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Creative flow as optimized processing: Evidence from brain oscillations during jazz improvisations by expert and non-expert musicians

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ABSTRACT

Using a creative production task, jazz improvisation, we tested alternative hypotheses about the flow experience: (A) that it is a state of domain-specific processing optimized by experience and characterized by minimal interference from task-negative default-mode network (DMN) activity versus (B) that it recruits domain-general task-positive DMN activity supervised by the fronto-parietal control network (FPCN) to support ideation. We recorded jazz guitarists' electroencephalograms (EEGs) while they improvised to provided chord sequences. Their flow-states were measured with the Core Flow State Scale. Flow-related neural sources were reconstructed using SPM12. Over all musicians, high-flow (relative to low-flow) improvisations were associated with transient hypofrontality. High-experience musicians' high-flow improvisations showed reduced activity in posterior DMN nodes. Low-experience musicians showed no flow-related DMN or FPCN modulation. High-experience musicians also showed modality-specific left-hemisphere flow-related activity while low-experience musicians showed modality-specific right-hemisphere flow-related deactivations. These results are consistent with the idea that creative flow represents optimized domain-specific processing enabled by extensive practice paired with reduced cognitive control.

1. Introduction

Flow is "a state in which people are so involved in an activity that nothing else seems to matter; the experience is so enjoyable that people will continue to do it even at great cost, for the sheer sake of doing it" (Csikszentmihalyi, 1990, p. 4). It has been the focus of hundreds of research articles and books and a subject of fascination in the world of creativity, education, business, game design, leisure sciences, recreation, and sports (Beard, 2015; Csikszentmihalyi, 2004; Jackson, 1992, 1995, 2000; Kiili, 2005; Motevalli et al., 2020; Perkins and Nakamura, 2012). Nevertheless, fundamental questions persist (Abuhamdeh, 2020; Kee and Wang, 2008; Reid, 2011; Sheldon et al., 2015). To help clarify flow's theoretical basis and role in creative production, we contrasted two general views: flow as a state of optimized task-specific processing resulting from extensive practice versus flow as a state of heightened domain-general associative ideation. This was done by analyzing electroencephalograms (EEGs) recorded from musicians of different levels of experience during a creative divergent-thinking task, jazz guitar improvisation.

1.1. Definition and background

Flow is thought to consist of multiple experiential dimensions: a sense of control and efficacy, merging of action and awareness, high concentration, distorted time perception, loss of self-consciousness, and intrinsic motivation (Csikszentmihalyi et al., 2014). Studies often ask participants to rate their subjective experience on these dimensions. Additionally, three conditions have been proposed as necessary for flow: a balance between challenge and skill, clear, proximate goals, and immediate feedback about progress and performance (Nakamura and Csikszentmihalyi, 2002). Some studies assume that flow ensues whenever these conditions are met (Alameda et al., 2022).

The concept of flow was originally identified through case studies and interviews regarding the creative processes of artists (Getzel and Csikszentmihalyi, 1976). Nevertheless, many studies have ignored the distinction between flow states occurring during creative tasks such as musical performance, dance, and writing, and those occurring during less-creative tasks such as video gaming, reading, and athletics (van der Linden et al., 2020).

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One common difference between creative and non-creative tasks is whether immediate, objective feedback about one's performance is available. Because a creative act involves the generation of a novel idea, product, or performance, ambiguity about the objective quality of the outcome is typical. People may therefore depend more on their subjective judgments to evaluate and regulate their creative effort than on feedback (Doyle, 2017).

Furthermore, when flow is measured during non-creative tasks, such as solving arithmetic problems, the task is typically not freely chosen by the participants. One view presupposes that for flow to occur an individual must freely choose an activity because it is intrinsically enjoyable (Huskey et al., 2018; Keller and Bless, 2008; Lee, 2005; Rheinberg, 2020; Rheinberg and Engeser, 2018). Although a person may experience pleasure while engaging in any activity that balances challenge and skill, it is likely that the rewarding quality of flow is especially prominent in an activity undertaken "for its own sake, with little concern for what they will get out of it, even when it is difficult'' (Csikszentmihalyi, 1990, p. 71). The present study therefore examined the neural correlates of flow in a naturalistic, self-selected, creative production task, jazz improvisation.

1.2. Large-scale brain networks and creative production

Although there have been hundreds of studies of flow, only a few pioneering ones have investigated its neural substrates (Alameda et al., 2022; Gold and Ciorciari, 2020; Huskey et al., 2018; Ulrich et al., 2016; van der Linden et al., 2020). In contrast, dozens of studies have investigated the neural basis of creativity, many with emphasis on large-scale networks (van der Linden et al., 2020) such as the default-mode network (DMN; Buckner and DiNicola, 2019; Menon, 2023; Raichle et al., 2001) and the fronto-parietal control network (FPCN, Menon and D'Esposito, 2022; sometimes referred to as the central executive network (CEN) or the executive control network (ECN), Beaty et al., 2016; Benedek et al., 2023; Chan et al., 2023). The DMN is typically active during self-referential thought, autobiographical memory retrieval, future thought, social information processing, mind-wandering, and other types of cognition that require relative disengagement from environmental stimuli (Buckner, 2013; Buckner, 2022). The FPCN supports executive processes, including maintenance of information in working memory and the inhibition of distracting information (Menon and D'Esposito, 2022).

In many tasks requiring externally directed attention, "task-positive" FPCN activity is associated with superior performance and concurrent "task-negative" DMN activity with degraded performance (Anticevic et al., 2012; Hinds et al., 2013; Raichle et al., 2001). However, tasks requiring internally focused attention, such as memory retrieval and creative ideation, can recruit what is apparently task-positive DMN activity, in some cases coupled with FPCN activity (Buckner and DiNicola, 2019; Kucyi et al., 2021). This has been observed in studies that use the Alternative Uses Test (AUT), a creative production task (Beaty et al., 2016; Benedek et al., 2023; Kühn et al., 2014). Other research has suggested that diffuse-attention states such as mind-wandering, which include DMN activity and presumably reduced cognitive control, may facilitate creative ideation and problem-solving (Erickson et al., 2018; Kounios and Beeman, 2014, 2015). However, even though DMN activity is thought to enable creativity under particular conditions, some theories of creativity suggest that FPCN executive control is necessary to guide successful creative production (Beard, 2015; Benedek et al., 2023).

1.3. Alternative conceptions of creative flow

The neural basis of flow has proven challenging to study because of its multi-componential nature and because of practical constraints on the induction of genuine flow states in controlled neuroimaging experiments. For example, some studies have simply assumed that flow is present when certain conditions, such as a balance between challenge and skill, are met (see Alameda et al., 2022). This has made it difficult to integrate evidence across studies, resulting in disparate views of how flow is instantiated in the brain. To advance neuroscientific theorizing about the flow state, the present study builds on previous foundational behavioral and neuroimaging studies by contrasting hypotheses suggested by, but not explicitly proposed in, prior work.

One view is that creative flow is a state of superior performance resulting from highly focused attention which excludes intrusive or self-conscious thoughts. This implies deactivation or suppression of the DMN because such activity would be task-negative and interfere with controlled, task-positive processing (Anticevic et al., 2012; Harris et al., 2017; Nakamura and Csiksentmihalyi, 2002; Ullén et al., 2010). For example, Ulrich et al. (2016), who operationalized flow as occurring when challenge and skill are balanced, found that while solving (noncreative) arithmetic problems flow was associated with increased activation of the inferior frontal gyrus (IFG), a part of the FPCN, while decreases in activation were observed in medial prefrontal cortex (mPFC), posterior cingulate cortex (PCC), and the medial temporal lobe (MTL), all nodes of the DMN. Other studies which focused on video game performance, purportedly inducing flow by balancing task difficulty and skill (Huskey et al., 2018; Yoshida et al., 2014) showed flow to be associated with increases in FPCN activity and synchrony. Thus, with the caveat that flow may not be present without a report of the flow experience (Løvoll and Vittersø, 2014), these studies suggest that flow may involve a decrease in DMN activity and an increase in FPCN activity.

A contrasting hypothesis is that creative flow is based on fluent associative ideation (i.e., Type-1 processing, Evans and Stanovich, 2013), especially during spontaneous creative production, as in musical improvisation (Bashwiner et al., 2016; Harmat et al., 2021; Lopata et al., 2017; McPherson and Limb, 2013; Rahman and Bhattacharya, 2016). This associative view suggests that high levels of DMN activity during flow support domain-general creative ideation (cf. Beaty et al., 2016; Benedek et al., 2023). For example, Limb and Braun (2008) examined the neural correlates of jazz improvisation relative to performance of a memorized melody by expert musicians and found greater activation of DMN nodes plus deactivation of right dorsolateral prefrontal cortex (DLPFC), a node of the FPCN. [Although Limb and Braun did not explicitly discuss flow, they proposed that these activations underlie a state whose description seems consistent with the flow experience (Beard, 2015)].

More recently, Vergara et al. (2021) reported reduced connectivity between the FPCN and DMN during vocal jazz improvisation which they interpreted as decreased top-down evaluation (cf. Pinho et al., 2015), suggesting that decreased connectivity between the FPCN and DMN may represent a domain-general neural signature of improvisational creative production. This evidence is in direct contrast with neuroimaging studies of creative ideation during the AUT which have found that increased coupling between nodes of the DMN and FPCN is associated with more creative responses (Beaty et al., 2016; Benedek et al., 2023).

1.4. The role of expertise in creative production and flow

A related question concerns the role of expertise. One view is that expertise is necessary for creative flow because flow depends on efficient task-specific processing which underlies the feeling of "effortless attention" (de Manzano, 2020). Experts are more likely to perform in a fluent, automatic fashion, and greater expertise has been associated with more frequent or intense flow states (Engeser and Rheinberg, 2008; Gold and Ciorciari, 2020; Moran et al., 2019). Flow may therefore be characterized by efficient recruitment of domain-specific functional networks. This view is supported by studies of the automaticity and creativity of expert-level performance (de Manzano, 2020). Accordingly, flow states that occur when performing highly practiced skills should involve less cognitive control and less FPCN activity (*transient* *hypofrontality*, Dietrich, 2004). According to this notion, FPCN activity observed during flow states (Ulrich et al., 2016) is associated with ancillary task-related working-memory demands (de Manzano, 2020).

Recently, Rosen et al. (2020) examined the behavioral and neural correlates of creativity during jazz improvisation. They recorded electroencephalograms (EEGs) during the improvisations and analyzed surface-Laplacian neural activity associated with the rated creativity of each participant's improvisations and domain experience (quantified as the number of gigs performed) and found that participants' most creative improvisations (relative to their least creative improvisations) were associated with stronger beta- and gamma-band oscillations in left posterior cortex. However, after statistically controlling for domain experience, the contrast between high-creativity and low-creativity improvisations was associated with three clusters of (mostly frontal) right-hemisphere theta-, alpha-, and beta-frequency band activity. They also found that participants' reports of flow during their improvisations (measured with the Core Flow State Scale; Martin and Jackson, 2008) significantly predicted greater improvisation creativity (as rated by experts).

Thus, because flow is correlated with performance creativity and because the neural mechanisms that enable creative performance depend on one's level of domain expertise, we hypothesize that the experience of flow during creative performance will have different neural correlates in high-versus-low experience performers.

1.5. The current study

The study of Rosen et al. (2020) examined neural and psychological correlates of performance creativity. The current study, which used the same dataset, analyzed the neural and psychological correlates of flow. Notably, this study employed more advanced methods to reconstruct the neural sources of flow-related EEGs thereby providing a unique opportunity to interrogate the involvement of large-scale brain networks. In particular, we examined the roles of the DMN and FPCN during creative flow experiences and whether the involvement of these networks is modulated by level of experience.

To summarize, this study contrasts two hypotheses implied by previous work on the neural bases of creativity and flow. According to the process-optimization view, creative flow is a state of optimized, expert processing in domain-specific networks characterized by minimal interference from task-negative DMN activity. Alternatively, according to the associative view, creative flow is a domain-general process ofenhanced ideation supported by heightened task-positive DMN activity. The role of FPCN-related top-down cognitive control over creative performance is an open question, with the process-optimization view implying reduced executive control over highly automatized processes (i.e., transient hypofrontality; Dietrich, 2004) while the associative-ideation view suggesting that creative flow may involve FPCN supervision of DMN ideation.

We tasked jazz guitarists of different levels of experience (operationalized as the number of previous gigs) with performing six improvisations ("takes") based on provided chord sequences and rhythmic accompaniment. We measured their flow states with the Core Flow State Scale (Martin and Jackson, 2008) immediately after the improvisation task. The improvisations were rated for creative quality by expert judges according to the Consensual Assessment Technique (Amabile, 1982) and self-rated quality by participants. We recorded their EEGs during the improvisations and reconstructed flow-related and experience-related neural sources using SPM12 (Litvak et al., 2011).

We found that high flow (relative to low flow) was accompanied by deactivation of frontal areas associated with executive processing (i.e., transient hypofrontality) and increased activity in auditory and visual processing areas. Highly experienced musicians in a high-flow state showed reduced activity in posterior DMN nodes relative to their low-flow performances; less-experienced musicians showed no significant flow-related differences in DMN or FPCN activity. These results support the optimized-processing view of creative flow.

This study made use of the underappreciated spatial resolution of modern EEG source localization methods (Michel and He, 2019). We reconstructed the neural sources of the EEGs using the MSP algorithm implemented in the SPM software package (Litvak et al., 2011; Hyder et al., 2014). (Other source reconstruction algorithms available in the SPM-M/EEG software package yielded virtually identical, although somewhat more spatially diffuse, results which we do not report here.) Although EEG source reconstruction is an inverse solution of an ill-posed problem and therefore does not provide a definitive snapshot of the spatial distribution of brain activity, in practice, advanced algorithms that take physiological and anatomical constraints into consideration substantially reduce the uncertainty of this approach. EEG source reconstruction can thus provide an accurate functional-neuroanatomical model of brain activity in "source space" that explains the "sensor space" data recorded on the scalp (Michel and He, 2019). As with all theoretical models, the results are subject to further testing and convergent validation.

2. Material and methods

This study of the neural correlates of flow is based on data previously used in a study of the neural correlates of creative quality by Rosen et al. (2020). The following description of methods is a shortened version of the detailed methods adapted from that open-source article.

2.1. Participants

The study was approved by the Drexel University Institutional Review Board. Thirty-two jazz guitarists (1 female) participated after providing written consent. Each participant received $50 compensation for their experimental session which lasted approximately 90 min. Their ages ranged from 18 to 55 (M = 27.90, SD = 9.38), and their musical training ranged from 4 to 33 years (M = 15.91, SD = 7.90). All participants were right-handed as indicated by the Edinburgh Handedness Inventory (Oldfield, 1971). The participants reported no history of neurological disorders or severe head trauma, substance abuse or dependence, current treatment with mood stabilizing medications, or severe hearing impairments. Inclusion in the study required guitarists to have performed and improvised in a live jazz setting at least three times and be able to improvise to novel chord sequences depicted in jazz notation on a lead sheet. Guitarists ranged in experience from 6 to 1500 live jazz performances (M = 344.88, SD = 481.49) and included students from local university jazz programs, professional jazz guitarists, jazz instructors, and jazz novices. Our measure of jazz experience, participants' number of live jazz performances, ranged over more than 2 orders of magnitude with a skewed distribution (skew = 1.52). We applied the natural logarithmic transformation to the number of jazz gigs. The power law of practice stipulates that skill increases logarithmically. Empirical evidence shows that improvement with practice is linear in a log-log space (Newell and Rosenbloom, 2013). For example, a musician's second performance gives him or her twice as much experience over the first, but the 501th performance is only an incremental increase over the 500th. A secondary motivation for the logarithmic transformation is to improve model fit optimization for wide ranges of data with substantial skew (Zumel et al., 2014).

Four jazz experts were recruited to judge the improvisations. These judges included a jazz saxophonist and university jazz instructor, two jazz guitarists who were also university instructors, and one jazz guitarist who was a private instructor. Judges had a minimum of 25 years of jazz performance experience; two of the four judges had over 40 years of experience. They were compensated $300 for approximately 7–8 h of rating time.

2.2. Experimental design and procedures

After participants reviewed and completed their consent forms, they were fitted with an EEG electrode cap, and impedances were checked and adjusted to below 15 kΩ. Once the setup was complete, resting-state EEGs (not analyzed here) were collected in four 2-min blocks, alternating between eyes-open and eyes-closed conditions. A music stand containing a binder of jazz lead sheets and experiment instructions was positioned to minimize head movement.

Each guitarist performed an 8-min jazz improvisation warm-up exercise while viewing their EEGs on a computer monitor in real-time. As the guitarists played, the experimenter provided them with feedback about how and when excessive movement and other artifacts were produced. The purpose of this warm-up was threefold: to accustom the guitarists to performance with minimal movement, to understand what types of movement would distort the EEG data, and to practice improvising with the jazz accompaniment at a comfortable volume.

The improvisation task was programmed using E-Prime 2.0 (Psychology Software Tools, Sharpsburg, PA). All music and auditory stimuli were recorded and delivered using Logic Pro v.10.3.1 (Apple Inc., Cupertino, CA) digital audio workstation via the M-Audio Fast Track Pro USB Interface (Cumberland, RI) and studio monitors. The jazz accompaniments included piano, bass, and drums and were created through *iReal Pro* for Mac OS X v.7.0.1 (Technimo, New York City, NY), a practice tool with a full rhythm section for any properly formatted jazz chart (see the supplementary materials for audio recordings, backing tracks, and lead sheets). The chord sequences were written with the assistance of a professional jazz bassist/jazz studies professor and a professional jazz violinist/music education professor. The novel lead sheets were composed with the goal of creating unique, 16-measure sequences that were of approximately equal difficulty while incorporating some familiar jazz patterns and vocabulary. All songs had a tempo of 144 beats per minute with a medium swing rhythm. Each take consisted of four rotations through the chord changes (64 measures). Each improvisation or "take" lasted just under 2 min.

Before the improvisation task, participants were presented with standard instructions to "Improvise with the music as you normally would as a soloist in a jazz setting." All instructions were presented visually and auditorily. Prior to each take, participants had 15 s to examine the chord sequence. The seven chord sequences were administered in the same order to all participants. The first improvisation was considered a practice take, unbeknownst to participants, and was not included in subsequent analyses. Some of the high-experience and low-experience musicians' first takes were presented at the beginning of rating blocks to provide judges with a sense of the range of quality for which they could compare subsequent improvisations. Upon completion of the 7 improvisations, participants completed the Core Flow State Scale (C FSS; Martin and Jackson, 2008) for each of their takes. The take order for the flow surveys was counterbalanced, such that half of the participants reported flow scores from take 1 to take 6 and the other half reported from take 6 to take 1. Then, the musicians responded to a more detailed demographic survey which contained questions about their music training, jazz experience (number of gigs determined high/low experience), as well as musicians' self-rated quality, complexity, and familiarity for each take/stimulus. Participants' self-rated quality scores were measured on a 7-point Likert scale and ranged from 1 to 7 (M = 4.31, SD = 1.41).

After all 192 improvisations were recorded, each improvisation was mixed and normalized to ensure that the guitar and accompaniment had comparable volumes across all subjects and songs. Performances were pseudo-randomized for judging with the constraint that the same musician could not be heard twice consecutively or more than twice within a single judging block. The judges rated 12 blocks of 18 improvisations (~30 min per block). Using the Consensual Assessment Technique (CAT; Amabile, 1982), judges rated the improvisations on a 7-point Likert scale for creativity, aesthetic appeal, and technical proficiency. The judges recruited for this study were unaware of the full extent of the experimental design and research goals, and they received no participant information when rating the improvisations. The rating order was different for each judge, and each rating "block" started with a practice improvisation from a high- and low-experience participant to give them a sense of the quality range of performances they were about to judge. Like the participants, judges were asked to utilize their own expertise in jazz to determine the criterion for their ratings.

2.2.1. *Core flow state survey*

The Core Flow State Scale (C FSS; Martin and Jackson, 2008) was used to collect information about the degree to which participants experienced flow for each of their improvisations. The core flow measure is relevant for studies where multidimensional flow is not as central as the more targeted subjective optimal experience itself. The Core Flow State Scale items were developed from research (Jackson, 1992, 1995, 2000) on the subject experience of flow. These expressions were adapted into a set of 10 short items (see supplementary materials for flow survey items). Example items included: "I am 'totally involved"; "It feels like 'everything clicks"; I am 'tuned in' to what I am doing." Items were rated on a 1 (Strongly Disagree) to 5 (Strongly Agree) scale for each improvisation. Our goal was to choose a measure that would broadly assess the degree of experienced flow rather than a fine-grain assessment of purported flow components.

2.2.2. *Consensual Assessment Technique for judged quality ratings*

The Consensual Assessment Technique (CAT; Amabile, 1982; Kaufman et al., 2010) tasks domain experts with rating creative products relative to one another. Judged-quality rating scales ranged from 1 to 7. Interrater reliability was high for all scales. The intraclass correlation coefficient (ICC) assessed reliability for judges' ratings of creativity (CR; $ICC = 0.83$, $N = 4$), technical proficiency (TP; $ICC = 0.87$, $N = 4$), and aesthetic appeal (AA; $ICC = 0.85$, $N = 4$).

2.3. *Behavioral statistics*

Multilevel regression (MLR) models were computed using the lme4 (Bates, 2010) software package in R: A Language and Environment for Statistical Computing v.3.4.4 (R Development Core Team, 2008). MLR models compare the log-likelihood (LL) goodness-of-fit measure to determine whether independent factors significantly improve model fit. Changes in -2LL are distributed as χ^2 with degrees of freedom equal to the number of parameters added (Mirman, 2016).

MLR models assess group-level and individual-level patterns simultaneously within a single analysis, taking into consideration fixed-effect and random-effect parameters. Because these analyses were at the improvisation-level rather than the subject-level, each observation (improvisation) is nested under subject, with each subject contributing six improvisations. MLR accounts for this type of hierarchical data structure. For all models, the random-effects structures included inter-subject variation.

2.4. *Electroencephalograms*

2.4.1. *EEG acquisition and data processing*

EEGs were recorded with 64 Ag/AgCL active-electrodes embedded in an elastic cap (Brain Products, Morrisville, NC) with a digitally linked mastoid reference and an electrode montage arranged according to the extended International 10–20 System.

Preprocessing was conducted with Matlab 2015b (Mathworks, Inc., Natick, Massachusetts, USA) using functions from the EEGLAB toolbox version 13.6.5. The EEGs were epoched into 1-s intervals, and a linear-detrend function was applied using the SIFT toolbox (Delorme et al., 2011; Mullen, 2010) to remove linear drift. Bad channels were identified via visual inspection and replaced by interpolation from surrounding electrodes. Data were passed through a semi-automated artifact-detection tool, and epochs were classified as clean or artifactual as follows: threshold (±300 mV); joint-probability (channel/global limit 5SD/3SD); kurtosis (6.5 SD/3.5 SD) and spectral profile (exceeding −100 to 28 db over 20–55 Hz); and a final manual review. These parameters were tuned to detect electromyographic activity and large singular artifacts.

EEGLAB's FASTICA algorithm was used to calculate ICA weights. The ADJUST toolbox automatically detects and removes artifactual ICA components representing blinks, eye movements, and other spatial discontinuities (Mognon et al., 2011). ADJUST detections included the 33% of the components with the highest mutual information to ensure that reliable and important components were removed (Groppe et al., 2009). The components that survived were then manually reviewed. Data were then passed through the semi-automated artifact-detection tool again with more conservative parameters: threshold (±40 mV); joint-probability (channel/global limit 4SD/3SD); kurtosis (6.5SD/2SD) and spectral profile (exceeding −100 to 25 dB over 20–55 Hz); and final manual review.

2.4.2. Statistical parametric mapping

Spectral power analysis was conducted at the sensor level using the SPM12 M/EEG software package while controlling for multiple comparisons from voxel-wise hypothesis testing (Litvak et al., 2011). In SPM-EEG, a General Linear Model (GLM) approach is used to compare the EEG power at the voxel-level, and clusters of neighboring significant voxels are compared to a random-field noise model null criterion to determine significance at the cluster-level (Erickson et al., 2018). The significance of the effect is determined by thresholding the size of the cluster of voxels that are larger than would be expected to occur by chance. For each improvisation from each participant, Fast Fourier Transforms of 1-s regularly epoched data were performed from 2 to 50 Hz in 1-Hz frequency steps (Hanning windowed), robust averaged, and log-transformed. Then these spectral data were transformed to 3D Scalp x Frequency NIFTI-1 format images ([x,y], mm; [z], Hz) and *z*-score normalized across electrodes within each frequency-step to equate subjects for global EEG power within each frequency step.

EEG Flow contrast analyses were based on the ratings of the 6 improvisations performed by each participant. Rather than using a median split to compare higher-flow and lower-flow takes, the EEGs corresponding to the takes rated to be in the middle quintile of quality were omitted to eliminate takes near the border between higher and lower flow that would reduce the discriminability between the groups of takes (e.g., Erickson et al., 2018). Thus, the EEG scans associated with the top 40% and bottom 40% ($n = 154$ scans) of flow-state score takes were analyzed.

A flexible-factorial model was created to determine any confounding factors and to examine the main effect of quality in high > low and low > high contrasts (Gläscher and Gitelman, 2008). Tests of main effects in each model were conducted with a conservative cluster-forming threshold of $p < .0001$ and interpreted at the cluster-level with family-wise error (FWE) corrected threshold of $P\_FWE < 0.05$ (Flandin and Friston, 2019). The inclusion of experience as a main effect and as a covariate in the flow models yielded significant spectral differences in the EEG between conditions. The six subjects closest to the median experience value were removed, and high- and low-experience groups were formed with the remaining 26 subjects (12 HE, 14 LE). Each SPM model was subjected to a group main-effect *F*-test to test for the presence of the effect and *t*-tests for directional effects (high > low and low > high).

2.4.3. EEG source reconstruction

The neural sources of significant sensor-level effects were localized using the 3-D source reconstruction functionality of SPM (c.f. Oh et al., 2020). As the significant sensor-level effect was observed at group-level statistical testing, the source reconstruction was performed using the group-inversion option in SPM as it compensates for individual variability in head anatomy and sensor positioning by assuming the same underlying source generators for all subjects (Litvak et al., 2011). The Multiple Sparse Prior (MSP) inversion algorithm was used. MSP takes the weighted sum of multiple prior components that correspond to different locally smooth focal regions, allowing for data-driven optimization of distributed source modeling (López et al., 2014).

For each inversion, the frequency window of each significant cluster was identified and used as an input to limit the frequency range, while using the entire time-window of each improvisation. To reveal the sources of significant sensor-space effects, source images were contrasted by high- and low-flow groups using the same GLM (General Linear Model) based flexible-factorial model used to test sensor-level effects with an uncorrected threshold of $p < 0.05$ and cluster size threshold of 10. Because the significance of an effect was already observed at the sensor-level, additional hypothesis testing at the source level posed the problem of circular analysis. Therefore, GLM statistics using source images were performed to place condition-specific constraints and subsequently visualize sources of high-versus low-flow takes. The anatomical locations were identified using a labeling tool based on the label data provided by Neuromorphometrics, Inc. (http://Neuromorphometrics.com).

3. Results

Overview. The central theoretical distinction of this study involves comparing the proposed optimized, domain-specific processing and enhanced domain-general ideation models of creative flow. The critical results are the EEG source reconstructions which reveal the neural sources and networks underlying flow-related and experience-related contrasts. Since the interpretation of those contrasts depends on the relationships among experience, performance quality, and flow-state intensity, we present those behavioral results first. Overall, both self-rated and judge-rated performance quality predicted flow over all subjects, although, for reasons addressed in the Discussion, judged quality significantly predicted flow only for low-experience musicians.

3.1. Behavioral data

3.1.1. Descriptive statistics for flow, performance quality, and experience

The behavioral data were analyzed to assess relationships among the musicians' levels of experience, flow-state intensity, and performance quality. For analyses including experience-level, participants were median-split into experience-level groups (omitting the middle quintile) using the number of previous public performances as a metric of experience (Rosen et al., 2020; 2017, 2020). There were 14 subjects (84 improvisations) in the low-experience group (M = 25.5, SD = 14.56, range = 6–50 performances) and 12 subjects (72 improvisations) in the high-experience group (M = 837.5, SD = 458.32, range: 200–1500 performances).

Expert jazz raters scored recordings of each improvisation for creativity, aesthetic appeal, and technical proficiency according to the Consensual Assessment Technique (Amabile, 1982). The three rating scales showed significant positive correlations ($p < 0.001$): creativity and aesthetic appeal, $r(190) = 0.97$; creativity and technical proficiency, $r(190) = 0.95$; and aesthetic appeal and technical appeal, $r(190) = 0.95$. Because of these strong correlations, a composite judged-quality score was calculated for each improvisation by taking the mean of the ratings across scales and judges. The judged-quality ratings ranged from 1.16 to 6.33 (M = 4.08, SD = 1.36); self-rated quality ranged from 1 to 7 (M = 4.31, SD = 1.36). Four self-rated quality scores from three subjects (2 high-experience and 1 low-experience), were at the "1" floor, and six improvisations from two musicians (1 low-experience and 1 mid-experience) were at the "7" ceiling. Flow scores ranged from 1 to 5 (M = 3.80, SD = 0.69), of which one improvisation from a low-experience musician was at the "1" floor; 11 improvisations were at the "5" ceiling from five musicians (4 high-experience, 1 medium-experience). Descriptive statistics are shown in Table 1.

3.1.2. Experience predicted quality but not flow

First, we ascertained whether experience was predictive of flow, judged quality, and self-rated quality. MLR model comparisons revealed that high experience was associated with significantly greater judged quality ($b = 1.458$, $SE = 0.407$, $t = 3.584$, $p < 0.001$) and self-rated quality ($b = 1$, $SE = 0.42$, $t = 2.379$, $p = .017$). There was a trend for high-experience participants to have higher flow scores ($b = 0.354$, $SE = 0.215$, $t = 1.648$, $p = 0.089$).

3.1.3. *Self-rated and judge-rated quality predicted flow over all subjects, and self-rated quality predicted flow for both groups, but judged quality predicted flow only for low-experience musicians*

Self-rated quality was associated with flow across all participants ($b = 0.315$, $SE = 0.03$, $t = 10.407$, $p < 0.001$), for low-experience musicians ($b = 0.366$, $SE = 0.048$, $t = 3.316$, $p < 0.001$), and for high-experience musicians ($b = 0.333$, $SE = 0.058$, $t = 5.698$, $p < .001$). Judge-rated quality was associated with flow across all musicians ($b = 0.175$, $SE = 0.048$, $t = 3.659$, $p < 0.001$) and for the low-experience group ($b = 0.15$, $SE = 0.068$, $t = 2.239$, $p = .025$). However, judge-rated quality was not significantly associated with flow for the high-experience group ($b = 0.118$, $SE = 0.076$, $t = 1.562$, $p = .128$; see Table 2.

3.2. *Statistical parametric mapping*

Flow-related EEG topographies and source reconstructions were analyzed with SPM12. EEGs corresponding to the middle quintile of flow scores were omitted to eliminate takes near the median split (Rosen et al., 2020). Sensor-space analyses and subsequent source reconstructions of the high-versus-low flow effects over all subjects included experience as a covariate to isolate flow-related neural activity that was independent of experience. These were followed by separate pre-planned analyses (based on Rosen et al., 2020) of flow-related effects for the high- and low-experience musicians. Source reconstruction was performed in frequency windows containing significant sensor-space clusters.

3.2.1. *Sensor-space analyses of flow-related and experience related activity*

The sensor-space analyses were a preliminary step toward the reconstruction of source-space activity (below). Over all musicians, SPM *t*-tests of sensor-level spectral-power contrasts for the high-minus-low flow contrast revealed 3 significant clusters over central and posterior left-hemisphere regions. High-flow was associated with 2 clusters of gamma-band activity centered at left-parietal electrode P3 (33–40 Hz, P_FWE = 0.003; 45–46 Hz, P_FWE = 0.020) and a low-beta cluster centered at left-central electrode C5 (13–16 Hz, P_FWE = 0.012). For the low-minus-high flow contrast, there was a significant gamma-band cluster centered at right temporo-parietal electrode TP8 (30–46 Hz, P_FWE <0.001).

Next, we assessed whether the high-minus-low flow effects differed for high- and low-experience musicians. For the high-experience group, there were 25 high-flow and 30 low-flow takes; for the low-experience group there were 36 high-flow and 34 low-flow takes. For the high-experience group, SPM *t*-tests of spectral power for the high-minus-low flow contrast revealed a significant beta-band cluster centered at right-central electrode C6. For the low-minus-high flow contrast, there were two significant clusters of left frontal beta-band activity, one centered at left-frontal electrode F3 (15–24 Hz, P_FWE = 0.002) and another at left fronto-temporal electrode FT9 (22–32 Hz, P_FWE = 0.021). For the low-experience group, the high-minus-low flow contrast yielded no significant clusters; however, the low-minus-high flow contrast revealed 2 significant gamma-band clusters centered at right frontocentral electrode FC6 (31–38 Hz, P_FWE = 0.011 and 45–49 Hz, P_FWE = 0.007).

Table 1
Means and standard deviations for flow and performance quality by domain experience.

Variable	Low- Experience	High-Experience	All
Flow	3.64 (0.72)	4.01 (0.62)	3.80 (0.69)
Judged Quality	3.44 (1.24)	4.94 (0.99)	4.08 (1.36)
Self-Rated Quality	3.75 (1.45)	4.75 (1.25)	4.31 (1.41)

Table 2
Chi-Square difference test model comparisons for the effects of quality on flow.

Model Parameters	Experience	Log-Likelihood	Chi-Squared ($\chi2$)	Degrees of Freedom (*df*)	*P*-Value
Judged Quality	All	−143.96	12.77	1	<.001**
	High	−58.74	2.39	1	0.128
	Low	−68.99	3.90	1	0.03*
Self-Rated Quality	All	−85.45	80.61	1	<.001**
	High	−29.75	24.48	1	<.001**
	Low	−33.43	38.31	1	<.001**

Note. Significance: *$p < .05$, **$p < .0001$.

3.2.2. *Source reconstructions of flow-related and experience-related activity*

The first source reconstruction shows flow-related differences in brain activity across all participants. These are followed by source reconstructions of flow-related differences separately for high-experience and low-experience musicians.

Significant flow-related source-space clusters are shown in Fig. 1. High-minus-low flow activity was observed in the (a) low-beta (13–16 Hz, P_FWE = 0.018) frequency window in the left inferior-temporal, left fusiform, and left and right posterior-cingulate gyri and in the (b) gamma-band (45–50 Hz; P_FWE = 0.03) in the left central and parietal operculum and the left middle- and superior-temporal gyri. Low-minus-high flow activity was observed in (c) the gamma-band (30–46 Hz; P_FWE 0.001) in the left and right superior-frontal and the right inferior-temporal and fusiform gyri.

3.2.2.1. *Experience-related source-reconstruction results.* Separate source reconstructions of flow-related effects for the high- and low-experience musicians are shown in Fig. 2. For the high-experience musicians, high-minus-low flow beta-band (20–26 Hz) activity was localized to the left superior- and middle-temporal gyri and the right inferior-occipital gyrus. For the low-minus-high flow effect, beta-band clusters (22–32 and 15–24 Hz) were observed in the left and right precuneus, left and right posterior-cingulate gyrus – importantly, all nodes of the DMN – and the left and right middle-cingulate gyrus and right inferior-temporal gyrus. For the low-experience musicians, there were no significant high-minus-low flow effects. The low-minus-high flow effect yielded two gamma-band clusters (31–38 and 45–49 Hz) localized to the right superior- and middle-temporal gyri.

4. Discussion

Although extensive psychological research has characterized the flow experience, that work has not yet led to a consensus about the neurocognitive mechanisms associated with that experience. We addressed this gap by contrasting alternative views of the neural substrates of creative flow implied by prior foundational research: as optimized expert task-specific processing with minimal task-negative DMN activity versus heightened DMN-supported, task-positive, domain-general associative ideation.

4.1. *Flow-state experience and performance quality*

As in previous work (Hohnemann et al., 2022), we found flow, overall, to be associated with superior objective (judge-rated)

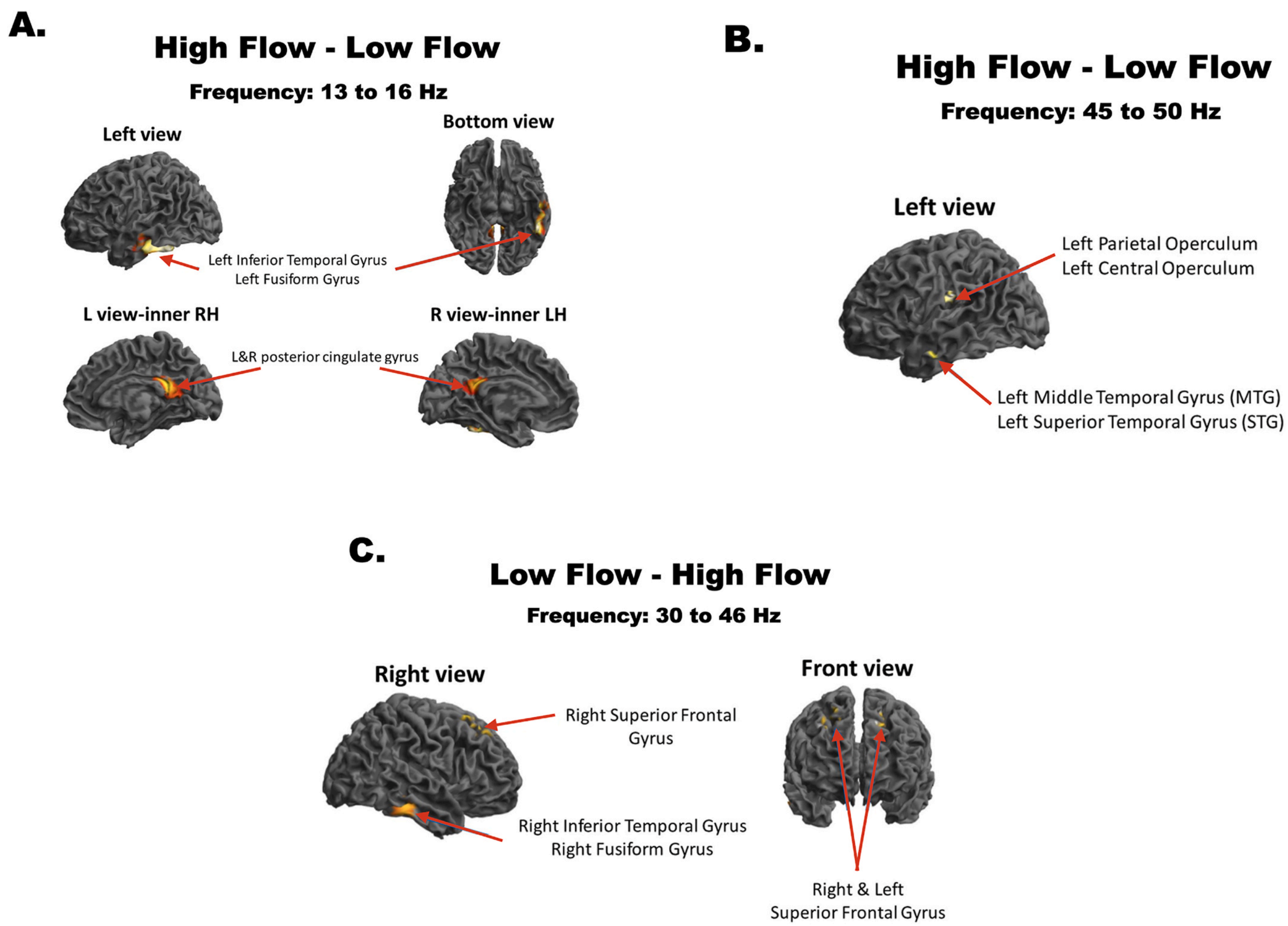

Fig. 1. Source reconstructions of activity in significant peak-voxel frequency windows from the sensor-space analyses. These SPM contrasts show the main effect of flow with experience as a covariate.

performance. High-flow improvisations were accompanied by superior self-judged quality ratings for both high- and low-experience musicians and by superior judge-rated quality for the low-experience musicians.

A novel finding is the absence of a significant relationship between judge-rated quality and flow for the high-experience musicians; those musicians reported relatively high flow even for improvisations that the judges did not rate highly. There are at least four potential explanations for this finding, any or all of which may play a role: (A) More flow scores at the ceiling for the high-experience group than for the low-experience group may have suppressed flow-related effects more for the high-experience group. (B) The high-experience musicians may have been biased to view their lower-quality improvisations as better than the more objective (and blinded) judges thought them to be. It is possible that the high-experience musicians' self-ratings of quality, which were higher in judged quality than those of the low-experience musicians, were colored by their experience of flow – "I experienced flow, therefore I played well." Consistent with this idea, the high-experience musicians' self-rated quality scores correlated significantly with flow. (C) The relationship between judge-rated quality and self-rated flow may not be linear. Flow and objective quality may become uncorrelated above a particular level because flow can contribute only so much to performance quality. Beyond this level, additional increases in flow may not increase quality. (D) Flow-state intensity and quality may be less tightly coupled for high-experience musicians compared to low-experience musicians because greater experience may automatize the improvisation process, inducing flow irrespective of quality.

4.2. *High-flow neural activity*

Controlling for experience, high-flow takes were associated with gamma-band clusters in the left parietal and central opercula and in the left middle- and superior-temporal gyri. The parietal operculum processes somatosensory awareness (Sirigu and Desmurget, 2021) and has greater functional connectivity with auditory and sensorimotor areas in musicians compared to non-musicians. It has been proposed as a hub of a network that enables multimodal integration of auditory and somatosensory information in support of musical performance (Tanaka and Kirino, 2018). Interestingly, there is high opioid-receptor binding in the operculum (Baumgärtner et al., 2006) which, speculatively, may underlie the positive affect associated with flow. The left middle-temporal gyrus has been implicated in diverse functions, including the multisensory recognition of positive emotional stimuli (Pourtois et al., 2005) and the composition of poems (Liu et al., 2015). The left superior-temporal gyrus is involved in speech comprehension and auditory short-term memory (Leff et al., 2009). Overall, these gamma-band clusters have face validity as nodes of a possible "creative flow network" for expert musical improvisation. Note that this group of high-flow clusters does not include significant DMN or FPCN activity (with the caveat that the relationship between the parietal operculum and the DMN is not entirely clear; Wang et al., 2020).

High-flow was also associated with low-beta clusters in the left inferior-temporal, left fusiform, and left and right posterior-cingulate gyri. The fusiform gyrus is best known for its involvement in face recognition but has also been implicated in higher-order aspects of

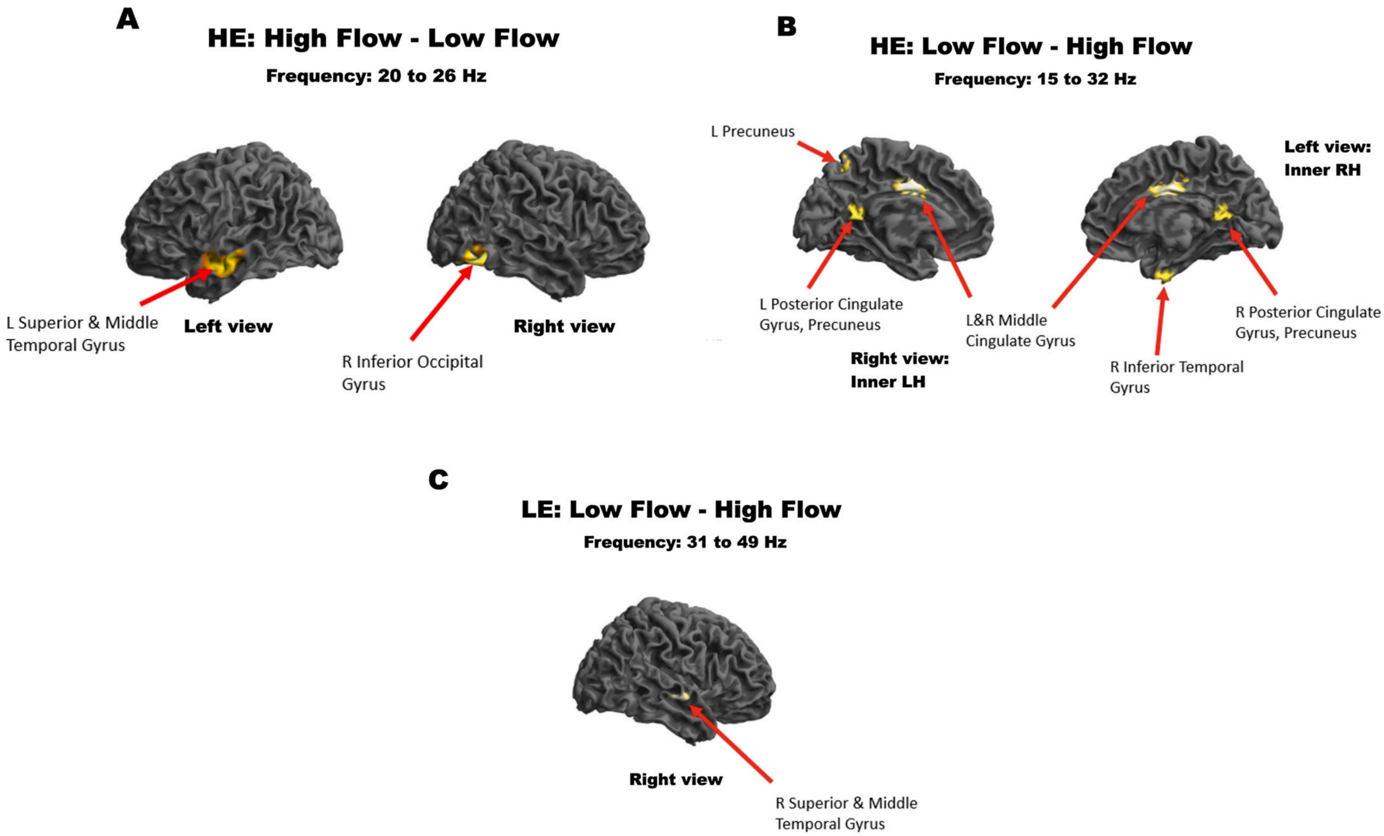

Fig. 2. Source reconstructions of flow-related effects for high-experience (HE) and low-experience (LE) musicians.

reading (Devlin et al., 2006) and the decoding of rhythmic elements of musical notation (Stewart, 2005). The left inferior-temporal gyrus has also been implicated in reading (Dien et al., 2013) and the processing of positively valenced music (Proverbio and Piotti, 2022). The posterior cingulate is a hub of the DMN. However, importantly, interpretation of these low-beta (13–16 Hz) clusters (e.g., as activation or inhibition) is problematic because, in contrast to faster beta and gamma oscillations, low-beta activity does not correlate with metabolic or hemodynamic measures of neural activity (Laufs et al., 2003; Leuchter et al., 1999).

4.3. Low-flow neural activity

Low-flow improvisations were associated with gamma-band clusters in the right inferior-temporal and fusiform gyri and in the superior-frontal gyri. Creativity ratings of musical improvisations have been found to correlate negatively with gray matter volume in the right inferior-temporal gyrus (Arkin et al., 2019), suggesting that activity in this area may reduce improvisation quality or, alternatively, that activity in this area is recruited to help improve improvisation quality when it is low. Gray-matter density in the right fusiform gyrus is correlated with musical expertise, likely resulting from practice reading musical notation (James et al., 2014). The superior frontal gyri, while not part of the classically defined FPCN, have been implicated in executive functions such as impulse control (Hu et al., 2016), task switching (Cutini et al., 2008), and working memory (Alagapan et al., 2019). Importantly, the fact that low-flow (relative to high-flow) improvisations were associated with greater superior-frontal gyrus activity suggests that reduced cognitive control may contribute to high-flow creative production (Dietrich, 2004; see also Chrysikou et al., 2014).

4.4. Flow-related activity in high-experience musicians

The high-experience musicians showed high-minus-low flow-related beta-band activity in the left middle- and superior-temporal gyri and the right inferior-occipital sulcus. The left superior- and middle-temporal gyri are involved in speech comprehension, auditory short-term memory, and multisensory recognition of positive emotional stimuli. The right inferior-occipital sulcus has been implicated in visual processing (Puce et al., 1996).

The low-minus-high flow-related beta-band activity in the high-experience musicians included a significant cluster in the right inferior-temporal gyrus, an area whose gray-matter volume has been found to correlate negatively with musical improvisation creativity (Arkin et al., 2019). Additionally, significant clusters were observed in posterior DMN nodes: the left and right precuneus and left and right posterior cingulate gyrus. Although the DMN has been proposed to underlie ideation in other divergent-thinking tasks such as the AUT (Benedek et al., 2023), here we found that greater DMN-node activity was present during high-experience musicians' low-flow, rather than high-flow, takes.

4.5. Flow-related activity in low-experience musicians

For the low-experience musicians, high-flow did not yield significant clusters of brain activity. However, for their low-flow takes, gamma-band activity was found to originate in the right superior- and middle-temporal gyri. Interestingly, this activity was contralateral to that of high-experience musicians' high-flow takes. The low-experience musicians showed no significant DMN or FPCN clusters.

4.6. Summary and implications

The present results afford an unprecedented view of the neural correlates of creative flow and their relationship to experience. Over all subjects, high-flow improvisations were associated with a network of left-hemisphere auditory, visual, and somatosensory areas while low flow involved right-temporal activity and other, presumably executive, activity in the superior frontal gyri. The finding of flow-related deactivation in the superior frontal gyri is consistent with the idea that high flow involves transient hypofrontality associated with a reduction in cognitive control (Dietrich, 2004).

Pre-planned follow-up analyses for the high- and low-experience groups shed further light, although these analyses have lower statistical power than the analyses over all subjects. There was a striking experience-related hemispheric effect: The high-experience musicians showed greater high-minus-low flow in parts of the left-temporal lobe; the low-experience musicians showed flow-related deactivation in parts of the right temporal lobe. Goldberg et al. (1994) proposed that the right hemisphere is engaged during tasks for which a person has little or no experience but that, with practice, activity shifts to the left hemisphere. Our findings are consistent with that principle and support the idea that flow is enabled by task-related experience.

Notably, the high-experience musicians showed flow-related deactivation in nodes of the posterior DMN. The fact that the most experienced and creative musicians improvising during a high-flow state showed reduced activity in posterior DMN nodes weighs against the idea that the DMN contributes domain-general, divergent-thinking creative production in this task (cf. Beaty et al., 2016; Benedek et al., 2023). In fact, it suggests the possibility that DMN activity is task-negative (e.g., daydreaming) and may interfere with creative flow in expert performers. That there was no significant flow-related modulation of DMN activity in the low-experience musicians, even though flow correlated with judge-rated quality for these performers, is also consistent with the idea that DMN may not contribute task-positive ideation to musical improvisation.

4.7. Limitations and future directions

Limitations of this study suggest directions for future research. Most notably, our sample-size was constrained by practical issues involved in recruiting jazz guitarists within a circumscribed geographical area. Replication with a larger sample would be desirable, as would generalization to other creative production tasks. For example, a drawing task would not only afford an opportunity to assess generalization across tasks but could also yield a larger pool of potential participants. Drawing or other creative production tasks may yield greater ecological validity than a jazz improvisation task because the latter necessarily imposed restrictions on performance, such as improvising over novel, unfamiliar chord sequences with a static accompaniment, that may have interfered with the flow experience, perhaps more for the low-experience musicians than the high-experience ones.

Regarding the precision of EEG source reconstructions, even if the present results prove to be of relatively modest spatial resolution, the main results of this study would be unchanged because they are not dependent on high-resolution findings: High flow during jazz improvisation is associated with transient hypofrontality and left-hemisphere activity in modality-specific areas. Low flow is associated with right-hemisphere modality-specific activity. Furthermore, flow-related neural activity depends on task-specific experience: high-experience musicians showed a decrease in posterior DMN-related nodes relative to low-experience musicians. Nevertheless, future work should attempt to replicate findings with fMRI to obtain superior spatial resolution and to explore potential subcortical activity that EEG is not well-suited to record.

5. Conclusions

These findings support the view that creative flow is an experiential correlate of a state of optimized, task-specific processing that results from domain-specific expertise paired with a reduction in cognitive control rather than a state of heightened domain-general associative ideation enabled by increased DMN activity supervised by the FPCN.

CRediT authorship contribution statement

David Rosen: Conceptualization, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. **Yongtaek Oh:** Conceptualization, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Data curation. **Christine Chesebrough:** Conceptualization, Writing – original draft. **Fengqing (Zoe) Zhang:** Conceptualization, Methodology, Supervision. **John Kounios:** Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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