 from the intercept, equivalent to 70.28%. A 70.28% difference indicates a big difference that can be considered substantial and is probably not just a random circumstance.

Figure 4

Visual representation of the statistical model for the connectivity values in the lower alpha bandwidth between FCz-C3/C4. The lower and upper boundaries represent the lower and upper values of the factors, and the middle line represents the center.

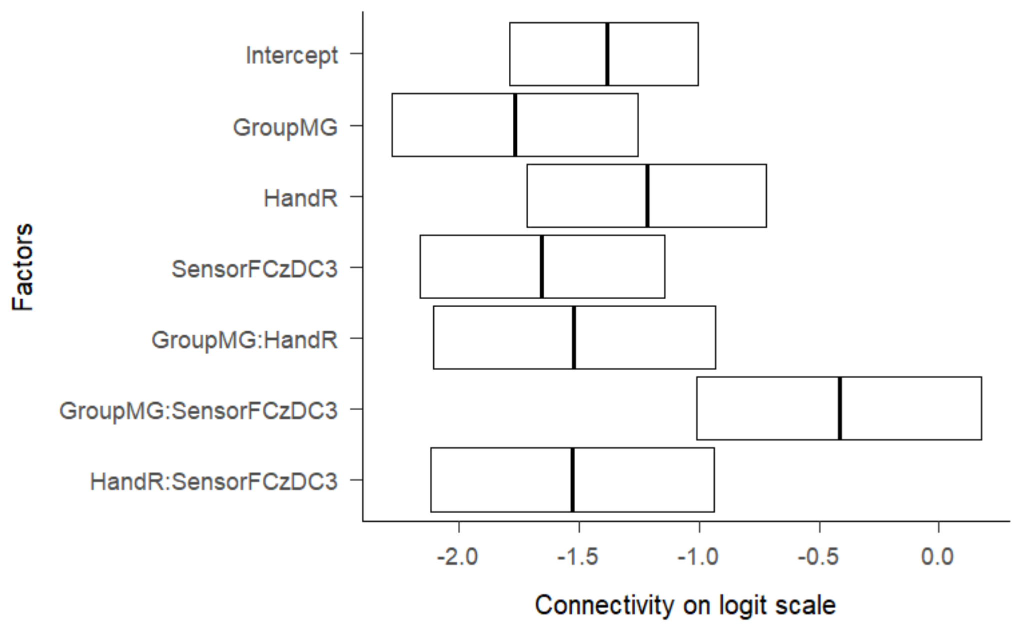


Table 2

Outcomes of the statistical model in the low alpha bandwidth focusing on the sensor pair FCz and C3/C4. With the intercept being the control groups' sensor-pair FCz/C4. Musicians and right-hand interaction include both sensor pairs FCz-C3 and FCz-C4. The interaction of musicians and the sensor pair includes both hands execution, and the interaction of right hand and sensor pair FCz-C3 includes both groups. All conditions and factors are compared to the intercept.

	Center	*Lower*	*Upper*
Intercept	-1.3814677	-1.7934894	-1.0020881
Musicians	-0.3842923	-0.8986901	0.1343706
Right Hand	0.1631315	-0.3347545	0.6670172
Sensor Pair FCz-C3	-0.2720880	-0.7825085	0.2444436
Musicians and Right Hand	-0.1395213	-0.7283141	0.4510758
Musicians and Sensor Pair FCz-C3	0.9658033	0.3736014	1.5550441
Right Hand and Sensor Pair FCz-C3	-0.1480055	-0.7370642	0.4427318

Additionally, the model showed other increased differences from the intercept. For example, the mean connectivity of sensor-pair FCz and C3 with 95% certainty differs by 0.27 (16.36%) on the logit scale from the intercept. 16.36% is also a bigger difference than in the other models. Furthermore, with 95% certainty, the mean of the musician group differs by 0.58 from the intercept (35.15%), which is an even larger difference — considering a difference of

16.36% and 35.15% between the sensor pairs or groups, respectively, these differences on their own could be considered substantial. However, considering that the interaction of these two variables showed an even larger difference in the estimated population connectivity means, it is likely that the interaction between the musician group and sensor pair FCz/C3 explains the differences from the intercept found in the musician group and the sensor pair themselves. Thus, these results indicate that musicians have higher connectivity between FCz and C3 during tasks on both hands, which means that musicians have an increased left hemispheric connectivity between FCz and C3 during left and right-hand execution compared to non-musicians.

With 95% certainty, the rest of the factor means in this model differed only by below 0.2 on the logit scale from the intercept, which is a difference of around twelve percent and thus minor.

Discussion

This paper focused on connectivity between brain regions during a fine motor sequence. More specifically, the goal was to explain previously observed behavioral differences during the execution of a fine finger sequence with the help of connectivity analysis. In the used dataset from Sobierajewicz et al. (2018), pianists were compared to non-musicians. The results of their paper suggested that pianists made significantly fewer errors than non-musicians and that after the first keypress, pianists pressed subsequent buttons faster than non-musicians. However, the previous ERP-related analyses could not explain the better performance, and a different approach was used in this paper. A connectivity analysis was used to determine how pianists' brains differ from normal brains during the execution of a fine finger movement sequence. The connectivity analysis suggested that pianists had increased left-hemispheric connectivity between FCz and C3 during the performance of fine finger movement compared to non-musicians. Furthermore, the musician group's higher connectivity between FCz and C3 was only found in the low alpha band (8-12 Hz) during the execution on both hands in the Go phase. The lower alpha band is commonly associated with inhibition (Ramos-Murguialday, & Birbaumer, 2015). Thus, pianists have higher connectivity between the SMA and left M1 during these movements' left and right-hand execution. However, the results of the open analysis did not yield any significant results.

The results do not suggest higher connectivity between SMA and ipsilateral M1 in the pianist group, rejecting this hypothesis. In contrast, the low alpha band confirmed the hypothesis that connectivity is higher between SMA and left M1 in the pianist group. Since the increase in connectivity in the left hemisphere is present during the movement of both hands, it is interesting that two papers across different measurement techniques indicated a left-hemispheric specialization in their findings. This study's results also indicate a left-hemispheric specialization as the left hemisphere displayed higher connectivity during both hands' execution. Thus, evidence for a left-hemispheric specialization related to finger movements can be found across multiple data collection methods, indicating that the left hemisphere indeed specializes in skilled finger movers.

The study by Hervé et al. (2005), using a tapping task, hypothesized a left-hemispheric specialization for fast repetitive movements in right-handers in areas consistent with the areas of increased connectivity in this paper. In contrast, Verstynen et al. (2005) found a left-hemispheric specialization by observing a connectivity pattern using fMRI in left-hemispheric motor areas. Furthermore, they found the pattern in a task where participants had to press buttons in sequences but did not find it on a chord tapping task. Thus, they hypothesized it to be for complex movements. Although the task of the study by Verstynen et al. (2005) is much more similar to the task used to produce the current dataset, it is unclear what the specialization is for.

In the current analysis, the specialization was only found in the lower alpha band, which could give more profound insights into the function of the found specialization. It is well known that alpha waves are associated with inhibition (Ramos-Murguialday, & Birbaumer, 2015). Thus, it is likely that the specialization is for the *inhibition of unwanted finger movements*. This could also explain why the specialization was found during a finger-tapping and another sequential task. In both tasks, the participant must be precise and inhibit accidentally pressing the wrong button or in a rhythm that he should not be pressing in. Thus, this paper hypothesizes that the specialization of the left hemisphere is for the *inhibition of unwanted finger movements.* This hypothesis could explain the performance differences between pianists and non-musicians; higher connectivity would indicate better inhibition of unwanted finger movements—thus better performance. Additionally, having a part of the brain specialized in inhibiting unwanted movements might free up the capacity of other parts of the brain, which might increase the response times of subsequent button presses, as found in the current data set (Sobierajewicz et al., 2018).

The fact that only the pianists showed increased left-hemispheric connectivity indicates that the increase in left-hemispheric connectivity is an integral part of the better performance that the pianists displayed on the task by having faster response times and higher accuracy (Sobierajewicz et al., 2018). Suggesting that only pianists used the left-hemispheric specialization. Since non-musicians did not use the specialization of the left hemisphere, it is likely that they have not developed this specialization at all or only to a lesser degree. The connectivity data support this since only pianists displayed higher connectivity in the left hemisphere. Thus, the increased connectivity could indicate the development of the specialization in skilled movers.

Considering that the study by Herszage et al. (2020) found higher resting-state connectivity between SMA and contralateral M1 during a similar task, it is likely that the specialization for the inhibition of unwanted finger movements is only visible while it is being used, making it unlikely to appear during the resting state. That could explain why a different connectivity pattern was found in this paper. Therefore, Herszage et al. (2020) might have found a different mechanism that gives musicians an additional advantage during the execution of a fine motor sequence. Thus, it is likely that multiple factors are at play that combine to give pianists an edge during motor execution. Future research should look deeper into different factors that add to better motor control and combine methods during the movement and the resting state.

It might be interesting to re-examine the data used in this paper and focus on the motor imagery part of the data since the specialization is likely to be for the inhibition of unwanted finger movements. Suppose this specialization is for the inhibition of unwanted finger movements. In that case, it might be more visible during motor imagery since even fewer finger movements need to be suppressed, providing further evidence for the hypothesis that the specialization is for the inhibition of unwanted finger movements. Thus, an analysis focussing on motor imagery could show that the specialization found in the left hemisphere is indeed linked to inhibition.

Most participants in this study were right-handed. This is an important factor to consider since it could be that the specialization for unwanted finger movements could also be in the left hemisphere of left-handers, but it is also possible that in left-handers, this specialization is in the right hemisphere. Unfortunately, it is impossible to know which of the two possibilities is accurate from the current analysis. Thus, it would make sense for future research to try to replicate a similar experiment and control for the handedness of the participant and see how the activation patterns differ based on that. Alternatively, it would also be possible to do a similar analysis with a predominantly left-handed sample and investigate if the specialization is still in the left hemisphere or shifted to the right.

In conclusion, this paper tried to explain faster and more accurate responses from pianists on a fine finger movement task. The main question was if differences in connectivity could explain these behavioral differences. The results suggested that pianists have higher connectivity between FCz and C3 during both hands execution. This paper suggests that this connectivity pattern indicates a left-hemispheric specialization *to inhibit unwanted finger movements*. Future research should look at the motor imagery data of this study since, in motor imagery, more movements need to be suppressed. Thus, it is likely that this specialization is also visible or even stronger visible in the motor imagery condition, which would support the hypothesis that the specialization is for the inhibition of unwanted finger movements. Additionally, a combined approach with resting-state connectivity and connectivity during the trial could give insights into different processes used by musicians that give them an edge in motor execution. Maybe combining those processes or additional ones can explain the behavioral differences between musicians and non-musicians.

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Appendix A

Code 1

Code example of setting the right channel types and montage

```
##EXAMPLE CODE##
##IMPORT DATA FILES##
#give file (individual) a name + save(path of file and saving directory)
fnmae_12 = r'D:\EEG\master\Masterdata\S04cg.vhdr'


#read file from folder
raw = mne.io.read_raw_brainvision(fnmae_12, preload = True)


raw.info.get('nchan')#number of channels <-- here 65


raw.plot()#plot raw data


        ##SET MONTAGE##
#fit head shape by digitization of montage
#give channel the right type (=eeg)
raw.pick_types (meg=False, eeg=True, eog=True, ecg=False, emg=True)
raw.set_channel_types(mapping={'vEOG' : 'eog'})#ocular signals
raw.set_channel_types(mapping={'hEOG' : 'eog'})#ocular signals
raw.set_channel_types(mapping={'LEMG' : 'emg'})#muscular signals
raw.set_channel_types(mapping={'REMG' : 'emg'})#muscular signals


##set electrode location (extended 10-20system) through montage
```

```
montage = mne.channels.make_standard_montage('standard_1020')

raw.set_montage(montage)
```

Code 2

Code example for the ICA procedure until manually selecting the components that should be excluded.

```
##Example Code##

##FILTERING DEVIANT SIGNALS

raw.filter(0.1, 30., fir_design='firwin') --> done in ICA


        ##ICA##

#ica
tutorial:https://mne.tools/stable/auto_tutorials/preprocessing/plot_40_artifact
_correction_ica.html


#data decomposition using ICA --> estimates independent components from raw
data

#first step is just initializing ica settings and does nothing


ica = mne.preprocessing.ICA()#default setting: (n_components=None, *,
max_pca_components=None, n_pca_components=None, noise_cov=None,
random_state=None, method='fastica', fit_params=None, max_iter=200,
allow_ref_meg=False, verbose=None)

#Additional Info:

#   1) n_components = None: => n_pca_components (deprecated) or 0.999999 (will
```

```
become the default in 0.23) will be used, whichever results in fewer
components. This is done to avoid numerical stability problems when whitening,
particularly when working with rank-deficient data.
#   2) random_state = None: => seed will be obtained from the operating system
ica.fit(raw)#proceeds in two steps: 1) Whitening the data by means of a pre-
whitening step (here:SD of each channel type) followed by PCA
#                                   2) Passing the n_components largest-
variance components to the ICA algorithm to obtain the unmixing matrix

#instead of manually selecting which ICs to exclude, we use dedicated EOG
sensors as a "pattern" to check the ICs against
eog_indices, eog_scores = ica.find_bads_eog(raw, 'vEOG')#automatically find the
ICs that best match the EOG signal
ica.exclude = eog_indices#excludes artefacts matching eog signals

#barplot of ICA component "EOG" match scores
ica.plot_scores(eog_scores)
# plot diagnostics
ica.plot_properties(raw, picks=eog_indices)
# plot ICs applied to raw data, with EOG matches highlighted + allows for
further exclusion of components
ica.plot_sources(raw)
#check if raw data has been cleaned
#raw.plot()
```

Code 3

Code example for the manual steps of ICA and saving the copy.

```
##Code example##
#execute until this point, from here you can select components you want to look at (ica.plot) and then go on
#and exclude them. Remember to include the ones that are marked by the program
ica.plot_properties(raw, [2,3])
ica.exclude =[2,3]

#since ica.apply changes raw we are making a copy
reconst_data = raw.copy()
ica.apply(reconst_data)#proceeds in 4 steps: 1)Unmixes the data with the unmixing matrix
#                                            2)Includes ICA components based on ica.exclude
#                                            3)Re-mixes the data with mixing_matrix
#                                            4)Restores any data not passed to the ICA algorithm (i.e. PCA components between n_components & n_pca_components)
reconst_data.plot()#final check of raw data, here the data should be full cleaned

#save cleaned raw data to use for epochs forming
reconst_data.save(r'D:\EEG\master\Masterdata\ica\s04cg_icaneu_raw.fif')
```

Code 4

Code example of naming the epochs that related to motor exection and plotting the locations

```
##Code Example##

##IMPORT DATA FILES##

#import ica file from preprocessing

test = r'D:\EEG\master\Masterdata\ica\s04cg_icaneu_raw.fif'


raw_test = mne.io.read_raw_fif(test, preload = True)


raw_test.plot()


#get and save stimuli times --> make an event

events, _ = mne.events_from_annotations(raw_test, event_id={'Stimulus/S 41':
1,'Stimulus/S 42': 2})






#get stimuli times --> form event markers which later the epochs will be
created around

event_dict = {'Start_Left_execution': 1, 'Start_right_execution': 2}


#create plot showing at what times selected stimuli are

fig = mne.viz.plot_events(events, event_id=event_dict,

                          sfreq=raw_test.info['sfreq'])
```

```
fig.subplots_adjust(right=0.6)#to make room for legend(description)<- smaller number bigger legend
```

Code 5

Code example of setting the reject criteria, rejecting bad epochs and saving good epochs.

```
##Code Example##
##CREATE EPOCHS & DROP BAD EPOCHS##

#epoching data after stimuli codes
#setting maximum & minimum acceptable peak-to-peak amplitudes for each channel type in an epoch
#set start time and end time of the epoche around event marker
reject_criteria = dict(eeg=150e-6) #150µV
flat_criteria = dict(eeg=1e-6)#1µV
tmin, tmax = -1, 1
epochs = mne.Epochs(raw_test, events, event_id=event_dict,
                    tmin=tmin, tmax=tmax, reject_tmax=0,
                    reject=reject_criteria, flat=flat_criteria,
                    reject_by_annotation=True, preload=True)

print(epochs.drop_log)
#graphic showing dropped epochs & shows the channels that caused the dropping
epochs.plot_drop_log()
```

```
#epochs not dropped yet, however, marked


#drop epochs later IF reject and/or flat criteria have already been provided
by:
epochs.drop_bad()


epochs.save(r'D:\EEG\master\Masterdata\epochs\s04cg_neu_epo.fif')
```

Code 6

Code example of the connectivity analysis

```
picks = mne.pick_types(epochs_1.info, eeg=True, meg=False, stim=False,
eog=True)


fmin, fmax = 7., 12.
sfreq = epochs_1.info['sfreq']
tmin = 0.0
epochs_1.load_data().pick_types(eeg=True)
con, freqs, times, n_filt_epochs, n_tapers = spectral_connectivity(
    epochs_1, method='pli', mode='multitaper', sfreq=sfreq, fmin=fmin,
fmax=fmax,
    faverage=True, tmin=tmin, mt_adaptive=False, n_jobs=1)
#Make the graphic
plot_sensors_connectivity(epochs_1.info, con[:, :, 0])
```

Appendix B

Table 1

Descriptive statistics of the connectivity in the low alpha band between FCz and C3/C4 divided by the Side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	FCz/C3	CG	0.15	0.11
		MG	0.25	0.14
	FCz/C4	CG	0.2	0.14
		MG	0.12	0.06
Right-hand	FCz/C3	CG	0.14	0.06
		MG	0.19	0.11
	FCz/C4	CG	0.23	0.17
		MG	0.11	0.02

Table 2

Descriptive statistics of the connectivity between FCz and C3/C4 in the high alpha band divided by the side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	FCz/C3	CG	0.13	0.08
		MG	0.12	0.05
	FCz/C4	CG	0.15	0.06
		MG	0.08	0.04
Right-hand	FCz/C3	CG	0.18	0.12
		MG	0.14	0.08
	FCz/C4	CG	0.13	0.08
		MG	0.13	0.07

Table 3

Descriptive statistics of the connectivity between FCz and C3/C4 in the low beta band divided by the side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	FCz/C3	CG	0.12	0.05
		MG	0.11	0.04
	FCz/C4	CG	0.11	0.03
		MG	0.13	0.04
Right-Hand	FCz/C3	CG	0.10	0.03
		MG	0.10	0.04
	FCz/C4	CG	0.11	0.04
		MG	0.10	0.03

Table 4

Descriptive statistics of the connectivity between FCz and C3/C4 in the high beta band divided by the Side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	FCz/C3	CG	0.14	0.06
		MG	0.11	0.04
	FCz/C4	CG	0.09	0.03
		MG	0.13	0.05
Right-hand	FCz/C3	CG	0.12	0.05
		MG	0.10	0.04
	FCz/C4	CG	0.13	0.06
		MG	0.09	0.05

Table 5

Descriptive statistics of the connectivity between Fz and O1/O2 divided by the side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	Fz/O1	CG	0.23	0.11
		MG	0.23	0.10
	Fz/O2	CG	0.23	0.12
		MG	0.20	0.15
Left-hand	Fz/O1	CG	0.25	0.14
		MG	0.14	0.11
	Fz/O2	CG	0.22	0.12
		MG	0.21	0.12

Table 6

Descriptive statistics of the connectivity between Fz and O1/O2 divided by the side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	CP3/P7	CG	0.13	0.14
		MG	0.17	0.12
	CP4/P8	CG	0.20	0.07
		MG	0.14	0.08
Right-hand	CP3/P7	CG	0.19	0.15
		MG	0.15	0.10
	CP4/P8	CG	0.19	0.15
		MG	0.21	0.13

Table 7

Descriptive statistics of the connectivity between Fz and O1/O2 divided by Side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	CP3/P7	CG	0.15	0.08
		MG	0.13	0.06
	CP4/P8	CG	0.15	0.07
		MG	0.14	0.07
Right-hand	CP3/P7	CG	0.21	0.12
		MG	0.17	0.05
	CP4/P8	CG	0.13	0.05
		MG	0.14	0.06

Table 8

Descriptive statistics of the connectivity between Fz and O1/O2 divided by the side of Execution (left or right hand) and group (control group (CG) or musician group (MG))

		Groups	Mean	SD
Left-hand	Fp1/FC3	CG	0.14	0.06
		MG	0.15	0.07
	Fp2/FC4	CG	0.11	0.04
		MG	0.11	0.06
Right-hand	Fp1/FC3	CG	0.10	0.05
		MG	0.12	0.06
	Fp2/FC4	CG	0.13	0.05
		MG	0.13	0.05

Appendix C

Table 1

Outcomes of the statistical model in the high alpha bandwidth focussing on the sensor pair FCz and C3/C4

	Center	*Lower*	*Upper*
Intercept	-1.3814677	-1.7934894	-1.0020881
Musicians	-0.3842923	-0.8986901	0.1343706
Right Hand	0.1631315	-0.3347545	0.6670172
Sensor Pair FCz/C3	-0.2720880	-0.7825085	0.2444436
Musicians and Right Hand	-0.1395213	-0.7283141	0.4510758
Musicians and Sensor Pair FCz/C3	0.9658033	0.3736014	1.5550441
Right Hand and Sensor Pair FCz/C3	-0.1480055	-0.7370642	0.4427318

Table 2

Outcomes of the statistical model in the low Beta bandwidth focussing on the sensor pair FCz and C3/C4

	Center	*Lower*	*Upper*
Intercept	-2.01936232	-2.2849066	-1.7739646
Musicians	0.18601678	-0.1416917	0.5149094
Right Hand	-0.03858223	-0.3771159	0.2961121
Sensor Pair FCz/C3	-0.01221114	-0.3481001	0.3237961
Musicians and Right Hand	-0.15919904	-0.5492238	0.2288346
Musicians and Sensor Pair FCz/C3	-0.09192386	-0.4791962	0.2932220
Right Hand and Sensor Pair FCz/C3	-0.03780314	-0.4234042	0.3489057

Table 3

Outcomes of the statistical model in the high beta bandwidth focussing on the sensor pair FCz and C3/C4

	Center	*Lower*	*Upper*
Intercept	-1.92784479	-2.2578054	-1.6253129
Musicians	0.11734355	-0.2934635	0.5287813
Right Hand	0.01167792	-0.4027954	0.4259183
Sensor Pair FCz/C3	0.08719222	-0.3248964	0.4990595
Musicians and Right Hand	-0.14685542	-0.6228703	0.3268741
Musicians and Sensor Pair FCz/C3	-0.12534171	-0.6024433	0.3523591
Right Hand and Sensor Pair FCz/C3	-0.03220657	-0.5090456	0.4427372

Table 4

Outcomes of the statistical model in the low alpha bandwidth focussing on the sensor pair Fz and O1/O2

	Center	*Lower*	*Upper*
Intercept	-1.0839229	-1.4644419	-0.7280610
Musicians	0.1041739	-0.5997049	0.3865000
Right Hand	-0.1024064	-0.5962371	0.3876487
Fz/O2	-0.2685483	-0.7692181	0.2260157
Musicians and Right Hand	-0.1917923	-0.7715796	0.3847540
Musicians and Fz/O2	0.1119905	-0.4686176	0.6891063
Right Hand and Fz/O2	0.2862334	-0.2890195	0.8632390

Table 5

Outcomes of the statistical model in the high alpha bandwidth focussing on the sensor pair Cp3/Cp4 and P7/P8

	Center	*Lower*	*Upper*
Intercept	-1.378317025	-1.8549206	-0.9351845
Musicians	-0.116020178	-0.7373159	0.4980199
Right Hand	0.019420048	-0.5971956	0.6277886
CP4/P8	0.347460274	-0.2563845	0.9442563
Musicians and Right Hand	0.109369062	-0.5906295	0.8127339
Musicians and CP4/P8	-0.163090109	-0.8604643	0.5378508
Right Hand and CP4/P8	0.003890153	-0.6956305	0.7085063

Table 6

Outcomes of the statistical model in the low beta bandwidth focussing on the sensor pair Cp3/Cp4 and P7/P8

	Center	*Lower*	*Upper*
Intercept	-1.707256725	-2.01998463	-1.41925429
Musicians	-0.130001750	-0.52668278	0.26903601
Right Hand	0.368729863	-0.01060441	0.75233376
CP4/P8	0.005130905	-0.39026998	0.39851453
Musicians and Right Hand	-0.030798148	-0.47910705	0.41756569
Muscians and CP4/P8	0.182494105	-0.26764999	0.63209405
Right handHand and CP4/P8	-0.381417364	-0.83248475	0.07073228

Table 7

Outcomes of the statistical model in the high beta bandwidth focussing on the sensor pair Fp1/Fp2 and Fc3/Fc4

	Center	*Lower*	*Upper*
Intercept	-1.66743573	-2.00413697	-1.3558727
Musicians	0.09608877	-0.32356632	0.5158001
Right Hand	-0.28537006	-0.72509963	0.1472040
Fp2/Fc4	-0.21010392	-0.64243882	0.2217477
Musicians and Right Hand	0.09250238	-0.40674067	0.5946637
Musicians and Fp2/Fc4	-0.09708054	-0.59544022	0.3998182
Right Hand and Fp2/Fc4	0.42670759	-0.07051326	0.9269260

Appendix D

Code 7

Code in R for the model of the lower alpha band

````
```{r eval=FALSE, include=FALSE}

install.packages("readxl")

devtools::install_github("schmettow/mascutils")

devtools::install_github("schmettow/bayr")

```

```{r}

library("readxl")

library(tidyverse)

library(rstanarm)

library(mascutils)

library(brms)

library(bayr)

options(mc.cores = 4)

```

```{r}

my_data <- read_excel("D:/old desktop/R_master/lowalpha.xlsx")

```
````

````
```{r}
M_3_la <-
  my_data %>%
  brm(Connectivity ~ Group + Hand + Sensor + Group:Hand + Group:Sensor +
Hand:Sensor,
      family = Beta(link = "logit"),
      data = ., iter = 100000)
```
```{r}
fixef_ml (M_3_la)
```
````