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The After-Glow of Flow: Neural Correlates of Flow in Musicians

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ABSTRACT

Flow is a state of optimal or peak experience, commonly associated with expert and creative performance. Musicians often experience flow during playing, yet the neural mechanisms underlying this elusive state have remained underexplored due to challenges posed by substantial artefacts in the neural data. Here, we bypassed these issues by focusing on the resting-state immediately following a flow experience. Musicians performed pieces expected to reliably induce a flow state, and, as a control, non-flow-inducing musical pieces. Following the flow state, we observed higher spectral power in the upper alpha (10-12 Hz) and beta (15-30 Hz) bands, primarily in the frontal brain regions. Connectivity analysis, using the phase slope index, showed a right frontal cluster influencing activities in the left temporal and parietal areas at the theta (5 Hz) band, particularly pronounced in musicians reporting high dispositional flow. Theta band connectivity within the frontoparietal control network facilitates cognitive control and goal-directed attention, potentially crucial for achieving the flow state. These results reveal large-scale oscillatory correlates associated with the immediate post-flow state in musicians. Importantly, this framework holds promise for exploring the neural basis of flow-related states in a laboratory setting while preserving ecological and content validity.

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PLAIN LANGUAGE SUMMARY

Flow is an optimal state that is of interest to many who have experienced it while engaged in an enjoyable and fulfilling activity, performing at their very best. Musicians often experience this state of flow during playing. However, we know little about the brain's activity during this unique state. One challenge in studying the brain during musical performances is the potential interference caused by movements, which can disrupt the recorded brain responses. To overcome this, we focused in this study on the immediate period following the flow state, right after musicians finished their performances. During this time, the musicians were asked to close their eyes and remain still, allowing us to collect EEG signals. In our study, musicians played music that they felt would put them into a state of flow. Additionally, as a control, they also played music that did not induce flow in themselves. By comparing these two scenarios, we could observe the brain's responses immediately after experiencing flow. The brain state immediately after flow showed more activity within certain frequency bands: the upper alpha (10-12Hz) and beta (15-30 Hz) frequency bands, with a particular emphasis on the frontal brain regions. In addition, connectivity analysis found a right frontal cluster influencing activity in the left temporal and parietal areas at the theta (5 Hz) frequency band, most notably in musicians who reported frequently experiencing flow. These results show that there are changes in brain activity that occur immediately after the performance, reflecting the flow experience. By adopting a novel approach that focuses on studying musicians, this study offers promising avenues for investigating brain activity during this captivating state of flow under controlled laboratory conditions.

Introduction

Flow refers to an altered state of consciousness involving highly focused engagement while participating in a challenging, enjoyable, and intrinsically rewarding activity (Csikzentmihalyi, 1990). It is considered an optimal psychological state (Jackson & Eklund, 2004) that is usually associated with high levels of performance and positive subjective experience. Hence, there is significant interest in studying the neural correlates of the flow state. Although flow is frequently reported by musicians (Butkovic, Ullén, & Mosing, 2015), our understanding of the underlying brain activity during this state is not properly characterized. Therefore, in this study, we recorded electroencephalography (EEG) to measure the brain activity of musicians while they were engaged in music-making leading to flow.

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Neural correlates of flow experience

One of the key conditions for flow is when the perceived challenges of a task align with an individual's skill, neither underutilizing nor overutilising their abilities (Nakamura & Csikszentmihalyi, 2014). Previous laboratory-based studies attempting to characterize neural activity during flow have manipulated task demands to create different conditions, from easy, which induces boredom, to difficult, inducing frustration (Keller & Bless, 2008). In contrast, a third condition that aims to create an optimal level of challenge, neither too easy nor too difficult for an individual's expertise in a given task, is more likely to induce a flow-like state. Therefore, ratings of flow experience will be higher when the challenge level matches the individual's skill level compared to situations when the challenge is too low or too high. The relationship between flow and challenge can thus be described as following a negative quadratic trend, forming an inverted U-shaped curve (Engeser & Rheinberg, 2008). In previous experimental designs investigating neural activity during flow, researchers utilized this challenge-skill balance as an indicator of flow while participants were solving mental arithmetic problems (Katahira et al., 2018; Ulrich, Keller, & Grön, 2016b) and playing computer games like Tetris (Barros, Araújo-Moreira, Trevelin, & Radel, 2018; Harmat et al., 2015; Yoshida et al., 2014).

Several of these studies have investigated the "transient hypofrontality hypothesis" (Dietrich, 2004), which suggests that during flow, the prefrontal cortex (PFC) becomes less active, allowing automatic and unconscious processing to dominate. This can be particularly helpful when performing well-practiced movements. Within a dual process framework that distinguishes between spontaneous (type 1 processes) and deliberate (type 2 processes) modes of processing, flow has been associated with type 1 processes characterized by fast and automatic processing; in contrast, type 2 processes involve slower and conscious deliberation and effortful recall from memory. Therefore, according to this hypothesis, flow is associated with reduced activity in the prefrontal regions, which typically show increased activity during tasks requiring mental effort (Dietrich, 2004; Ullén, De Manzano, Theorell, & Harmat, 2010). However, findings relating to the hypofrontality hypothesis have been mixed. One study found no association between flow scores and activity in the frontal regions (Harmat et al., 2015), while two studies reported increased activity in the prefrontal cortex during the challenge-skill balance condition (Barros, Araújo-Moreira, Trevelin, & Radel, 2018; Yoshida et al., 2014). One interpretation is that the hypofrontality hypothesis may be too broad and may apply only to specific areas of the prefrontal cortex. For instance, Barros et al. (2018) found increased activations within the lateral part of the frontoparietal network during a flow condition, which they interpreted as an active engagement of attentional resources during flow. These activations were accompanied by deactivation in the medial PFC, which the authors linked to reduced mind-wandering and self-referential processing.

Ulrich et al. (2014) conducted an fMRI study examining flow during mental arithmetic and observed reductions in neural activity in the medial PFC, posterior cingulate cortex, and medial temporal lobe, including the amygdala; these regions are part of the default mode network (DMN). Conversely, they also observed increased activity during flow in the inferior frontal gyrus (IFG), left putamen, and posterior cortical regions, areas that are associated with a "multiple demand system," involved in various demanding cognitive tasks. Many studies have also found decreased activity in the DMN during flow, indicating the downregulation of task-irrelevant processes due to focused attention (Huskey, Craighead, Miller, & Weber, 2018; Ju & Wallraven, 2019; Ulrich, Keller, & Grön, 2016b). Additionally, increased activity during flow has also been observed in brain regions associated with cognitive control, such as the dorsolateral prefrontal cortex (DLPFC) and the visual orienting and alertness attentional networks (Huskey, Craighead, Miller, & Weber, 2018). A reduction in default mode network activity and an increase in executive control during flow seems, on the surface, to be counterintuitive to thinking of flow as a type 1 process.

Several EEG studies have examined differences in spectral power between flow and non-flow states, yielding mixed results. An exploratory study using EEG to study flow designed a computer game to induce flow, immersion, and boredom (Nacke, Stellmach, & Lindley, 2011); no significant differences in the EEG spectral power were found between flow and boredom. Another computer game experiment found that spectral power in the alpha (8–12 Hz), low beta (12–15 Hz), and mid-beta (15–20 Hz) bands reliably distinguished between flow, boredom, and frustration (Berta, Bellotti, De Gloria, Pranantha, & Schatten, 2013). Katahira et al. (2018) used the mental arithmetic task and found increased theta (4–7 Hz) band activity in frontal areas during flow and overload conditions. The authors also observed increased alpha (10–13 Hz) power in the frontal and right central areas as task difficulty increased, and the EEG activities correlated with self-reported flow experience, especially ratings of concentration and task difficulty.

These studies have primarily operationalized flow based on challenge-skill balance in cognitive tasks such as mental arithmetic and simple computer games. Such a balance has been linked to reduced self-referential processing (Ulrich, Keller, & Grön, 2016a), increased intrinsic motivation (Huskey, Craighead, Miller, & Weber, 2018; Meng, Pei, Zheng, & Ma, 2016), and greater cognitive control and attention (Katahira et al., 2018; Núñez Castellar et al., 2019). Though these studies offer novel contributions to the neuroscientific literature on flow, there are inherent limitations in relying solely on the challenge-skill balance as the criterion for inferring flow. While the challenge-skill balance may be a central condition of flow, it is not a sufficient condition for flow, and using it as the sole determinant of flow can lead to unreliable results (Moller, Meier, & Wall, 2010). A meta-analysis investigating the antecedents of flow found that the correlation between challenge-skill balance and flow was only moderate and decreased when intrinsic motivation was taken into account (Fong, Zaleski, & Leach, 2015). In addition, the difficulty of capturing flow is compounded when the experiments are conducted in the sterile environment of a laboratory, where participants typically engage in an unfamiliar task within an evaluative context. These factors can work against the already slim chances of experiencing flow in a laboratory since flow is more likely to occur in individuals who are highly skilled in an activity, and performance anxiety is not conducive to flow (Abuhamdeh, 2020). Further, a task is more likely to induce flow if it is personally meaningful to the individual and can be carried out for prolonged periods without interruption (Nakamura & Csikszentmihalyi, 2014). In particular, the automaticity predicted by the transient hypofrontality hypothesis may require domain-specific expertise, more than is possible from participants learning a novel task for an experiment. Therefore, neural mechanisms underlying flow in the lab-based activities could differ from those underlying flow induced by complex real-life activities like music performance.

Naturalistic inductions of flow

Given the limitations of the challenge-skill balance model in a novel experimental task, alternative operationalizations of flow that do not solely rely on this approach can be explored. Klasen et al. (2012) conducted a study where computer gamers played a first-person shooter game inside an MRI scanner. Independent raters then evaluated recorded gameplay based on the nine characteristics of flow. Moments rated as more conducive to flow were associated with increased activity in the neocerebellum, left and primary somatosensory cortex, and motor areas. The authors suggested that the experience of flow involves the activation of a reward-motor loop, which synchronizes brain areas sensitive to reward with task-relevant cortical and cerebellar areas (Klasen, Weber, Kircher, Mathiak, & Mathiak, 2012).

Advancements in mobile neuroimaging have opened up exciting opportunities for collecting data during complex, personally engaging, and ecologically appropriate, activities frequently associated with flow. For example, Leroy and Cheron (2020) collected EEG data from a tightrope walker to study brain responses before, during, and after a tightrope walk. They found that flow during the walk was accompanied by alpha oscillations, which disappeared after a stressful situation that occurred unexpectedly during the walk. These findings suggest that the flow state involves the recruitment of additional brain areas beyond those associated with online control of the skill, with activation observed in structures of the basal ganglia (Leroy & Cheron, 2020). Of note, these findings seem more in line with the predictions of the transient hypofrontality hypothesis.

Hence, there is a contradiction in flow research about the role of automaticity and frontal neural activity that is arguably task-related (van der Linden, Tops, & Bakker, 2021). For instance, a computer game like Tetris may require more explicit control and, accordingly, involve more frontal activity (Harmat et al., 2015), while flow in tasks such as music performance or sports, which involve effortless automatic processing of well-learned actions, may be associated with reduced frontal activity. This task discrepancy may explain some of the contradictory findings in flow research, where flow in cognitive tasks and simple computer games is associated with increased frontal activity and activated brain areas related to strong attentional focus and controlled processing while studying flow during tightrope walking yielded findings more in line with hypofrontality (van der Linden, Tops, & Bakker, 2021). Of note, a bias toward cognitive tasks, for the practical purposes of avoiding movement artifacts during neuroimaging, may result in more evidence against hypofrontality in existing studies on flow.

The differences in brain responses between complex activities in a natural setting and flow data obtained through the challenge-skill balance paradigm in a laboratory highlight the importance of including those activities that naturally induce flow in neuroscientific studies. One possible approach is to examine the self-induction of flow by skilled practitioners, such as the tightrope walker as studied by Leroy and Cohen (2020), or expert computer gamers engaged in free gameplay of their preferred game. However, this approach has the limitation of relying on retrospectively categorizing events rather than experimentally controlling them. Additionally, it is challenging to predict whether a recording session will result in flow or an unexpected event. To advance this research, it would be beneficial to investigate a large group of experts who can deliberately induce their own flow experiences. Comparing flow and non-flow experiences within the same activity would provide valuable insights. We consider musicians an appropriate expert group for such a study. Music is recognized to offer various opportunities to enter the flow state (Bakker, 2005), and different conditions can be more predictably induced by selecting specific musical pieces. Therefore, conducting a study with musicians would contribute significantly to our understanding of flow experiences and their neural correlates.

Flow in music performance

In a study conducted by de Manzano, Theorell, Harmat, and Ullén (2010), it was demonstrated that playing music can serve as an effective naturalistic flow experience. The researchers examined professional pianists and identified psychophysiological correlates, specifically EMG, cardiovascular and respiratory measures, associated with flow (de Manzano, Theorell, Harmat, & Ullén, 2010). To keep sensorimotor processing and physical output similar across five sessions, the pianists were instructed to play a single piece of music five times (de Manzano, Theorell, Harmat, & Ullén, 2010). This study, though informative, lacked a control condition where participants played music but without experiencing flow. Hence, it is challenging to attribute the findings solely to the flow state during music performance, as they could be associated with the act playing music itself. Additionally, as the flow scores remained consistent across time, it raises questions about whether playing the same piece is sufficient to discern differences in physiological measures exclusively related to the experience of flow. Therefore, it is necessary to include a contrasting piece as a control condition, where the musician is still actively performing but not experiencing flow.

Marin and Bhattacharya (2013) found that pianists reported experiencing flow more when playing in certain musical styles. Among the various styles, the Romantic style was the most familiar, preferred, and flow-inducing (Marin & Bhattacharya, 2013). This indicates that musicians know the music that frequently induces flow in them and the music that does not. Familiarity and preference for a particular musical genre may be related to the frequency of experiencing flow in that genre, but certain musical styles may also be particularly conducive to flow. Self-induction of intense musical experiences has already been successfully used to study other powerful musical phenomena, such as chills. Using self-selected music already known to affect them, participants could reliably self-induce the desired experience during neuroimaging experiments (Salimpoor, Benovoy, Larcher, Dagher, & Zatorre, 2011).

Neuroimaging studies on performing musicians have been conducted in the context of creativity, often using musical improvisation as a model for studying creative thinking. Such studies are also interested in the hypofrontality hypothesis and the extent to which creativity and improvisation depend on type 1 spontaneous processes or type 2 deliberate processes. Initially, Dietrich (2004) associated the state of flow with type 1 processes and creativity with type 2 processes as conscious deliberation over the quality of ideas would be necessary for selecting creative ones. The type 2 processes for the evaluation and selection of creative ideas were thought to involve the dorsolateral prefrontal cortex (DLPFC). However, subsequent research on musical improvisation has shown different patterns of brain activity. For example, studies have revealed increased activity in the medial PFC and decreased activity in the DLPFC during improvisation (Limb, Braun, & Greene, 2008). Additionally, activation of the DMN was also observed during improvisation (Pinho, de Manzano, Fransson, Eriksson, & Ullén, 2014), implying a shift toward a spontaneous processing mode. Such studies have often drawn links between flow experience and improvisation. Improvisation is recognized as an activity that is likely to induce a flow state, so findings such as more widespread DLPFC deactivation (McPherson, Barrett, Lopez-Gonzalez, Jiradejvong, & Limb, 2016) and attenuated connectivity in prefrontal areas (Vergara et al., 2021), have been interpreted as reflecting aspects of flow and specifically as evidence for hypofrontality. Therefore, it is worth noting that the findings on musical improvisation have been contradictory to the findings of experimentally induced flow; the latter typically involve a reduction of DMN activity and an increase of DLPFC activity. This discrepancy may be related to task specificity, suggesting that experimentally induced flow in a cognitive task may not be directly comparable to flow induced by music performance. Importantly, these studies were conducted with highly skilled improvisers who possessed the automaticity that comes with extensive practice and experience. This is in contrast to the tasks employed in flow research, which typically involve novel activities that participants are unfamiliar with and have to learn during the experiment. However, the abovementioned improvisation studies do not include a measure of flow experience during improvisation. As not every act of improvisation inevitably leads to a state of flow, it becomes difficult to conclusively link their findings to the experience of flow.

Neuroimaging studies on improvisation have found differences related to expertise. Lopata, Nowicki, and Joanisse (2017) found increased frontal alpha in the right hemisphere during improvisation, which correlated positively with experience and improvisation quality in trained improvisers but negatively in improvisers without formal training. Rosen et al. (2020) found similar results in a sample of jazz guitarists that performance quality, after controlling for experience, was associated with the right hemisphere, mostly frontal, activity. The results were interpreted in the context of the dual process theory in which novices rely more on frontally mediated type-2 executive processing, while experts rely more on type 1 associative processing mediated by more posterior brain regions. It is plausible that the experts in these improvisation studies possess the skills to better meet the challenges they face during music performance, thereby increasing their likelihood of experiencing flow (Cohen & Bodner, 2019b). Musical training has been found to correlate with dispositional flow, indicating that musicians with higher levels of training are more likely to enter a state of flow (Tan, Yap, & Bhattacharya, 2021).

To measure flow experience during music performance, EEG would be an ideal neuroimaging modality. Unlike fMRI, EEG allows greater freedom of movement, enabling the measurement of flow experience across a wide range of activities. This is particularly advantageous for studying musicians as it allows EEG data to be collected from a wider variety of musicians, without being restricted to instruments that can be safely used in an MRI environment.

The current study

The aim of this study was to explore the feasibility of imaging the neural activity associated with flow in a complex and typically flow-inducing activity in a more controlled approach. To explore the effect of naturalistic flow inductions, musicians were asked to bring a piece of music that they knew would induce a state of flow. As a control, they were also asked to bring a piece that they knew would not get them into a flow. Based on the findings of Marin and Bhattacharya (2013), we hypothesized that musicians would report higher levels of liking and familiarity for the flow-inducing pieces than the non-flow-inducing pieces, and they would experience a higher flow state after performing the self-selected flow-inducing pieces, indicating a successful flow-induction.

In this study, we recorded high-density EEG signals from musicians in both flow-inducing and non-flow-inducing conditions. However, because movement from playing an instrument can cause large artifacts that would adversely affect the analysis, we focused our analysis on the EEG data during a post-performance resting state immediately after musicians stopped playing. This approach of recording post-activity measurements, instead of during the activity itself, has been used earlier to mitigate movement artifacts (Leroy & Cheron, 2020; Yoshida et al., 2014) and to avoid interfering with the activity itself (Henz, John, Merz, & Schöllhorn, 2018). This post-performance EEG data, recorded while participants were still and had their eyes closed, was expected to be relatively free of large artifacts and temporally close to the actual experience, making it a suitable proxy for capturing the experience itself. In addition, as we have included various types of musicians in our study, the resting state after playing was deemed a more suitable comparison, where all participants engaged in the same state of having their eyes closed and not actively performing.

We investigated the immediate aftereffects of flow on brain oscillations and functional connectivity during the resting period of 1 min immediately after the completion of the musical piece. Due to the unpredictable nature of flow occurrence in a piece and the limited number of flow states that can be reliably induced within an experimental session, traditional event-related potentials (ERPs) were not suitable for our purpose. Instead, we analyzed the EEG data in terms of spectral power and functional connectivity and investigated the differences between the flow and non-flow conditions. After previous EEG research findings on flow, we hypothesized that significant effects distinguishing the flow condition from the non-flow condition would be observed in the theta, alpha, and beta frequency bands. However, to provide a comprehensive characterization, we also examined spectral power in the delta and gamma frequency bands in an exploratory manner. The functional connectivity was estimated by the phase slope index (PSI), which allowed us to infer a directional measure of connectivity (Nolte et al., 2008). Considering the potential variations of effectiveness with which musicians could self-induce flow in this open-ended experiment, we also examined the influence of dispositional flow by comparing spectral power and connectivity measures between musicians with high and low dispositional flow. Given the wide range of abilities of the musicians participating in the study, we also included expertise to test if any differences in EEG spectral power and functional connectivity measures between conditions interacted with expertise. Overall, we aimed to shed light on the neural correlates of flow states during music performance by analyzing post-performance EEG data, and exploring the role of dispositional flow and musical expertise in these brain activities.

Methods

Participants

Forty-eight amateur and professional musicians (mean age = 24.25 years, *SD* = 4.076 years, 20 males, 28 females, 4 left-handed) took part in this study. Their musical background varied in terms of skill level and musical involvement. Participants played their main instrument for a range of 6 to 29 years (mean = 15.5 years, *SD* = 5.23 years). The participants represented a diverse range of musicians, including 9 wind players, 5 singers, 6 guitarists, 12 string players, and 16 pianists. Sixteen participants were enrolled in undergraduate or postgraduate music performance programs at a conservatory or university. Among the remaining participants, 15 had graduated from a music performance course and remained active in the music scene to varying degrees. Seventeen participants had never studied music at the tertiary level but frequently played as a hobby. Participation in the study was entirely voluntary, and all participants provided written informed consent. The study was approved by the local ethics committee and conducted following the Declaration of Helsinki. Three participants were part of the pilot data and did not have post-flow data available for analysis due to modifications made to the experiment after the pilot phase. One participant was excluded from the analysis due to not following the instructions. Thus, a total of 44 participants were considered in the analysis of the post-flow EEG data.

Materials

Two flow questionnaires were used to measure dispositional (trait) and state flow in the study. The Dispositional Flow Scale-2 (DFS-2) (Jackson & Eklund, 2004) was employed to assess dispositional flow. The DFS-2 consists of 36 items reflecting the nine dimensions of flow and is reliable in assessing flow in musicians (Sinnamon, Moran, & O'Connell, 2012). Participants rated the frequency of their experiences related to the nine dimensions of flow on a 5-point scale (1 = never to 5 = always). Participants were instructed to answer it as a general measure of their flow experience when playing their instrument, regardless of whether it was during practice or performance. To measure state flow, we used the Flow State Scale-2 (FSS-2) (Jackson & Eklund, 2004), which consists of the same 36 items in the DFS-2, but responses on the same 5-point scale were collected after musicians finished playing each piece, and musicians were instructed to respond to the items based solely on their experience with the specific piece they had just performed. The FSS-2 is suitable for studying musicians' state flow (Wrigley & Emmerson, 2013).

Musical expertise was assessed using the Goldsmiths Musical Sophistication Index, version 1.0 (Gold-MSI) (Müllensiefen, Gingras, Musil, & Stewart, 2014), which consists of 39 items (α = .90) and includes five subscales (active musical engagement (F1), perceptual abilities (F2), musical training (F3), singing abilities (F4), emotional engagement with music (F5)). It also provides one overall measure of general musical sophistication. Responses were obtained on a 7-point Likert scale (1 = Completely disagree to 7 = Completely agree).

At the end of the experiment, participants were also asked to rate each piece they brought on a 10-point scale, indicating how much they liked the piece and how familiar they were with it.

Experimental procedure

The study was a within-participant, repeated measures design where all participants took part in both conditions, flow and non-flow. Participants were provided with the following brief description of flow:

> Flow state refers to the feeling or state of mind we sometimes get into while playing music where we're so focused on the music that other things seem to disappear from your awareness. Often your perception of time will change. It's usually a very euphoric experience and it's associated with peak performance. Some people call it being "in the zone."

Participants were instructed to bring two familiar and fluent pieces for the two conditions of the experiment: one piece that they knew would induce a flow state (the flow condition), and one piece that they would not induce a flow state (the non-flow condition). Each piece was repeated three times in a block design, resulting in three consecutive flow trials and three consecutive non-flow trials. A block design was chosen based on its higher signal-to-noise ratio (SNR) and statistical power over event-related design (conditions are randomized), both of these features are relevant for flow that unfolds over an extended period (Palazzo et al., 2020; Valente, Kaas, Formisano, & Goebel, 2019). Further, by maximizing the SNR and statistical power, the likelihood of detecting any difference between conditions is increased.

During the musical performance of each piece, EEG data were recorded. Participants were given the choice to either stand or to sit while playing, based on their comfort and preference. Some preferred the mobility of standing up, while others felt more comfortable sitting down to play. These preferences could be due to varying musical experiences, such as orchestral musicians being used to sitting while playing, while singers and those playing in jazz bands often perform while standing. For ease of performance, participants either played from memory or from a score, based on personal preference. Two participants brought recordings of accompaniment to play along with. Although these differences introduced potential confounds in the experimental conditions, this also ensured high autonomy during the experiment and therefore maximized the chances of experiencing flow while playing in the unusual laboratory setting while brain data was being recorded. It is, however, important to note here that the EEG data analysis focused on the period after both performances when participants were in a seating position and not reading music. This ensured consistency in the analysis and minimized any large artifacts.

The order of the conditions was counterbalanced, with half of the participants beginning with the flow-inducing piece and the other half beginning with the non-flow-inducing piece. Participants were told that the experiment focused on their subjective experience while playing and that the quality of their performance was not relevant to the study. This instruction aimed to encourage participants to focus on their internal experience and to minimize any concerns about any external evaluation of their musical performances, allowing them to fully engage in the flow-inducing state.

As mentioned earlier, we focused on the EEG data in the resting period immediately after participants finished playing. This period is referred to as the post-playing state. Therefore, upon finishing each piece, participants were instructed to sit down, if they were not already seated, close their eyes for 1 min. This duration was chosen to ensure adequate data for conducting EEG power analysis including the low-frequency delta (1–4 Hz) range, while also keeping the overall duration of the experiment manageable. This brief period allowed for capturing the immediate brain activity influenced by the specific state of playing, flow or non-flow. After this post-playing resting state, participants completed the FSS-2 to report their subjective experience of flow while playing the piece. This provided vital information about the degree of state flow experienced during each condition, allowing for a comprehensive analysis of the relationships between brain responses and subjective flow states.

EEG recording and Preprocessing

EEG signals were recorded using 64 active electrodes placed according to the extended 10–20 electrode placement system and amplified by a BioSemi ActiveTwo amplifier (www.biosemi.com). The vertical and horizontal eye movements (EOGs) were recorded by four additional electrodes placed above and below the right eye and from the outer canthi of both eyes, respectively. Two additional electrodes were placed on both left and right earlobes, and their average was used as a reference. During recording, the signals were band-pass filtered between 0.16 and 100 Hz. The sampling frequency was 512 Hz.

The MATLAB toolbox EEGLAB (Delorme & Makeig, 2004) was used to clean and pre-process EEG data. The EEG data were re-referenced to the average of the two earlobes. The data were high-pass filtered at 0.5 Hz and epoched from −2 s before and 60 s after participants stopped playing and closed their eyes. The post-flow data was relatively free from large artifacts. No eye-blink corrections were needed because the data were recorded while participants had their eyes closed. The data were visually inspected before subsequent analysis.

EEG spectral analysis

The EEG signals were first analyzed in terms of the constituent oscillatory components, which involves splitting up the broadband signal from each electrode into standard frequency bands. We computed the power-spectral density using Welch's method by dividing the 1 min period into 2 sec windows with an overlap of 500 msec. The periodogram was calculated for each electrode position and trial for each participant. EEG spectral power values were subsequently averaged in each of the classical EEG frequency bands: delta (1–4 Hz), theta (4–8 Hz), lower alpha (8–10 Hz), upper alpha (10–12 Hz), beta (12–30 Hz), lower gamma (30–45 Hz) and upper gamma (55–70 Hz). The resulting power values were converted to relative power (i.e. power in a specific frequency band divided by the total power across frequency bands). Finally, the relative power values were averaged among 3 flow and 3 non-flow states.

To statistically compare the spectral power differences between the two conditions, flow and non-flow, we used an exploratory approach based on a non-parametric cluster-based permutation test (Maris & Oostenveld, 2007). This data-driven approach is widely used in the field of EEG/MEG studies (Lindsen, Jones, Shimojo, & Bhattacharya, 2010; Luft & Bhattacharya, 2015; Meyer, Lamers, Kayhan, Hunnius, & Oostenveld, 2021). This approach is preferred over standard parametric tests because it avoids the multiple comparison problem and controls the Type-1 error rate (Pernet, Latinus, Nichols, & Rousselet, 2015). It consists of two steps. First, clusters in the two-dimensional space of frequency and electrode were defined by grouping neighboring data points showing a significant effect ($p < .05$) of condition (flow vs non-flow) in paired two-tailed t-tests, and a cluster-level statistic was computed by summing the t-values of the data points in each cluster. In this study, electrodes were considered to be neighbors in the spatial sense if the distance below them was less than 4 cm. Second, the Monte-Carlo permutation was used to obtain the exact probability that a cluster with the maximum cluster-level statistic was observed under the assumption that the spectral profiles of the two conditions were equal. We used 500 permutations in this analysis, and the threshold for inclusion in the cluster was set at 0.05. This analysis was conducted using the Fieldtrip Toolbox (Oostenveld, Fries, Maris, & Schoffelen, 2011).

The cluster-based permutation test was applied to the relative spectral power values in 7 frequency bands. Two participants were removed from the upper alpha band power analysis due to extreme outliers. To investigate the association between oscillatory activities and self-reported flow, power values from significant electrode clusters were calculated and subsequently correlated with the scores obtained from the flow state questionnaire, including both overall flow state scores and scores of the specific dimensions of flow. We applied the Holm-Bonferroni correction to the correlations to control for multiple comparisons (Holm, 1979).

To examine the potential influence of dispositional flow and musical expertise, participants were divided into two groups based on a median split of their scores on the dispositional flow scale (high vs low) and the overall Gold-MSI score (high musical expertise vs low musical expertise). These groups were then used as between-subject factors in two-way mixed analysis of variances (ANOVA). The power values obtained from the significant electrode clusters were included as the dependent variables. The within-subjects factor was the condition (flow vs non-flow) and the between-subjects factor was either dispositional flow (high vs low) or musical expertise (high vs low).

EEG Connectivity Analysis

To measure the directed functional connectivity between electrode regions, we used the phase slope index (Nolte et al., 2008), a bivariate index quantifying the consistency of the phase lag/lead between two signals. It is based on the imaginary part of the coherence and is robust against spurious connectivity due to volume conduction effects (Schiff, 2005); of note, PSI is only sensitive to lagged connectivity as it does not capture any instantaneous or zero-lag connectivity. To maximize the differences between flow and non-flow conditions, we selected the epochs associated with the highest-rated flow and lowest-rated non-flow and calculated the PSI for the 1 min time window. We analyzed the PSI from AF8 to all electrodes for all frequencies and identified the frequency at which the PSI value was maximum. This analysis revealed a peak in PSI values at 5 Hz, and this frequency belonging to the theta band became the frequency of interest. The PSI at this frequency was subsequently extracted for a two-way mixed ANOVA to compare the functional connectivity between two conditions, flow vs nonflow, as well as between two groups of participants, high vs low in dispositional flow.

Results

Behavioral data

As expected, participants reported higher flow state scores after playing the self-selected flow-inducing piece compared to the non-flow-inducing piece. The average flow state score, as measured by the Flow State Scale (FSS-2), was significantly different ($t(43) = 9.08$, $p < .001$) between the flow condition ($M = 4.02$, $S.D. = .385$) and the non-flow condition ($M = 3.34$, $S.D. = .400$). Further, participants rated their flow-inducing piece significantly higher in both liking and familiarity (Liking: $t(42) = 5.89$, $p < .001$; Familiarity: $t(42) = 3.89$, $p < .001$). These self-reported ratings (Figure 1) altogether suggest that the manipulation of the experimental conditions was effective in inducing different subjective experiences of flow and non-flow.

A two-way repeated measures ANOVA with time and condition as within-subject factors were run to examine whether flow state scores differed across the

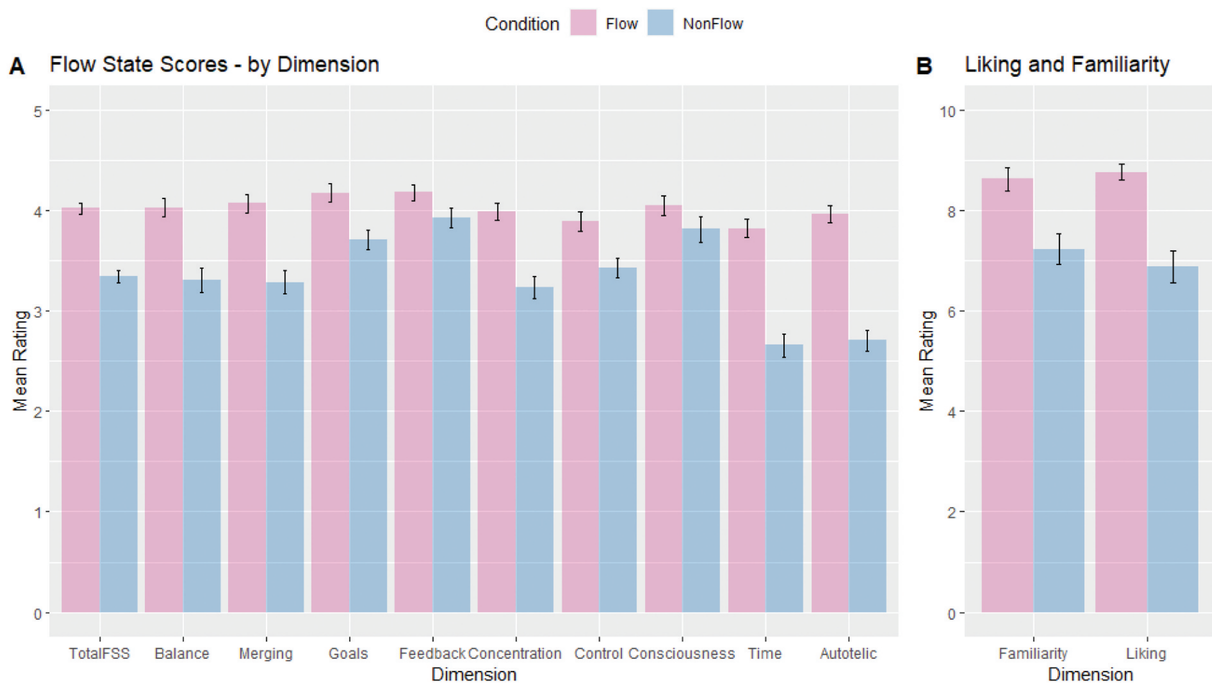

Figure 1. Flow state scores (FSS) and liking and familiarity ratings are significantly higher for the flow piece than the non-flow-inducing piece. A) barplot for mean FSS scores. FSS scores are significantly higher, both overall and in all nine dimensions, for the flow condition. B) barplot for liking and familiarity ratings.

repetitions of the flow and non-flow pieces. We observed a main effect of time ($F(2, 258) = 3.782$, $p = .024$). Figure 2b shows that there was a slight increase in flow state scores from the first to the third repetition of both the low-inducing and non-flow-inducing pieces. This suggests that participants may have become more immersed and engaged in the playing experience over time, regardless of the specific condition. However, there was no significant interaction between condition and time ($F(2, 258) = 1.364$, $p = .257$). This suggests that the increase in flow state scores across repetitions was not significantly different between the flow and non-flow conditions.

A two-way mixed ANOVA was also conducted to examine the influence of dispositional flow on flow state scores. We found a significant main effect of dispositional flow ($F(1, 84) = 8.566$, $p = .004$). Participants with high dispositional flow reported higher flow state scores for both the flow and non-flow conditions (Figure 2a). This suggests that individuals who generally experience more flow during music performance were more likely to report higher flow state scores in both experimental

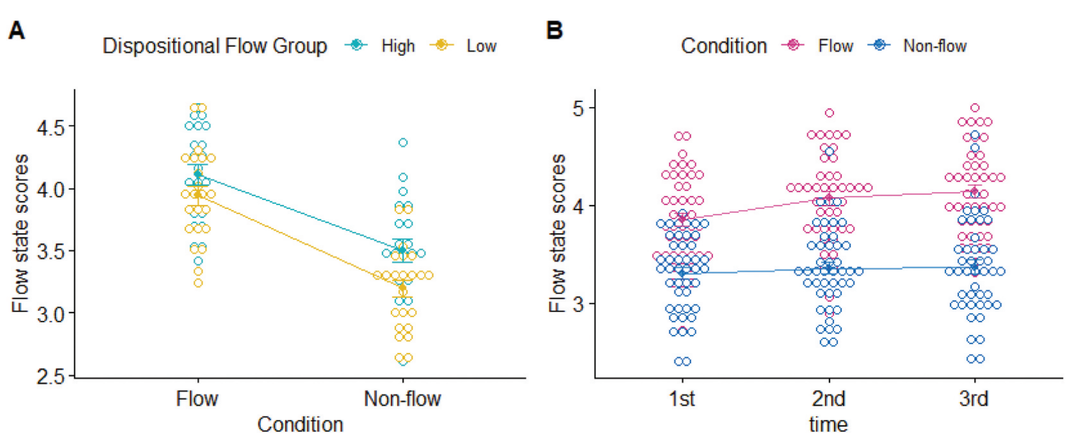

Figure 2. Flow scores by dispositional flow and session. A) dotplot of flow state scores according to dispositional flow. Participants high in dispositional flow tended to report higher flow state scores in both flow and non-flow conditions. B) dotplot of flow state scores by repetition. The reported flow increased slightly from the first to the third time the piece was played.

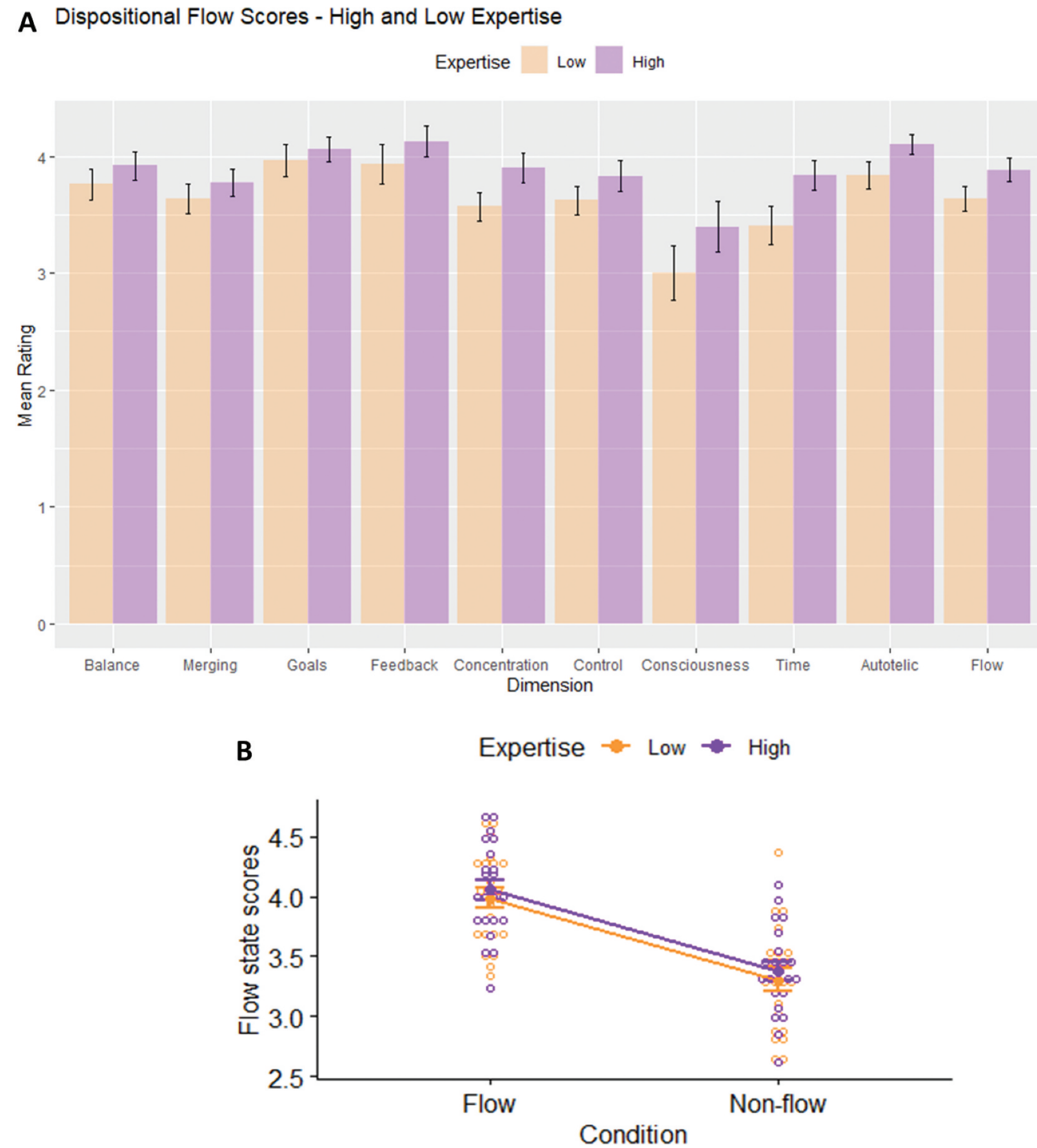

Figure 3. Dispositional flow and flow state scores by expertise. There were no significant differences in dispositional flow and state flow scores between high and low expertise groups.

conditions. However, the interaction between dispositional flow and condition was not significant (F (1,84) = 0.739, p = .39). This indicates that the effect of dispositional flow on flow state scores did not differ between the flow and non-flow conditions. Further analysis revealed that the dispositional flow was not significantly correlated with flow state scores during the flow condition (r =.203, p = .187); however, there was a significant positive correlation for the non-flow condition (r = .527, p < .001). This suggests that participants with higher dispositional flow were more likely to experience flow characteristics during the non-flow condition.

The analysis examining the influence of musical expertise (as measured by Gold-MSI) on dispositional flow scores revealed no significant differences in average dispositional flow scores between participants in the high and low music expertise groups. Further, the music expertise did not significantly interact with condition (Figure 3). These findings indicate that musical expertise did not have a significant effect on individuals' dispositional flow scores or their experience of flow state during the experimental conditions.

EEG data

Brain oscillations

Figure 4 shows scalp maps of statistical contrast (i.e. t-values) between the flow and non-flow conditions for seven frequency bands.

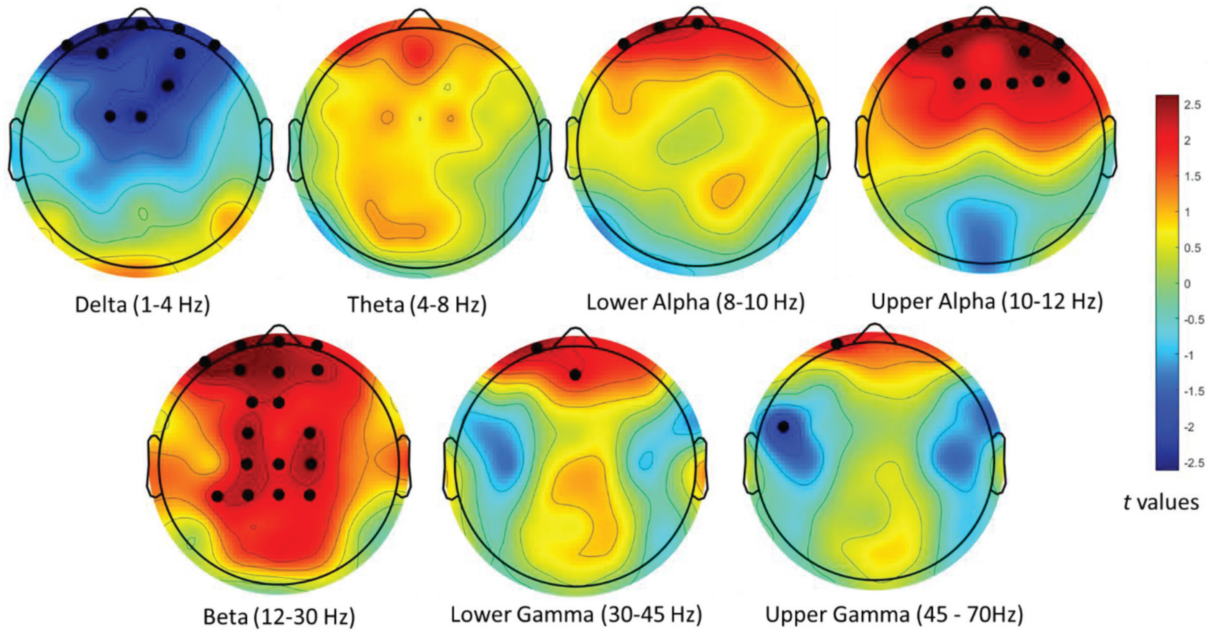

Figure 4. Topoplots of *t*-values by comparing EEG power of seven frequency bands between flow and non-flow states. Red indicates that spectral power is higher in the flow condition, while blue indicates higher power in the non-flow condition. Statistically significant ($p < .05$) electrodes are indicated by black dots.

The non-parametric cluster analysis revealed significant clusters in the frequency bands of upper alpha (cluster statistic = 30.465, $p = .0359$) and beta (cluster statistic = 42.57, $p = .01$). Power values from the significant electrodes within these clusters were averaged and compared to flow state scores. However, the neural differences observed in the upper alpha and beta bands did not correlate with the behavioral differences in flow state scores. In an exploratory analysis (see supplementary material), correlations were examined between differences in upper alpha and beta power and the flow dimensions. We found only one significant correlation between upper alpha power and the dimension of time perception ($r = 0.51$, $p = .02$), which, however, did not survive correction for multiple comparisons. These findings indicate that although significant differences were observed in the upper alpha and beta frequency bands, they did not directly align with the behavioral differences in flow state scores.

Figure 5 shows the results of two-way mixed ANOVAs conducted on the power values extracted from the significant electrodes to test the effects of the between-subject variables of dispositional flow and music expertise. The results showed that dispositional flow was not a significant predictor for spectral power in the upper alpha band or beta band (alpha: ($F(1,40) = 0.529$, $p = .471$, beta: $F(1,42) = 0.014$, $p = .907$). Additionally, the interaction between dispositional flow and condition was not significant for either of the frequency band (alpha: ($F(1,40) = 0.464$, $p = .500$, beta: $F(1,42) = 1.750$, $p = .193$). Similarly, no main effect of expertise was found (alpha: ($F(1,40) = 0.000151$, $p = .990$, beta: $F(1,42) = 2.023$ $p = .162$). However, the interaction between expertise and condition was significant for upper alpha ($F(1,40) = 6.172$, $p = .017$); this effect was primarily driven by the high expertise group, as the difference between flow and non-flow conditions was more pronounced in this group. Of note, this finding initially did not reach significance ($F(1,42) = 1.76$, $p = .192$) and only became significant after removing two participants, one from each group, identified as extreme outliers, one in the high expertise group and one in the low expertise group. Furthermore, there seems to be a larger difference between conditions in the beta band for the high expertise group compared to the low expertise group, although the interaction was not significant ($F(1,42) = 3.074$, $p = .087$). No values of beta power were identified as being extreme outliers. Additional moderator analyses were conducted with dispositional flow and expertise as continuous variables, without applying a median split to the between-subject variables. The results were similar to the findings with median splits applied (see Supplementary Material) but the increased power from the continuous between-subject variables resulted in a significant interaction between expertise and condition for power in the beta band. Overall, these findings suggest that dispositional flow did not significantly

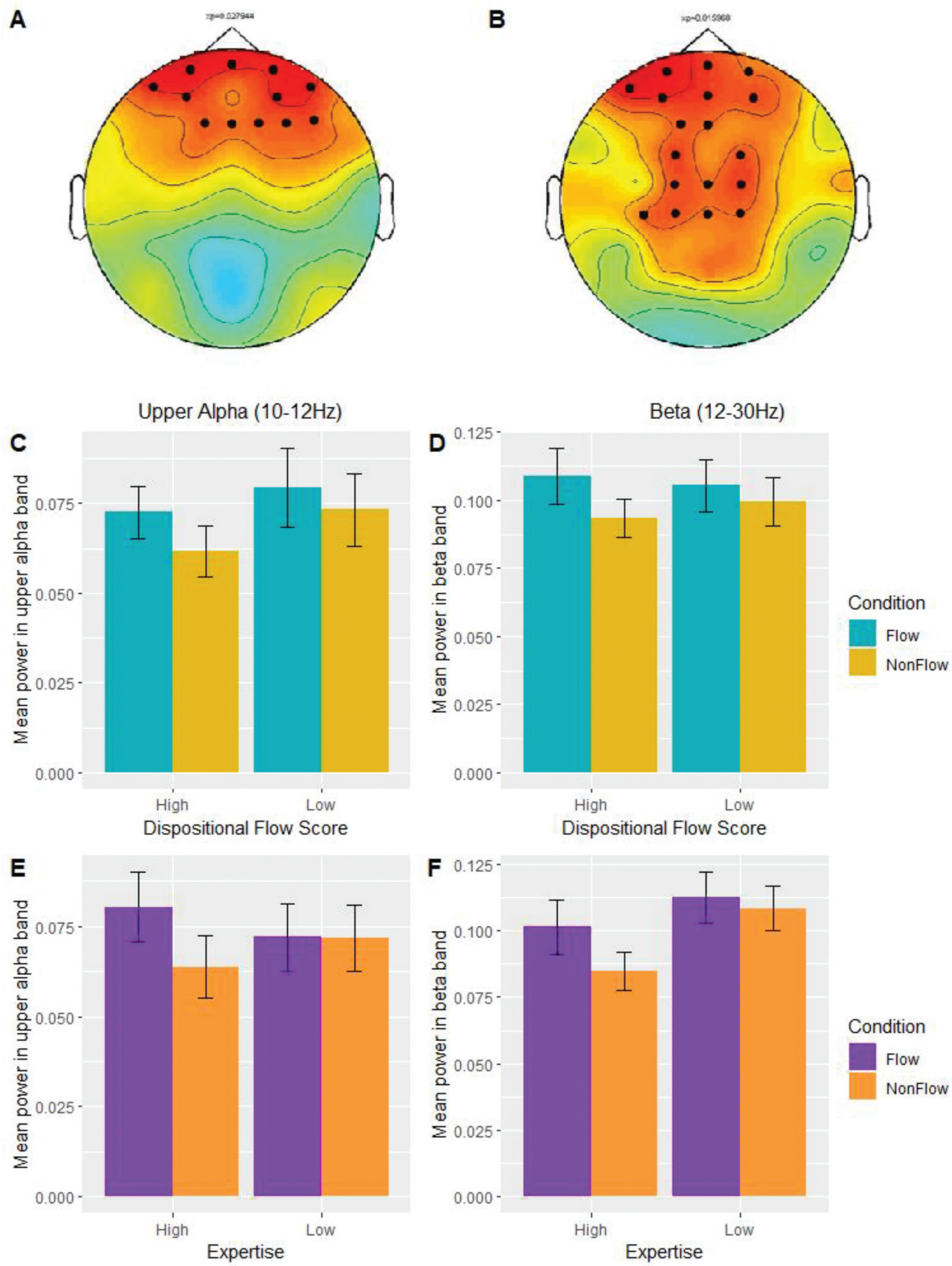

Figure 5. The between-condition differences in neural activity in significant electrode clusters do not differ based on dispositional flow, but differences in the upper alpha band are driven by the contrast in participants high in expertise. A) topoplot of electrodes showing significant differences between flow and non-flow from a non-parametric cluster analysis of power in the upper alpha band. Dispositional flow did not have a significant main or interaction effect. B) topoplot of electrodes showing significant differences between flow and non-flow from a non-parametric cluster analysis of power in the beta band. Dispositional flow did not have a significant main or interaction effect. C) barplot showing differences in upper alpha band power between conditions in participants high and low in dispositional flow. D) barplot showing differences in beta band power between conditions in participants high and low in dispositional flow. E) barplot showing differences in upper alpha band power between conditions in participants high and low in expertise. There is a significant interaction between condition and expertise ($F(1,40) = 6.172$, $p = .017$), with the mean difference between conditions mostly found in the high expertise group. F) barplot showing differences in beta band power between conditions in participants high and low in expertise. The interaction between expertise and condition is not significant ($F(1,42) = 3.074$, $p = .087$).

influence spectral power in the upper alpha and beta bands, while expertise showed a significant interaction with condition in the upper alpha and beta bands.

Functional connectivity

The functional connectivity analysis also showed differences between conditions (Figure 6). The PSI values show increased information flow from a right frontal cluster (FP2, AF4, AF8, F4, F6) to central and parietal areas in the flow condition. In contrast, in the non-flow condition, there was an increase in information being sent to the right frontal cluster from the parietal regions. A subsequent ANOVA showed that this significant difference between flow and non-flow was primarily mainly found in participants with high dispositional flow scores ($F(1,42) = 4.724$, $p = .035$). On the other hand, expertise did not significantly predict the observed differences in connectivity ($F(1,42) = 0.006$, $p = .938$). Additional moderator analyses with dispositional flow and expertise as continuous variables had similar results (see *Supplementary Material*).

These findings suggest that the pattern of connectivity varied between flow and non-flow conditions, with participants high in dispositional flow showing the most pronounced differences. Expertise, however, did not play a significant role in this regard.

Discussion

This study aimed to examine whether naturalistic flow induction using music, an activity commonly associated with flow experience, would successfully induce flow states in a laboratory setting. Additionally, a non-flow control state was induced by doing the same activity but not flow-inducing. Finally, by comparing brain responses immediately after the activity, the study aimed to identify distinct neural differences associated with the flow state. The results indicated significant differences in state flow scores between the flow and non-flow conditions, suggesting that participants successfully brought musical pieces that induced the desired states, flow or non-flow, in them. Further, flow-inducing musical pieces were rated significantly higher in both liking and familiarity, which aligns with previous findings that suggest the role of liking and familiarity in music-induced flow experiences in musicians (Marin & Bhattacharya, 2013). Importantly, we observed significant differences in brain oscillatory activity and functional connectivity immediately after playing flow-inducing pieces compared to the same time period immediately after playing non-flow-inducing pieces. This suggests that neural processes associated with flow states can be observed even after the completion of the activity that induced flow, indicating a continued influence of the flow experience even after the activity has ended.

We observed a significant effect in upper alpha frequency power in the frontal areas, with higher power observed in the flow condition compared to the non-flow condition. The alpha oscillations in the brain are known to reflect an active inhibition mechanism across cortical networks (Klimesch, Sauseng, & Hanslmayr, 2007). Increased alpha oscillations have also been associated with a decrease in the blood oxygen level-dependent (BOLD) signal measured using functional magnetic resonance imaging (fMRI) (Scheeringa et al., 2011). The inhibition in the frontal areas during the flow state may provide some evidence for the transient hypofrontality hypothesis (Dietrich, 2004), although the broad coverage of EEG (i.e. poor spatial resolution) limits the specificity compared to more nuanced findings based on fNIRS and fMRI (Barros, Araújo-Moreira, Trevelin, & Radel, 2018; Ulrich, Keller, & Grön, 2016c). Since we observed this effect after musicians had stopped playing, it could suggest that this inhibition might have lasted beyond the end of a performance. However, a more recent study on flow has linked frontal alpha oscillations to cognitive control processes and attentional engagement (Núñez Castellar et al., 2019). It may be related to the suppression of irrelevant information which might occur while switching between different subcomponents of the task or the control of motor activities involved in the task (Jensen & Mazaheri, 2010; Klimesch, Sauseng, & Hanslmayr, 2007; Maclin et al., 2011; Mathewson et al., 2012). Other studies on flow have linked frontal alpha oscillations with working memory (Katahira et al., 2018) and sustained attention (Knierim, Nadj, Hariharan, & Weinhardt, 2018). However, without specific controls for these cognitive mechanisms in our study, it remains challenging to conclusively link frontal alpha oscillations to any specific cognitive process. It is important to note, however, that the time period analyzed in our study was an eyes-closed resting state, which typically induces a shift to internally directed attention (Boytsova & Danko, 2010). Therefore, the links between frontal alpha and attentional processes may be more relevant in this context. Furthermore, it is also worth mentioning that listening to music, whether calming or stimulating, has been shown to increase upper alpha amplitude and power in the frontal and parietal regions (Iwaki, Hayashi, & Hori, 1997; Kawasaki, Karashima, & Saito, 2009). Because we controlled for the effects of music by including a non-flow condition that also involved playing music, the observed alpha effects cannot solely be attributed to music-induced emotion or arousal.

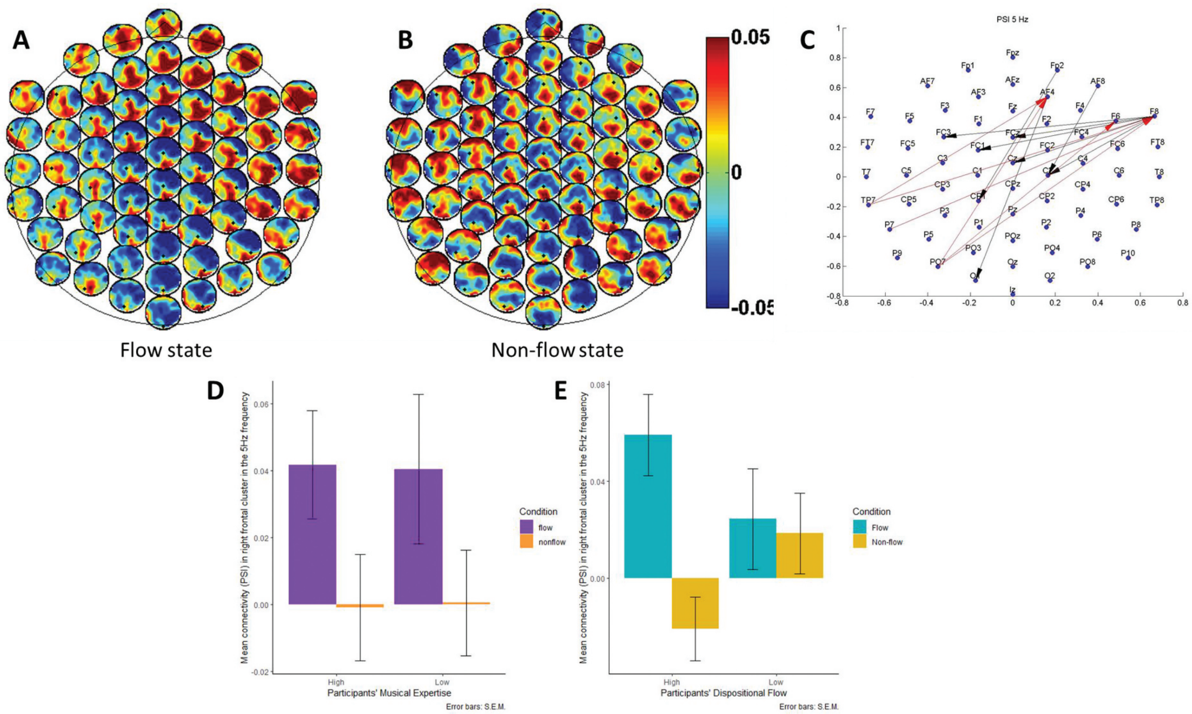

Figure 6. Functional connectivity (PSI) in theta band significantly differs between flow and non-flow, but only for participants high in dispositional flow. A) heads-in-head plot of PSI values at 5Hz in the post-playing resting state after flow. B) heads-in-head plot of PSI values at 5Hz in the post-playing resting state after non-flow. C) arrows showing the direction of information transfer in flow (black arrows) compared to non-flow (red arrows). In flow, information is sent from a right frontal cluster to central and parietal regions, while in non-flow, there is an increase in information being sent to the right frontal cluster from parietal regions. D) barplot showing mean PSI values across conditions in participants with high and low expertise. The pattern of connectivity does not differ based on expertise. E) barplot showing mean PSI values across conditions in participants high and low in dispositional flow. The connectivity pattern to and from the right frontal cluster is only found in participants high in dispositional flow.

However, the effects of flow cannot be strictly distinguished from those of arousal induced by music. Given the emotional nature of music, it is possible that the observed effects could be a neural correlate of flow state that is specific to musicians.

Greater frontal upper alpha synchronization, particularly in the right hemisphere, has also been observed during improvisation, particularly during high-quality performances (Rosen et al., 2020) and in improvisers with formal training in improvisation (Lopata, Nowicki, & Joanisse, 2017). The authors suggest that compared to musicians not formally trained in improvisation, trained improvisers are more likely to experience flow as their increased skill level enhances the likelihood of reaching a challenge-skill balance. The frontal alpha synchronization is proposed to be a marker of spontaneity and creativity arising from intuitive Type 1 processing (Lopata, Nowicki, & Joanisse, 2017). Further, well-trained musicians are capable of inhibiting frontal executive control processes and recruiting more implicit and automatic processes during improvisation (Rosen et al., 2020). Consistent with Lopata, Nowicki, and Joanisse (2017) and Rosen et al. (2020), our study revealed a larger difference in frontal alpha power between flow and non-flow conditions among musicians with higher expertise. This finding further supports the notion that the observed frontal alpha activity may represent a mechanism also present during the state experienced by trained improvisers during an improvisation task. However, it is important to note that the interaction between expertise and condition emerged only after removing an outlier in the low expertise group who showed a large contrast between flow and non-flow conditions despite being less musically trained. This could suggest that this pattern of activity may not be exclusive to highly expert musicians. It is possible that in our experiment, participants with lower expertise were able to adapt the task demands to their skill level effectively, enabling them to engage in similar mechanisms as the experts.

Beta activity is usually associated with motor activity. One interesting study has suggested that frontal beta oscillations may reflect the post-processing of successful motor activity (Feingold, Gibson, DePasquale, & Graybiel, 2015). Based on intracranial recording in monkeys, the study demonstrated larger beta oscillations following correct movements compared to incorrect ones. This suggests that beta oscillations may be involved in the evaluation or consolidation of motor performance. In the context of flow, which is associated with peak performance and challenge-skill balance (Engeser & Rheinberg, 2008), it is reasonable to assume that more correct movements are made in the flow condition than in the non-flow condition. Therefore, it is possible that the observed increase in the frontocentral beta activity reflects the enhanced processing of successful motor actions during the flow state. Additionally, the frontocentral beta has been found in improvising musicians during high-quality performances and is linked to movement facilitation (Rosen et al., 2020). This further supports the idea that beta oscillations may play a role in motor-related processes during musical performance. The fact that there is a more pronounced difference between flow and non-flow conditions in musicians with higher expertise suggests that they exhibit a greater contrast in movement facilitation when playing in a state of flow compared to when they are not. However, it is important to note that beta activity could also be related to inhibition. Alpha and beta activity in the frontal cortex may reflect top-down inhibition of bottom-up information carried by gamma oscillations, thereby exerting top-down control over neural processing (Miller et al., 2018).

The functional connectivity results showed a significant difference in activity within a right frontal cluster between the flow and non-flow conditions. Interestingly, this pattern of activity was only found in individuals with high dispositional flow, suggesting that this right frontal brain region area may play an important role in flow experience. Recent research has linked theta band connectivity to attentional processes. Theta connectivity within the frontoparietal control network has been reported to facilitate cognitive control and goal-directed attention (Cooper et al., 2015; Fellrath, Mottaz, Schnider, Guggisberg, & Ptak, 2016). As flow is a state of goal-directed attention, individuals who are more likely to experience flow while playing music may exhibit better attentional control in the presence of distractions, leading to increased theta connectivity. Past studies have linked flow to the right dorsal lateral prefrontal cortex, which has been linked to the experience of increased reward during flow (Huskey, Craighead, Miller, & Weber, 2018). While the functional theta connectivity observed in our study originated from the right frontal areas, further analysis using the source space reconstruction method will be needed to precisely locate the neural sources of this theta connectivity. Additionally, network analysis will be needed to confirm whether this pattern of connectivity represents activity within the frontoparietal network. Taken together, the findings from spectral power and functional connectivity results suggest a top-down control of attention in the flow state. This interpretation is not necessarily contradictory to a model of frontal deactivation as a sign of spontaneity, as proposed by Dietrich (2004), who noted that flow may be a state of hypofrontality, with the notable exception of executive attention required to direct and sustain attention on the activity (Dietrich, 2004). In addition, Beaty, Benedek, Silvia, and Schacter (2016) have proposed a framework suggesting that a coupling between the DMN and the frontoparietal control network allows for a complex interplay of processes during creative tasks, involving both bottom-up generative and top-down evaluative monitoring. The possible involvement of the frontoparietal network, also known as the executive control network, ECN (Uddin, Yeo, & Spreng, 2019), along with the frontal deactivation, may reflect the interactions between the DMN and ECN that enable both bottom-up spontaneity and top-down evaluation (Beaty, Benedek, Silvia, & Schacter, 2016).

Our findings also share similarities with other EEG studies that have investigated experimentally induced flow. The observed differences in the upper alpha and beta bands are consistent with an earlier study that utilized support vector machine classification on EEG data collected during a plane battle video game. This study found that alpha (8–12 Hz), as well as lower-beta (12–15 Hz) and mid-beta (15–20 Hz) power, most reliably distinguished between flow, boredom, and frustration states (Berta, Bellotti, De Gloria, Pranantha, & Schatten, 2013). Unlike Katahira et al. (2018), we did not find significant differences in theta band power. This could be due to the differences in the tasks employed. Katahira et al. (2018) analyzed data collected during a mental arithmetic task that likely involved a greater working memory load and mental effort than our resting state collected after a musical performance. In addition, music performance, particularly when playing a familiar and well-liked piece, may be characterized by a heightened sense of being in the present moment and automaticity. This task-related difference explains how flow experienced during a typical flow-inducing complex activity could differ from experimentally induced flow and show greater hypofrontality.

It is important to note that the findings in this study were based on eyes-closed resting state data, which differs from other flow studies that typically analyze data collected during the task, where participants usually had their eyes open. Another study examining flow during mental arithmetic reported decreased alpha activity, suggesting a reduction in the DMN activity, as alpha activity has been shown to correlate with DMN (van der Linden, Tops, & Bakker, 2021). However, it is difficult to draw definitive conclusions regarding DMN in this study. While alpha activity correlates with DMN in the eyes-open resting state, it has also been shown to correlate with the cingular-opercular network in the eyes-closed resting state (Sadaghiani & Kleinschmidt, 2016). Therefore, the specific neural networks involved in flow states during different tasks and resting conditions require further investigation.

Implications

This study demonstrates that it is possible to study flow using naturalistic stimuli and that highlights distinct differences in the neural correlates between the state immediately following flow and the state following non-flow, as measured by EEG. Expertise showed a significant interaction with condition for alpha and beta power but surprisingly, did not significantly influence the pattern of connectivity between flow and non-flow conditions. However, the theta band connectivity pattern associated with flow was primarily found in musicians with high dispositional flow. These findings suggest that future neuroimaging studies aiming to induce flow naturally should target individuals with high dispositional flow and carefully control for expertise. Moreover, engaging experts in an activity that typically elicits flow may result in a more spontaneous mode of thinking and neural activity, resembling hypofrontality, as compared to using novel computer-based tasks in laboratory settings.

Our findings show similarities to previous studies on improvisation, especially regarding spectral power in the upper alpha band in the right frontal regions (Lopata, Nowicki, & Joanisse, 2017; Rosen et al., 2020), which suggests that their findings on improvisers may also apply to flow state. Their improvisers may have experienced flow during their highly creative states. Since we measured post-flow neural activity, a plausible conclusion is that flow could induce a brain state conducive to creativity. However, our current methods are limited in differentiating between creativity and flow during music performance. A potential solution would be to measure both creativity and flow in the same neuroimaging experiment (Rosen et al., 2020) to control for both constructs when comparing neural activity. In addition, alternative methods of analyzing neural activity, such as microstate analysis (Vidaurre et al., 2016), could help address the question of DMN and CEN activity during concurrent flow and creativity. Moreover, our results indicate that post-performance measurement can serve as a useful proxy for during-performance measurement, extending the validity of this approach. Furthermore, the observed findings were not limited to improvising musicians; they also generalized to non-improvising musicians, suggesting that aspects of the states measured in our study and in other improvisation studies may also apply to non-improvising musicians. Cognitive mechanisms such as an internal focus of attention, creativity, and facilitation of movement during performance are relevant to musicians even when they are not improvising (Lopata, Nowicki, & Joanisse, 2017; Rosen et al., 2020).

Our findings have implications for musicians as well. They not only shed light on the mechanisms underlying a highly motivating experience in music, which encourages continued participation and improvement (Marin & Bhattacharya, 2013) but flow has also been proposed as a way to deal with performance anxiety (Cohen & Bodner, 2019a). Understanding the neural activity associated with flow could potentially inform the development of neurofeedback interventions that could enhance the likelihood of experiencing flow rather than performance anxiety during musical performance.

Study limitations

Studies conducted so far have faced challenges in effectively assessing the flow state due to the inherent difficulties of inducing flow state on demand and the complexities associated with its operationalization and measurement (Abuhamdeh, 2020). In addition, the constrained environment of a neuroimaging laboratory imposes further physical limitations when studying flow. Although this study employed naturalistic stimuli to induce flow and included a control condition for comparison, it has several limitations that can be improved as follows.

Firstly, it is difficult to ascertain if the participants' understanding of flow was the same as our construct. It would be useful to conduct qualitative interviews with participants to determine if it matches the stated definition of flow, while also ensuring consistency across participants. Secondly, this study relied exclusively on participants' self-reports of their experience of flow state, particularly their perception that the music they played induced a state of flow. To complement self-report measures, it would be beneficial to include psychophysiological correlates of flow as objective indicators of participants' flow experience. These measures are well-researched and could provide additional evidence to support participants' self-reported flow ratings. In addition, it may be useful to combine multiple operationalizations of flow. For example, participants in this study instinctively brought non-flow-inducing pieces that were less familiar to them, resulting in a possible mismatch between the challenge level and their skill level. To address this, participants could be instructed to bring pieces that are deliberately too easy to induce boredom and something too difficult to induce frustration. By contrasting flow states with states of boredom (low challenge, negative affect) and overload (high challenge, negative affect), the findings would be more comparable to other studies (Ulrich et al., 2014; Katahira et al., 2018).

An obvious limitation of this study is that it examined the brain activity after participants played in a flow state, rather than during the actual flow-inducing activity. As a result, the findings may not directly be comparable to other studies that collected data during the activity. It is important to acknowledge that neural activity in the post-flow state may differ from neural activity during the flow state, and there is a possibility of rebound effects after the activity has ended. Therefore, caution should be exercised when comparing these findings to studies that focus on neural activity during the flow-inducing activity. Further research is needed to explore the similarities and potential differences between neural activity during and after the flow state.

Using an eyes-closed resting state in this study was advantageous in reducing artifacts. However, it also limits the comparability of the results to other studies that measure neural activity during the task when participants usually have their eyes open. It is worth noting that spectral power, especially in the lower frequency bands, tends to be higher during eyes-closed resting states compared to eyes-open resting states (Barry, Clarke, Johnstone, Magee, & Rushby, 2007; Geller et al., 2014). Additionally, the connectivity and topography of functional networks can differ between eyes-closed and eyes-open states (Xu et al., 2014). Therefore, discussing band power as proxies for network activity can be challenging, as the relationship between spectral power and network activity can vary depending on whether eyes-closed or eyes-open resting states were collected (Sadaghiani & Kleinschmidt, 2016). While this study maintained consistency by examining eyes-closed resting states in both flow and non-flow conditions, it is important to consider the differences between eyes-closed and eyes-open states when comparing data collected during the activity and post-activity data, especially if the post-activity data was collected with eyes closed.

We observed only one significant correlation between alpha power and the time perception subscale of flow, but this correlation did not survive for multiple comparisons. As a result, the relationship between neural and behavioral measures of flow in this study is not clear. This makes the link between flow experience and the neural findings less clear and opens up the possibility that the neural findings may reflect cognitive processes other than flow. For example, frontal alpha power has been associated with reward, cognitive control (Sadaghiani & Kleinschmidt, 2016), emotion, top-down suppression of distractors (Núñez Castellar et al., 2019), or an internal focus of attention (Klimesch, Sauseng, & Hanslmayr, 2007), all of which can be involved during music performance apart from flow experience. However, the presence of frontal alpha power specifically after self-induction of flow, as well as during other flow-inducing activities such as gaming and tightrope walking (Berta, Bellotti, De Gloria, Pranantha, & Schatten, 2013; Leroy & Cheron, 2020; Núñez Castellar et al., 2019), suggests a potential connection to the flow experience. The similarities between these findings and those observed in improvising musicians also suggest a potential link to a creative mental state (Lopata, Nowicki, & Joanisse, 2017; Rosen et al., 2020). Disentangling flow from a related phenomenon like creativity could be difficult. To improve the interpretability of future findings, it would be beneficial to design experiments based on recent theories of the neural mechanisms underlying flow and specifically target and test those mechanisms (Gold & Ciorciari, 2021; van der Linden, Tops, & Bakker, 2021).

Specifically for musicians, the EEG findings here could also be attributed to other cognitive mechanisms relating to the music rather than flow experience. It was assumed that the direction of association between flow and EEG measures would remain consistent, independent of the average emotional and physiological state, which could be affected by the mood of the musical piece being performed. However, this assumption could be problematic as EEG is also sensitive to mood and mental exertion. Musicians may also associate certain moods and tempi with the experience of flow more than others. This potential confounding factor is significant because music-related emotion does affect EEG activity, particularly in the frontal regions (Trainor & Schmidt, 2003). With a larger sample, it would be possible to group participants based on the tempo and mood of the music they perform, which would help control for the effect of tempo and mood and provide an opportunity to examine how music-related emotion specifically influences the flow state.

Musicians taking part in the study brought a large variety of instruments and music that varied in style and complexity. In addition, to maximize the chances of experiencing flow, musicians played under conditions that they felt most comfortable with, which could involve playing from memory or playing from a score or playing with accompaniment. The heterogeneity of the sample contributes to the ecological validity of the findings, allowing us to examine an experience that is common across various instruments and musical styles. This also shows that neural activity previously observed only in improvisers on instruments like piano or guitar can be found in other musicians. However, the differences in instrumentation and musical styles could also potentially introduce variability, which warrants further investigation in future experiments with a larger and more diverse sample of musicians.

Further directions

The post-performance design as adopted in our study allows for the inclusion of a wide range of musicians, not just limited to pianists (Lopata, Nowicki, & Joanisse, 2017) and guitarists (Rosen et al., 2020). One advantage of measuring post-activity data is that it alleviates concerns about maintaining the quality of neural data during the activity itself. This allows for a more ecologically valid experience, where the focus can be on inducing the specific phenomenon of interest, such as flow. It is worth noting that the concept of flow is domain-general, i.e. it has been described in similar terms across various activities. By examining post-activity data, researchers can establish a common point of reference across different activities, making it a viable approach for studying the domain-general neural correlates of flow. Furthermore, post-activity neural data analysis can be effectively combined with data collected during the activity. This integration enables a more comprehensive understanding of the neural processes associated with flow. Further, by examining both pre- and post-activity data, researchers can gain insights into the neural changes that occur as a result of the flow experience. Knowledge of the neural correlates of flow could be combined with physiological measures like electrocardiography and galvanic skin responses to possibly time-lock flow state onset in data collected during the activity.

We suggest that this is hopefully just the beginning of studying naturalistic inductions of flow with neuroimaging. Motion is always a source of noise and artifacts in neural data, but some neuroimaging methods are less vulnerable. For example, fNIRS is less susceptible to head and body motion artifacts than fMRI, has a reasonable temporal resolution, and can be performed while subjects perform tasks in a natural and comfortable environment (Yoshida et al., 2014). In addition, improved data processing methods, such as artifact subspace reconstruction (Blum, Jacobsen, Bleichner, & Debener, 2019), are promising tools for removing movement artifacts, even during online data acquisition. Finally, there are exciting promises offered by the newly developed wearable magnetoencephalography system that allows free and natural movement (Boto et al., 2018), while recording brain activity with high temporal and spatial precision.

Alongside the tools that allow us to study neural activity during complex tasks like tightrope walking and music performance, it is crucial to develop both the theoretical framework and experimental designs that accommodate the unique nature of flow. Flow is a rare and unpredictable phenomenon, and studies like Leroy and Cheron (2020) show the need for flexible experimental designs that can adapt to unexpected occurrences. However, the challenge arises in interpreting data from such unstructured experiments. One solution is to incorporate the concept of scalable experiments, as seen in the field of mobile brain/body imaging (Parada, 2018). At one end of the scale, highly structured experimental designs, like the challenge-skill balance inductions offer tight control over the experimental conditions. While this control facilitates the linkage of neuroscientific findings to specific aspects of flow, such as attention and cognitive control, it can limit the depth of flow experienced. On the other end, less structured experiments allow participants the freedom of action and movement, allowing flow to unfold naturally in all its complexity, as exemplified by Leroy and Cheron's (2020) study on tightrope walking. Although these less structured experiments increase the chances of flow, the increased and unregulated complexity complicates the interpretation of the results. This type of semi-structured experiment can strike a balance between structure and freedom. They increase the chances of flow by incorporating more complex and personally meaningful tasks but still face challenges with interpreting the findings due to the ill-posed nature of the question being investigated. The purpose of scalable experiments is not to suggest that any particular approach is better than the others, but rather to allow researchers to transition between experiments with varying levels of structure and benefit from their respective strengths. For example, highly structured experiments can uncover signals that serve as markers in experiments with less structure and more complex tasks. This way, interpretability becomes easier even in unstructured experiments conducted in unpredictable environments. Further, models trained on neural data collected from highly controlled experiments, closely linked to behavioral data, can then be applied to extract information from data collected in more unstructured experiments (Woo, Chang, Lindquist, Wager, & Author, 2017).

Finally, we suggest that sharing data, both neural and behavioral, and code would be crucial for the integration of flow studies conducted at various levels of complexity and structure. Enabling the principles and practices of the open science movement will greatly enhance the progress of flow research (Arza & Fressoli, 2017; Huston, Edge, & Bernier, 2019; Lebel, Campbell, & Loving, 2017). This will facilitate research in different populations, with different data modalities, and on different scales. By collecting and comparing data, researchers can integrate findings and contribute to a broader framework of flow neuroscience.

Conclusion

In this study, we investigated the neural correlates of flow using a naturalistic induction of flow and developed a method to cope with the challenges of measuring EEG during flow-inducing activities. We showed distinct differences in the brain activity patterns between the states following flow and non-flow experiences zin musicians. Flow was associated with a higher power in the upper alpha and beta bands over the frontal brain. Further, frontal regions exerted greater influence over temporal and parietal regions at the theta band, but only in musicians with high dispositional flow. Additionally, we examined the impact of expertise and dispositional flow on the state flow experience. We observed that while expertise correlated with dispositional flow, it did not significantly predict higher state flow scores. Dispositional flow did not significantly contribute to differences in power in the beta and upper alpha bands between flow and non-flow, but expertise played a role in higher upper alpha power during flow. Notably, dispositional flow drove primarily the differences in connectivity between flow and non-flow. Overall, our semi-structured exploratory study showed some parallels to lab-based studies, supporting the notion that even in an artificial and constrained environment, essential aspects of the flow experience can still be captured. However, the differences in the findings highlight the unique insights gained from studying flow in activities that typically induce flow, particularly regarding the role of hypofrontality in the flow state. Of particular note, the resting state immediately after musical performance exhibited measurable differences between induced conditions. This suggests that it could be used as a suitable proxy when it is not feasible to collect useable brain data during the actual performance itself. In conclusion, this study demonstrates the feasibility of designing an experiment that closely resembles the music-making experience and provides novel insights into the flow experience that is essential to music's significance.

Author contributions

J.B., J.T., and C.D.B.L. designed the research; J.T. collected and analyzed the data; C.D.B.L. provided data analysis expertise; J.T. wrote the draft.; J.B. edited the draft, and all authors contributed to the final version; J.B. provided overall research supervision.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Data availability statement

The processed data and code for analyses will be made available on Github, and raw data will be made available upon reasonable request.

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