# A Complexity-Science Framework for Studying Flow: Using Media to Probe Brain–Phenomenology Dynamics

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We have no known conflict of interest to disclose.

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**Abstract**

Consciousness spans a range of phenomenological experiences, from effortless immersion to disengaged monotony, yet how such phenomenology emerges from brain activity is not well understood. Flow, in particular, has drawn attention for its links to performance and wellbeing, but existing neural accounts rely on single-region or small-network analyses that overlook the brain's distributed and dynamic nature. Complexity science offers tools that capture whole-brain dynamics, but this approach has rarely been applied to flow or to its natural comparison states of boredom and frustration. Consequently, it remains unclear whether tools drawn from complexity science can objectively separate phenomenological experiences while also clarifying their neural basis. Here we show that a complexity science approach distinguishes flow from boredom and frustration. We induced each phenomenological experience with a difficulty-titrated video game during functional magnetic resonance imaging and collected concurrent behavioral and self-report data. Whole-brain analyses revealed that flow is marked by lower global entropy, higher dynamical agility, and decreased dynamical complexity, whereas boredom and frustration exhibit different configurations of brain-dynamics metrics. Notably, these findings integrate previously separate prefrontal, network-synchrony, and cerebellar observations within a single dynamical systems framework and identify complexity-based markers that map the neural correlates of media-related benefits.

*Keywords:* complexity science, synchronization, metastability, flow, neurophenomenology, fMRI

## Highlights

- Complexity science is a strong perspective for studying media-induced phenomenology
- Dynamic complexity signatures are sensitive to distinct phenomenological experiences
- Increased flow is explained by decreases in neural entropy rate
- Dynamical complexity better explains flow than synchronization or metastability
- Complexity science better describes the neurobiology of flow versus existing models

# A Complexity-Science Framework for Studying Flow: Using Media to Probe Brain–Behavior Dynamics

## 1. Introduction

Human consciousness encompasses an array of phenomenological experiences, each representing a dynamic interplay of perception, cognition, and emotion. The modern scientific study of phenomenology was pioneered in the late 19th century by William James (1890), who argued that emotional experiences are characterized by dynamic interactions between our internal self and the external world. In the years since, researchers have investigated an ever-growing variety of phenomenological experiences that characterize typical and abnormal brain function. Such inquiry still includes topics such as affect and emotion (Barrett, 2017; Cacioppo et al., 1999), but has since expanded to encompass additional experiences, including meditation (Van Dam et al., 2018), mindfulness (Zhou et al., 2023), self-transcendence (Kang et al., 2018), self-affirmation (Falk et al., 2015), acute psychosis (Horga & Abi-Dargham, 2019; Insel, 2010), sleep and dreaming (Solms, 2021), flow (Csikszentmihalyi, 1990), the psychedelic experience (Carhart-Harris et al., 2014; Carhart-Harris & Friston, 2019; Girn et al., 2023), audience responses to media (Grall et al., 2021; Hasson et al., 2008; Schmälzle, 2022; Schmälzle et al., 2024; Schmälzle & Grall, 2020; Schmälzle & Huskey, 2023a; Weber et al., 2024), player responses to video games (K. Mathiak & Weber, 2006; Weber et al., 2006, 2018), and more. Descriptive accounts of these phenomenological experiences abound, as do proposed mechanisms. Yet, a conclusive understanding of their neural substrates remains elusive. Why?

A significant challenge lies in the difficulty of studying these experiences within controlled experimental paradigms. Advances in naturalistic neuroimaging (Finn et al., 2022; K. Mathiak & Weber, 2006; Schmälzle & Huskey, 2023a; Sonkusare et al., 2019) have addressed

some limitations, but the majority of cognitive neuroscience often remains confined to models focused on isolated cognitive processes (e.g., attentional vigilance, working memory, reward signaling) within a single (i.e., locationist) or relatively small set (e.g., connectionist) of brain regions (Noble et al., 2024). This reductionist approach persists despite evidence that large-scale, whole-brain dynamics underlie a broad spectrum of cognitive functions (Westlin et al., 2023), including relatively low-level processes such as strategic attention and recognition memory (Davison et al., 2015; Telesford et al., 2016). If lower-level cognitive processes resist simple locationist or connectionist models, then what hope is there for using these paradigms to explain complex phenomenology implicating multiple interacting cognitive processes?

Neurophenomenology (Lutz & Thompson, 2003) connects first-person experience with moment-by-moment brain dynamics. Complexity science extends this bridge by modeling the brain as a nonlinear dynamical system and quantifying its emergent, information-rich patterns; thereby providing insights that surpass region-by-region accounts (Bassett & Gazzaniga, 2011; Hancock, Rosas, et al., 2022; Kelso, 1995; Seguin et al., 2023). In this article, we focus on flow experiences (Csikszentmihalyi, 1990) as a test-case for studying complex phenomenological experiences from a complexity science perspective. We use media to elicit flow, which allows us to observe linkages between neural complexity signatures and media-elicited phenomenological experience in a way that clarifies longstanding questions in flow research and provides a roadmap for inquiry into the neural basis of a wide variety of phenomenological experiences, including those elicited by media, and their subsequent outcomes (Weber et al., 2015).

### 1.1 Flow, Media, and Wellbeing

Flow, first described five decades ago by psychologist Mihaly Csikszentmihalyi (1975), is an emergent phenomenological experience characterized by focused attention, altered

temporal awareness, reduced self-reflective thought, and high intrinsic reward. Flow is implicated in a variety of positive wellbeing outcomes, including successful goal pursuit (Bernecker & Becker, 2021; Tepper & Lewis, 2021), increased resilience (Tabibnia, 2020), adaptive coping during uncertainty (Rankin et al., 2019; Sweeny et al., 2020), resistance to burnout (Mosing et al., 2018), and more (Csikszentmihalyi, 1990). Importantly, media can elicit flow (Sherry, 2004), and experiencing flow during media use has also been linked to a number of wellbeing outcomes (Chiang et al., 2011; Vella et al., 2013).

Despite years of research, the neural mechanisms underlying flow remain fragmented, with competing models (for a review, see Kee & Huskey, in press). One influential model posits that flow results from a large-scale deactivation of the prefrontal cortex (Dietrich, 2004), whereas another argues that medial prefrontal cortex downregulation, causally driven by the dorsal raphe nucleus, contributes to flow (Ulrich et al., 2016a).[1] Flow has also been theorized as resulting from a synchronization between attentional and reward networks (Weber et al., 2009).[2] A final model argues that these earlier specifications can be integrated by considering the cerebellum (Gold & Ciorciari, 2021).

These models, often developed from different experimental protocols, data analysis strategies, theoretical and philosophical commitments, have struggled to converge on a unified account of flow's dynamic neural basis. A source of this lack of consensus could be the limitations of reductionist frameworks that focus on isolated regions (locationist) or static networks (connectionist), rather than the distributed, time-varying patterns that characterize complex phenomenological experiences.

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[1] This team implicates other brain activation patterns in flow (Ulrich et al., 2016b), and many of these brain activation patterns replicate (Ulrich et al., 2022).

[2] This theory draws heavily on ideas from complexity science, but constrains these ideas to specific networks.

**1.2 The Present Study**

Building on recent work (Girn et al., 2023; Pessoa, 2022; Turkheimer et al., 2022), we argue that flow is best understood using the latest tools and perspectives of complexity science (Hancock, Rosas, et al., 2022; Hancock et al., 2025; Turkheimer et al., 2022). Complexity science seeks to uncover general laws governing complex systems, integrating concepts from statistical physics, dynamical systems theory, and information theory (Holland, 2014; Thurner et al., 2018; Waldrop, 1993). It conceptualizes the brain as a complex system composed of discrete but integrated subunits that interact in non-linear ways to give rise to spontaneously organizing macroscopic patterns that cannot be reduced to the individual parts; that is, a complex system with the properties of multiplicity, interdependence, non-linearity, self-organization, and emergence (Jensen, 1998; Ladyman et al., 2013).

In this study, we manipulated the phenomenological experience of flow—using boredom and frustration as canonical comparisons—and used tools drawn from complexity science to challenge and potentially unify pre-existing neuroscientific models. We applied a comprehensive set of complexity analyses to functional magnetic resonance imaging (fMRI) data, compared them across conditions, and examined relationships with the subjective experiences of flow and enjoyment, as well as with a behavioral correlate of flow. Our objective was to understand which, if any, of these complexity signatures is most sensitive to differences between flow, boredom, and frustration, as well as which best explain subjective and behavioral measures. By isolating complexity-based brain signatures that distinguish the positive phenomenological experience of flow from aversive phenomenological experiences like boredom and frustration during media engagement, our study directly advances this special issue's goal of investigating the neural mechanisms that mediate the risks and benefits of modern media use.

# 2. Methods

## 2.1 Previous Reporting and General Overview

The fMRI and behavioral data analyzed in this manuscript were previously reported on by Huskey and colleagues (2022). This earlier manuscript evaluated fMRI data from a network neuroscience perspective (Fornito et al., 2016; Sporns, 2011). Here we completely re-evaluate the data, this time from a complexity science perspective. These new analyses allow us to evaluate previously untested questions, and examine the neural basis of flow from an entirely novel meta-theoretical and analytical paradigm. In what follows, we provide a brief overview of the procedure, before detailing the analytical approach.

### *2.1.1 Participants*

A total of $n$ = 35 participants were recruited from The Ohio State University and the surrounding community ($\text{mean}_{\text{age}}$ = 25.00, 45.71% female, 71.43% students, 48.57% Caucasian, and a mean self-reported video game ability of 4.11 out of 7.00). All participants were right-handed, had normal or corrected to normal vision, and did not demonstrate any contraindication to fMRI scanning. All study procedures were approved by The Ohio State University's Institutional Review Board.

## 2.2 Stimulus and Experimental Manipulation

In the scanner, participants played a video game called *Asteroid Impact* following a previously validated experimental technique for inducing flow (Huskey et al., 2018). Specifically, flow is theorized to result from a balance between task difficulty and individual ability at the task (Csikszentmihalyi, 1990). Accordingly, we manipulated three experimental conditions: low-difficulty or boredom (difficulty < ability), high-difficulty or frustration (difficulty > ability), and balanced-difficulty or flow (difficulty = ability). Participants played all

three conditions, and condition order was randomly assigned. In *Asteroid Impact,* players use a mouse cursor to control a space ship with the goal of collecting targets on the screen while avoiding asteroids. Difficulty was manipulated by adjusting the speed of asteroids in one of three ways: (1) asteroid speed was slow and did not change (low-difficulty), (2) asteroid speed was consistently fast and did not change (high-difficulty), (3) an algorithm adjusted asteroid speed based on player performance (balanced-difficulty). A resting-state scan was also gathered after participants had played all three rounds of the game.

## 2.3 Dependent Measures

### *2.3.1 Self-Report Measures: Flow and Enjoyment*

The Autotelic Experience subscale of the Event Experience Scale was used to measure self-reported flow (Jackson & Eklund, 2004). Self-reported video game enjoyment was also measured (Bowman et al., 2013).

### *2.3.2 Behavioral Measure: Reaction Time*

Attentional engagement, a behavioral correlate of flow (for rationale and validation, see Huskey et al., 2018), was evaluated using a behavioral measure: reaction time (Lang et al., 2006). A total of 68 audiovisual (semi-opaque red circle; sine waveform, 440.0 Hz) probes were shown equally in each of the four corners of the game. Speeded responses were recorded using a previously validated technique (Calcagnotto et al., 2021).

## 2.4 fMRI Preprocessing

For complete functional magnetic resonance image (fMRI) acquisition and data cleaning details, we direct readers to (Huskey et al., 2022). In brief, all fMRI data were preprocessed using *fMRIPrep 20.0.5* (Esteban et al., 2019) and denoised using XCP engine (Ciric et al., 2018). To optimize our data for the frequency domain analyses reported in this manuscript, we made

two minor deviations to the data cleaning pipeline: (1) we used a slightly more permissive bandpass filter (0.01 - 0.08 *Hz* vs. 0.016 - 0.08 *Hz,* for further details, see below), and (2) we did not apply global signal regression (GSR; our previous analyses show trivial differences in quality control metrics when GSR is vs. is not applied to this dataset; for full details, see supplemental section 4 in Huskey et al., 2022).

**2.5 Parcellation**

We parcellated the pre-processed fMRI data by averaging time-courses across all voxels for each region defined in the anatomical parcellation AAL (Tzourio-Mazoyer et al., 2002) considering all cortical, subcortical, and cerebellar regions ($n$ = 116). We chose the AAL parcellation as subcortical and cerebellar regions are relevant in flow studies (Gold & Ciorciari, 2021; Huskey et al., 2022).

**2.6 Bandpass Filtering**

To isolate low-frequency resting-state signal fluctuations, we bandpass filtered the parcellated fMRI time-series within 0.01-0.08 *Hz* with a discrete Fourier transform (DST) computed using a fast Fourier transform (FFT) algorithm in MATLAB 2021b. We applied Carson's empirical rule (Carson, 1922; Pachaud et al., 2013) on the analytical signal which was calculated using the Hilbert transform of the real signal (Gabor, 1946), to confirm non-violation of the Bedrosian theorem for our band-passed signals.

**2.7 Functional Connectivity Through Phase-Alignment**

We estimated functional connectivity (FC) with the non-linear measure of phase-coincidence or phase-alignment which may be more suitable than linear measures, such as Pearson correlation, for analyzing complex brain dynamics. Specifically, non-linear methods provide insight into interdependence between brain regions at both short and large time and

spatial scales allowing the analysis of complex non-linear interactions across space and time (Pereda et al., 2005; Quian Quiroga et al., 2002). From a practical perspective, unlike correlation or covariance measures, phase alignment can be estimated at the instantaneous level and does not require time-windowing. When averaged over a sufficiently long-time window, phase-alignment values provide a close approximation to Pearson correlation, varying within the same range of values (Cabral et al., 2017; Honari et al., 2021).

Following Cabral et al. (2017), we first calculated the analytical signal using the Hilbert transform of the real signal (Gabor, 1946). Then, the instantaneous phase-alignment between each pair of brain regions was estimated for each time-point as the cosine difference of the relative phase. Phase-alignment at a given timepoint ranges between -1 (regions in anti-phase alignment) and 1 (regions in phase alignment). A three-dimensional tensor of size $NxNxT$ where $N$ is the dimension of the parcellation, and $T$ is the number of timepoints in the scan, was extracted for each participant for each condition.

**2.8 LEiDA – Leading Eigenvector Dynamic Analysis**

To reduce the dimensionality of the instantaneous phase-alignment (iPA) space for our dynamic analysis, we employed the Leading Eigenvector Dynamic Analysis (LEiDA; Cabral et al., 2017) method. The leading eigenvector $V_1(t)$ of each $iPA(t)$ is the eigenvector with the largest magnitude eigenvalue and reflects the dominant FC (through phase-alignment) pattern at time $t$. $V_1(t)$ is a $Nx1$ vector that captures the main orientation of the fMRI signal phases over all anatomical areas. Each element in $V_1(t)$ represents the projection of the fMRI phase in each region into the leading eigenvector. When all elements of $V_1(t)$ have the same sign, this means that all fMRI phases are orientated in the same direction as $V_1(t)$, indicating a global mode governing all fMRI signals. When the elements of $V_1(t)$ have both positive and negative signs,

this means that the fMRI signals have different orientations behaving like opposite anti-nodes in a standing wave. This allows us to separate the brain regions into two 'communities' (or poles) according to their orientation or sign, where the magnitude of each element in $V_1(t)$ indicates the strength of belonging to that community (Newman, 2006). Complete details and graphical representations for this procedure are well documented (Figueroa et al., 2019; Lord et al., 2019; Vohryzek et al., 2020). The outer product of $V_1(t)$ reveals the FC matrix associated with the leading eigenvector at time $t$.

### *2.8.1 Mode Extraction*

To identify recurring spatiotemporal modes ($\psi$) for phase-alignment patterns (modes, a term borrowed from physics, are different patterns of brain waves with the same frequency and a fixed phase relationship), we clustered the leading eigenvectors for each of the 4 time-series (flow, boredom, frustration, resting state) with k-means clustering with 300 replications and up to 400 iterations for 5 centroids. We choose 5 centroids as these spatiotemporal patterns have been shown to exhibit extremely high test-retest reliability in healthy subjects (Hancock, Cabral, et al., 2022). K-means clustering returns a set of K central vectors or centroids in the form of $Nx1$ vectors $V_c$. As $V_c$ is a mean derived variable, it may not occur in any individual subject data set. To obtain time courses related to the extracted modes ($\psi_k$) at each TR we assign the cluster number to which $V_c(t)$ is most similar using the cosine distance.

### *2.8.2 Mode Representations as Connectograms*

We visualized functional connectivity as connectograms by taking the functional connectivity matrices for each mode and retaining regions that were in anti-phase alignment.

**2.9 Neurosynth Functional Associations**

Probabilistic measures of the association between brain coordinates and overlapping terms from the Cognitive Atlas (Poldrack et al., 2011) and the Neurosynth database (Yarkoni et al., 2011) were obtained as previously demonstrated in Hansen et al. (2021). The probabilistic measures were parcellated into 116 AAL regions and may be interpreted as a quantitative representation of how regional fluctuations in phase-alignment are related to psychological processes. The resulting functional association matrix represents the functional relatedness of 130 terms to 116 brain regions (see Supplementary Table ST1 for a full list of terms).

**2.10 Cerebellar Connectivity**

Regions in the cerebellum are connected to cortex and subcortical regions. We assessed the differences in cerebellar (CB) connectivity with the non-parametric Friedman test between the 3 conditions. The degree of connectivity was taken as the contribution of the specific CB region to the leading eigenvectors at each timepoint (Hancock et al., 2023).

**2.11 Global and Local Complexity Dynamics**

Signatures of complex phenomena extracted from neuroimaging data have been developed and estimated from the early 2000's. However, even for one of the most popular signatures, metastability, agreement on what and how to estimate this signature is heavily debated (Hancock et al., 2025). Therefore, in the absence of a gold standard measure for complexity in the brain, we decided to estimate several signatures that have been proposed in the literature to investigate which may be sensitive to behavioral phenomena, while also gaining clarity on the specific brain-network complexity signatures associated with flow.

The signatures of complexity herein are, unless otherwise stated, derived from time-varying phase relations between brain regions obtained through Hilbert transformation of the

fMRI signals. When the phase relationship is mean-field phase, as used in synchronization, metastability, and coalition diversity calculations, we are investigating "absolute coordination" (for complete details, including mathematical derivations, see Hancock et al., 2025). When the phase relationship is phase difference, as used in dynamical complexity, dynamical alignment, dynamical agility, ignition flexibility, ignition hierarchy, integration, and segregation calculations, we are investigating "relative coordination" (Hancock et al., 2025).

Some signatures were calculated using the complete phase matrix (*NxN*), which we subsequently denote with PHM, whereas others using the complete phase-alignment matrix (*NxN*) are denoted with PALM. A final set of signatures were calculated with the Leading or first eigenvector of the phase alignment matrix; an approach known and denoted as LEiDA (1xN).

In addition to these complexity signatures, we also evaluate intrinsic-driven ignition, which is a phenomenon where global activation patterns arise in response to spontaneous local activity. If spontaneous (i.e., intrinsic) local activity in one region induces activity in other regions, it is considered to have caused an "ignition" in those regions (Deco & Kringelbach, 2017). In this study, we investigate both spontaneous (i.e., rest) and evoked (i.e., task related) ignitions.

In what follows, we briefly review and define the complexity signatures evaluated in this manuscript. For each signature, we point interested readers to relevant work defining its derivation and application (for a brief summary, see Table 1).

#### *2.11.1 Overview of the Global Signatures of Complexity*

Synchronization (PHM) measures the degree of synchronization between neural regions across the whole brain. It is calculated as the mean-field phase, which is more commonly known

as the average of the Kuramoto Order Parameter (Shanahan, 2010). The synchronization measure is bound between [0, 1].

Metastability (PHM) quantifies variability in synchronization, reflecting the switching between communities (i.e., regions in sync), and has been proposed as a key signature of metastability (Deco & Kringelbach, 2016). It is defined as either the variance or the standard deviation of Kuramoto Order Parameter, which is bound between [0, 0.272 (var), 0.552 (std)], and takes the mean-field phase into consideration (Shanahan, 2010).

Coalition Diversity (PHM) measures the diversity of the communities that form through synchronization. It is calculated as the variance or the standard deviation of synchronization across all regions at each time point, averaged over the entire scan. Coalition diversity, also sometimes referred to as chimerality or a chimera state (Abrams & Strogatz, 2004), is bounded between [0, 0.272 (var), 0.552 (std)] (Shanahan, 2010).

Dynamical Complexity (LEiDA) measures the balance between integration and segregation of brain regions, and has been proposed as an alternative signature of metastability. It is calculated as the mean variability in the contributions of the brain regions to the overall phase direction. Dynamical complexity is bound between [-1,1], and takes both in-phase and anti-phase alignment into consideration (Hancock et al., 2025).

Dynamical Alignment (PALM) is a measure of the number of regions in anti-phase alignment. It is calculated through spectral decomposition and is measured as the average spectral radius or first eigenvalue of the complete phase alignment matrix over time. It is bound between [$0,N$] where $N$ represents the number of regions in the parcellation (de Alteriis et al., 2024). If statistical relationships rather than phase relationships are used to derive the FC matrix, spectral decomposition will result in $N$ eigenvectors and $N$ eigenmodes. Hence, if the spectral

radius is small, it indicates that the FC matrix has high dimensionality (i.e., only a small amount of variance in the FC matrix is explained by the first eigenvector). However, with phase alignment, there are just 2 eigenvectors and 2 eigenvalues. As a result, the spectral radius returns the number of regions in anti-phase alignment and its mean value across the duration of a scan provides an indication of the extent of regional coordination through anti-phase alignment (de Alteriis et al., 2024).

Dynamical Agility (PALM) measures how frequently the brain switches between different connectivity configurations (i.e., regions in-phase and anti-phase). It is calculated through spectral decomposition and is measured as the standard deviation of the spectral radius or first eigenvalue of the phase alignment matrix. For $N = 116$, it is bound between [0, 63.53] (de Alteriis et al., 2024; Lombardo et al., 2020).

Reconfiguration Speed (PHM) is a measure of the speed of the smooth flow across continually morphing connectivity configurations. It is calculated as the correlation distance between consecutive phase alignment matrices. It is bound between [0,1] (Battaglia et al., 2020).

Ignition Flexibility (PALM) quantifies the variability in the size of ignitions triggered by spontaneous neural activity. When spontaneous activity in one region triggers ignition in others, the extent of ignition is measured as the normalized value of the largest connected component in the adjacency matrix of ignitions bound between [0,1]. The standard deviation of this measure is the ignition variability, and the average of ignition variability over all regions is a measure of dynamical flexibility bound between [0,0.552]. This measure has been proposed as an additional measure of metastability (Alonso Martínez et al., 2020; Deco & Kringelbach, 2017).

Ignition Hierarchy (PALM) measures the spatiotemporal hierarchy of ignition. When spontaneous activity in some brain regions triggers widespread ignition across the brain, while

spontaneous activity in other brain regions does not, the brain dynamics can be characterized as being highly hierarchical. When spontaneous activity in one brain region triggers ignition in other regions, the extent of the ignition is measured as the largest connected component in the adjacency matrix of ignitions bound between [0,1]. The mean of this measure is ignition and the standard deviation across regions is a measure of spatial diversity or ignition hierarchy (Alonso Martínez et al., 2020; Deco & Kringelbach, 2017).

Integration (PALM) measures the brain's capacity to maintain connectivity between different regions. The time-averaged phase alignment matrix is scanned through all possible thresholds ranging from 0 to 1 in increments of 0.01. At each threshold, the matrix is binarized and the size of its largest connected component is calculated. Integration is then calculated as the integral of the size of the largest connected component as a function of the threshold bound between [0,1] (López-González et al., 2021).

Segregation (PALM) measures modularity, reflecting how a system breaks down into distinct subcomponents. The time-averaged phase alignment matrix was binarized for pairs of brain regions with phase alignment > 0.5, and the Louvain algorithm was then applied to subdivide the binary matrix into modules. The Newman modularity (*Q)* of the optimal partition was considered a measure of segregation and it is bound between [0,1] (López-González et al., 2021).

Dynamical Criticality (mean fMRI signal over all regions) measures the system's proximity to edge-of-chaos criticality. This is a modified version of the 0-1 chaos test (K statistic) based on a non-linear transformation of the K statistic. Low values of this measure indicate clearly periodic or clearly chaotic dynamics, while high values indicate dynamics that are neither (Toker et al., 2022). It is bound between [0,1].

Entropy Rate (mean fMRI signal over all regions) is a newer complexity estimator for time series extending Lempel-Ziv (LZ) complexity. The entropy rate measures how many bits of innovation are introduced by each new data sample and is related to how hard it is to predict the next value of a sequence. This normalized LZ, $C_{LZ}$, is a principled, data-efficient estimator of the diversity of the underlying neural process (Mediano et al., 2024). It is bound between [0,1].

Functional Connectivity Dynamics (PALM) captures the spatiotemporal statistics of resting-state activity (E. C. A. Hansen et al., 2015). Our application of this complexity signature is not based on amplitude, however, but on phase-lagged coupling structure over time (Aquino et al., 2022; Pang et al., 2023). This matrix is commonly used to fit computational models to empirical data (Schirner et al., 2022), and the mean is used here as a global metric.

Global Fluidity (PALM) is the standard deviation of the functional connectivity dynamics (FCD). This signature reflects the fluidity of fluctuating internal coalitions (Petkoski et al., 2023). It is bound between [0,0.552].

### *2.11.2 Overview of the Local Signatures of Complexity*

There are several approaches for defining communities for the calculation of local signatures of complexity. These include using anatomical coordinates to assign regions to Resting State Networks (RSNs; Doucet et al., 2019), using Independent Component Analysis (ICA) to extract networks (Hellyer et al., 2015), and using regional phase alignment to extract spatiotemporal modes with k-means clustering (Hancock, Cabral, et al., 2022; Hancock et al., 2023). The first two methods restrict membership of regions to a single network, while the last method allows regions to participate in multiple communities. This approach acknowledges that individual brain regions are not confined to a single community or network, but constantly change their alliances, both spontaneously and in response to a task.

#### *2.11.3 Intra-Mode Complexity Signatures*

Synchronization (PHM), metastability (PHM), dynamical complexity (LEiDA), local dynamical alignment (PALM), and local agility (PALM) are computed for spatiotemporal modes using the same methods as for the global brain network. However, these metrics are calculated either across regions (i.e., synchronization, metastability, dynamical complexity) or across timepoints (i.e., local dynamical alignment, local agility) based on assignment to specific spatiotemporal modes identified through k-means clustering. When calculated over regions, we are investigating the dynamics of the dominant mode. When calculated over timepoints assigned to the dominant mode, we are investigating all regional activity at that timepoint.

#### *2.11.4 Inter-Mode Complexity Signatures*

Occurrence (LEiDA) measures the amount of time a particular spatiotemporal pattern occurred as a fraction of the overall scan, whereas duration (LEiDA) captures the average of all consecutive time periods spent in that pattern (Cabral et al., 2017).

### 2.12 Statistical Analysis

#### *2.12.1 Non-Parametric Statistical Tests*

We investigated whether any of the complexity signatures differed statistically between task and rest, as well as among the flow, boredom, and frustration conditions. To compare these conditions, we used non-parametric repeated measures ANOVA (Friedman test) and 2-sided t-tests (Wilcoxen). This approach was chosen because most distributions were not normally distributed when assessed with a Shapiro test (see Supplementary tables ST2 and ST3).

#### *2.12.2 Linear Regression Modeling*

We sought to explore the explanatory power of complexity signatures in relation to subjects' self-reported measures of flow and enjoyment, as well as behavioral measure of

reaction time. Before running our linear regression models, we removed correlations above 0.7 between the explanatory variables (complexity signatures) to avoid variance inflation due to multicollinearity (see Supplementary Figures SF1-SF3). To find the best-fitting models for explaining flow, enjoyment, and reaction time, we employed stepwise regression. That is, models were built with 1 to *n* non-correlated explanatory variables (complexity signatures). The average prediction error (RMSE) of the *n* best models was then estimated with 10-fold cross-validation with 3 repetitions (Kuhn & Johnson, 2013). The model that minimized the RMSE was selected. Comprehensive results may be found in the Supplementary tables ST4-ST10. Linear modeling was performed with the Caret package (Kuhn, 2008) implemented in R.

**2.13 Software tools**

Parcellation, LEiDA, and all complexity signature calculations were implemented in MATLAB (MATLAB, 2021). Neurosynth functional associations were derived in Python 3.8.5. All other statistical analyses were performed in RStudio Team version 2023.09.1 Build 494.

**2.14 Open Science Practices, Supplemental Information**

This manuscript conducts new analyses on data previously published by Huskey and colleagues (2022), who made the raw functional magnetic resonance imaging data available on OpenNeuro (https://openneuro.org/datasets/ds003358/versions/1.0.0) and the raw self-report and behavioral data are posted to the Open Science Framework (OSF; https://osf.io/bxvhr/). New code was written to analyze these data, which is available on GitHub (https://github.com/franhancock/COMPLEXITY_GLOBAL_AND_LOCAL). Supplemental information referenced in this manuscript are posted to OSF (https://osf.io/f73qm/).

# 3. Results

## 3.1 Global Complexity Signatures

We calculated 15 global signatures of complexity (Table 1), each characterizing different aspects of whole-brain dynamics for four conditions (i.e., flow, boredom, frustration, resting state). A non-parametric Friedman test (for repeated measures) was applied to assess differences between conditions in all 15 complexity signatures. All results were corrected for multiple comparisons using a false discovery rate correction (FDR; Benjamini & Hochberg, 1995; Benjamini & Yekutieli, 2001). Significant differences were found for 11 of the 15 complexity signatures (Figure 1)—though none of the signatures differentiated flow from boredom or frustration.

Nevertheless, several global complexity signatures were able to distinguish task-positive phenomenological experiences (boredom, flow, frustration) from the qualitatively distinctive task-negative state of rest. Notably, entropy rate was the only complexity signature that uniquely differentiated between rest and flow (Figure 1M; $\chi^2(3)$=12.52, $p_{adj}$=0.0058). A post-hoc pairwise comparison indicated that this difference specifically pertained to higher entropy rate values in the flow condition compared to rest ($W$=83, $p_{adj}$=0.002, *effect size*=0.514).

Two additional results are noteworthy, namely the signatures of dynamical alignment (Figure 1E) and global fluidity (Figure 1O). The Friedman test yielded $\chi^2(3)$=10.73, $p_{adj}$=0.013 for dynamical alignment and $\chi^2(3)$=12.56, $p_{adj}$=0.0057 for global fluidity, respectively. Post-hoc pairwise comparison indicated that dynamical alignment was higher in the flow ($W$=142, $p_{adj}$=0.032, *effect size*=0.358) and the frustration conditions ($W$=150, $p_{adj}$=0.032, *effect size*=0.268) than in the rest condition. Global fluidity was also higher in the flow

($W$=117,$p_{adj}$=0.009, *effect size*=0.358) and frustration conditions ($W$=135, $p_{adj}$=0.014, *effect size*=0.297) than during rest.

Finally, there are six instances where all three phenomenological experiences (flow, boredom, frustration) differ significantly from rest: dynamical complexity (Figure 1D), ignition hierarchy (Figure 1H), integration (Figure 1J), segregation (Figure 1K), dynamical criticality (Figure 1L), and global functional connectivity dynamics (Figure 1N). The Friedman test yielded $\chi^2(3)$=25.165, $p_{adj}$<0.001 for dynamical complexity, $\chi^2(3)$=41.48, $p_{adj}$<0.001 for ignition hierarchy, $\chi^2(3)$=50.15, $p_{adj}$<0.0001for integration, $\chi^2(3)$=48.6, $p_{adj}$<0.0001 for segregation, $\chi^2(3)$=62.71, $p_{adj}$<0.0001 for dynamical criticality, and $\chi^2(3)$=41.96, $p_{adj}$<0.0001 for global functional connectivity dynamics. Post-hoc pairwise comparison indicated that dynamical complexity was lower in the flow ($W$=546, $p_{adj}$<0.0001, *effect size*=0.486), boredom ($W$=501, $p_{adj}$<0.0001, *effect size*=0.416), and frustration ($W$=516, $p_{adj}$<0.0001, *effect size*=0.467) conditions than during rest; ignition hierarchy was higher in the flow ($W$=19, $p_{adj}$<0.0001, *effect size*=0.668), boredom ($W$=45, $p_{adj}$<0.0001, *effect size*=0.596), and frustration ($W$=17, $p_{adj}$<0.0001, *effect size*=0.632) conditions than during rest; integration was higher in the flow ($W$=4, $p_{adj}$<0.0001, *effect size*=0.743), boredom ($W$=10, $p_{adj}$<0.0001, *effect size*=0.716), and frustration ($W$=5, $p_{adj}$<0.0001, *effect size*=0.717) conditions than during rest; segregation was lower in the flow ($W$=593, $p_{adj}$<0.0001, *effect size*=0.767), boredom ($W$=582, $p_{adj}$<0.0001, *effect size*=0.707), and frustration ($W$=584, $p_{adj}$<0.0001, *effect size*=0.750) conditions than during rest; dynamical criticality was higher in the flow ($W$=0, $p_{adj}$<0.0001, *effect size*=0.832), boredom ($W$=0, $p_{adj}$<0.0001, *effect size*=0.826), and frustration ($W$=0, $p_{adj}$<0.0001, *effect size*=0.818) conditions than during rest; and global functional connectivity dynamics was higher in the flow

($W$=7, $p_{adj}$<0.0001, *effect size*=0.707), boredom ($W$=15, $p_{adj}$<0.0001, *effect size*=0.666), and frustration ($W$=12, $p_{adj}$<0.0001, *effect size*=0.689) conditions than during rest.

**3.2 Local Complexity Signatures**

Evaluating local complexity signatures enables a more precise and comprehensive interrogation of brain dynamics during boredom, flow, and frustration, complementing our global analyses. In what follows, we first examine these local signatures descriptively, then evaluate them inferentially.

***3.2.1 Extracted Modes, Their Descriptive Characteristics, and Spatiotemporal Properties***

While several different approaches exist for decomposing whole-brain data into local information, we rely on k-means clustering of leading eigenvectors of phase alignment to extract five centroids that correspond to five spatiotemporal modes for each experimental condition. This approach has proven effective for assessing the test-retest reliability of the modes (Hancock, Cabral, et al., 2022), and for classifying psychiatric versus healthy subjects (Hancock et al., 2023). Analytically, Mode 1 is the global mode where all regions are in phase alignment. This global mode enables effective communication and coordination across the whole brain (Cabral et al., 2017; Demirtaş et al., 2019; Hancock, Cabral, et al., 2022; Hancock et al., 2023; Vohryzek et al., 2020). Therefore, we focus on characterizing Modes 2-5.

The top 10% of regional coupling in the extracted modes for the flow, boredom, and frustration conditions are illustrated in Figure 2, with additional color coding indicating the relevant Yeo networks. Qualitatively, we observe that in Mode 2—unlike the flow condition—both boredom and frustration show coupling with Vermis 10 in the cerebellum, a region associated with pain, timing, and coordination (see Neurosynth meta-analysis below). In Mode 3, we see less visual network (VIS) coupling in the frustration condition compared to the flow

condition, and an absence of VIS coupling in the boredom condition. Mode 4 coupling is similar for both the flow and boredom condition, but additional coupling with the VIS and cerebellum regions is visible in the frustration condition. Finally, Mode 5 appears very different across the three conditions. Specifically, in the boredom condition, there is less cerebellum coupling than in the flow or frustration conditions, and the frustration condition shows an absence of dorsal attention network (DAT) and limbic (LBC) coupling.

To gain further insights into the qualitative differences between these modes, for each phenomenological experience, we employed the Neurosynth meta-analysis (Poldrack et al., 2011; Yarkoni et al., 2011) to abstract key psychological concepts during the flow, boredom, and frustration conditions (Figure 3). For all conditions, the mapping revealed that the regions in Mode 2 were related to decision-making, emotions, and anticipation, whereas Mode 3 was associated with movement and working memory in both the flow and frustration conditions, and movement across all three conditions. Mode 4 was associated with attention and memory across all conditions, and emotional regulation in both the flow and boredom conditions, with emotional regulation was less present in the frustration condition. Finally, Mode 5 associations differed across the three conditions. In the flow condition, the main associations were for navigation, coordination, and memory. Although navigation was also associated with Mode 5 in the boredom condition, retrieval and spatial attention replaced coordination and memory. Finally, in the frustration condition, whilst the association with coordination was present, as in the flow condition, navigation and memory were replaced with motor control and movement. Taken together, these descriptive results reveal the cognitive and psychological processes associated with the brain regions that contribute to the spatiotemporal modes for each phenomenological experience.

Finally, we examined the spatiotemporal characteristics of modal sequence for each subject during the flow condition (Figure 4). Results reveal substantial between-participant heterogeneity in modal dominance across time, a result consistent with prior evidence demonstrating highly flexible brain-network organization during flow (Huskey et al., 2022).

### *3.2.2 Inter-Mode Complexity Signatures*

We estimated the inter-mode characteristics of duration and occurrence across the three task conditions. We did not find any statistically significant differences between the conditions for occurrence (Figure 5D). We did however, find that subjects remained longer in Mode 4 during the boredom condition as compared to the frustration condition (Figure 5E, $W = 829$ , $p_{adj} = 0.03$, *effect size*=0.374).

### *3.2.3 Intra-Mode Complexity Signatures*

In addition to the inter-mode signatures of duration and occurrence, we calculated intra-mode complexity signatures of synchronization, metastability, dynamical complexity, dynamical alignment, and dynamical agility. We found significant differences in several complexity signatures in Mode 4. Specifically, there was significantly more dynamical alignment (i.e., increased order) in the flow condition compared to the frustration condition (Figure 5F, $W = 814$, $p = 0.03$, effect size=0.351 ), and in the boredom condition relative to the frustration condition (Figure 5F, $W = 879$, $p = 0.003$, *effect size*=0.448). Dynamical agility (i.e., variability in degree of order) was also significantly higher in the flow condition compared to the frustration condition (Figure 5G, $W = 807$, $p = 0.038$, *effect size*=0.341) and in the boredom condition compared to the frustration condition (Figure 5G, $W = 814$, $p$=0.038, *effect size*=0.351). No other significant differences in the local complexity signatures between the flow and boredom conditions were found (Figure 5A-G).

Notably, our analyses revealed differences in cerebellar phase alignment in Mode 5 during flow, compared to boredom and frustration (Figure 2). Given that the cerebellum was recently theorized to play a critical role in flow (Gold & Ciorciari, 2021), we evaluated differences between boredom, flow, and frustration, within this mode, but restricted to the cerebellum. Post-hoc pairwise comparisons for cerebellum crus1 R ( CB_crus1_R; *Effect size* = 0.39) and cerebellum crus2 R (CB_crus2_R; *Effect size* = 0.228) indicated significantly lower contributions to Mode 5 in the flow condition as compared to the boredom condition (see Figure 5H-I). From a Neurosynth meta-analytical perspective, this indicates reduced contributions from CB regions associated with memory, reading, encoding, semantic, and autobiographical memory when Mode 5 was dominant (see Supplementary figure SF4 for all comparisons).

**3.3 Examining Brain-Self-Report and Brain-Behavioral Relationships**

Explanatory data analysis was used to capture relationships between complexity signatures and cerebellar contributions to the self-report (i.e., flow, enjoyment) and behavioral (i.e., reaction time) scores in the flow, boredom, and frustration conditions. Linear regression models were constructed separately for the global and local signatures, as well as cerebellar contributions. Our rationale was aimed at identifying differences between the conditions that could potentially disambiguate brain dynamics during flow, boredom, and frustration. Results are summarized in Table 2, whereas comprehensive model results may be found in the Supplementary tables ST3-9. Models that produced the highest coefficient of variation for each score type in each condition are reported below.

### *3.3.1 Best Explanatory Models in the Flow Condition*

**Flow**. The best model explained 19% (16% adj, $p = 0.011$) of the variance in flow scores. Entropy rate made a statistically significant contribution to the model, such that for any unit decrease in entropy rate, the model explained higher flow scores.

**Enjoyment.** The best model explained 15% (12% adj., $p = 0.026$) of the variance in enjoyment scores. Dynamical agility in Mode 5 was the complexity signature that made a statistically significant contribution to the model. For any unit increase in dynamical agility, the model explained higher enjoyment scores.

**Reaction time.** The best model explained 14% (11% adj., $p =0.029$) of the variance in secondary task reaction times. Dynamical complexity in Mode 2 was the complexity signature that made a statistically significant contribution to the model. For any unit decrease in dynamical complexity, the model explained longer reaction time scores.

### *3.3.2 Best Explanatory Models in the Boredom Condition*

**Flow**. The best model explained 44% (34% adj., $p = 0.004$) of the variance in flow scores. Synchronization and metastability in Mode 3 made statistically significant contributions: while holding dynamical complexity, duration, and dynamical agility constant, higher flow scores were associated with decreased synchronization and increased metastability.

**Enjoyment**. The best model explained 38% (32% adj., $p = 0.002$) of the variance in enjoyment scores. Synchronization and metastability in Mode 3 made statistically significant contributions to the model. When holding dynamical agility constant, the model explained higher scores for enjoyment for any unit decrease in synchronization or any unit increase in metastability.

**Reaction time**. The best model explained 36% (32% adj., $p = 0.001$) of the variance in secondary task reaction time. Cerebellum 3 R (CB_3_R) and cerebellum 8 R (CB_8_R) contributions in Mode 5 were statistically significant terms, such that the model explained fast reaction times for any unit decrease in CB_3_R contributions or any unit increase in CB_8_R contributions.

#### *3.3.3 Best Explanatory Models in the Frustration Condition*

**Flow**. The best model explained 29% (27% adj., $p = 0.001$) of the variance in flow scores. CB_3_R contributions in Mode 5 made a statistically significant contribution to the model such that, for any unit increase in CB_3_R contributions, the model explained higher flow scores.

**Enjoyment.** The best model explained 44% (38% adj., $p = 0.001$) of the variance in enjoyment scores. Synchronization and metastability in Mode 2 made statistically significant contributions to the model. When holding dynamical agility constant, the model explained higher scores for enjoyment for any unit decrease in synchronization or any unit increase in metastability.

**Reaction time.** The best model explained 40% (34% adj., $p = 0.002$) of the variance in secondary task reaction time. Cerebellum 7b R (CB_7b_R) and cerebellum 8 L (CB_8_L) contributions in Mode 5 were statistically significant terms in the model such that when holding cerebellum 3 L (CB_3_L) contributions constant, the model explained fast reaction times for any unit decrease in CB_7b_R contributions or any unit increase in CB_8_L contributions.

### 3.4 Examining Hypo-Frontality

The regions of the dorsolateral prefrontal cortex (DLPFC) are, unfortunately, not clearly defined in MNI coordinates (Pàmies-Vilà et al., 2023). We used the study of Limb & Braun

(2008) who documented MNI coordinates for the bilateral medial DLPFC, lateral DLPFC, and superior DLPFC, to map the DLPFC to AAL116 regions. We identified bilateral Frontal Mid (middle frontal gyrus) and Frontal Inf Tri Right (inferior frontal gyrus, triangular part) as the AAL116 atlas equivalents. Inspecting Mode 3 and Mode 4, we found that bilateral Frontal Mid was absent in Mode 3 but present in Mode 4 for the flow condition, and absent in Mode 3 but Frontal Mid R was present in Mode 4 for the boredom condition (see Table 3 and Figure 6). Frontal Inf Tri Right was absent in Mode 3 but present in Mode 4 in the flow condition. This region was present in both Mode 3 and Mode 4 in the boredom condition.

It appears that in the flow condition, hypo-frontality of subregions of the DLPFC exists during periods when Mode 3 is dominant (i.e., during periods associated with movement). The DLPFC, however, contributes to phase alignment in the flow condition when Mode 4 is dominant (i.e., during periods associated with attention).

## 4. Discussion

To date, the exploration of the neural dynamics of flow has been dominated by reductive (i.e., locationist, connectionist) theories. A complexity science approach, however, captures the multiple and interacting cognitive processes that underlie the flow experience, and offers a perspective the locationist and connectionist paradigms cannot provide. This study extends flow research in this direction by applying a battery of complex systems analyses to characterize three phenomenological experiences: flow, boredom and frustration. More specifically, we analysed the differences between complexity signatures at the global and local (mode) level across four conditions, and explored the explanatory power of 15 global and 7 local signatures, as well as the contributions of 18 cerebellar regions for self-reported and behavioral scores. Our results add nuance to, and in some cases challenge, existing neural models of flow.

## 4.1 The Neural Complexity Signatures of Flow

Our results revealed that entropy rate during the flow condition was higher than at rest. Neither the boredom nor frustration conditions showed this difference. Interestingly, we found commonalities in several complexity signatures between the flow and frustration conditions, and flow and boredom conditions. At a global level, dynamical alignment and global fluidity were higher in the flow and frustration than at rest. This indicates that both conditions demonstrate a higher degree of regional coordination, and fluidity of configuration change, than the rest condition. Additionally, we found that in Mode 4, dynamical alignment and dynamical agility were higher in both the flow and boredom conditions than the frustration condition. This implies that, at the Mode 4 level, both the flow and boredom conditions demonstrate a higher degree of regional coordination and configuration switching than the frustration condition.

Understanding which of the 22 signatures of complexity and 18 cerebellar regions best explained the self-reported and behavioral measures, we developed several linear regression models. The best-performing models revealed 6 signatures and 3 cerebellar combinations that were sufficient to explain subjective and behavioral measures across all task conditions, including: entropy rate, synchronization, metastability, dynamical agility, dynamical complexity, and phase alignment contributions from 4 cerebellar regions. We discuss these results in greater detail, below.

### *4.1.1 Entropy Rate*

The finding that self-reported flow was negatively related to entropy rate was surprising. Prior research notes that flow is an altered state of consciousness that may share some neural dynamics commonalities with other altered states such as the psychedelic state (Kotler et al., 2022). Increases in entropy rate have been associated with a variety of altered states of

consciousness (Mediano et al., 2024; Vivot et al., 2020) including, during the acute psychedelic experience (Schartner et al., 2017; Timmermann et al., 2019), meditation (Vivot et al., 2020), and music improvision (Dolan et al., 2018). Entropy rate has also been shown to increase during task performance, and, notably, elevated entropy rate, as reported by Dolan et al. (2018) and Rosen et al. (2024), has been linked to subjective experiences of "creative flow" during music improvisation. This interpretation aligns with evidence that higher entropy states are perceived as subjectively *richer* experiences (Bonnelle et al., 2024; Carhart-Harris, 2018). Given the nature of the presently used tasks, our results suggest a potential distinction between flow states occurring during highly creative tasks where higher entropy rate is conducive to flow, and those occurring during less-creative tasks (as in the present case) where higher entropy rate is detrimental to flow.

One limitation of our project is that it was not well-suited to investigate linkages between entropy rate and objective task performance during flow. Addressing this issue remains an important direction for future research. Nevertheless, these results also point to new avenues for future research, particularly efforts to understand the impact of pharmacological interventions on flow. Of note, the ability for psychedelics to increase entropy rate (Schartner et al., 2017; Timmermann et al., 2019) appears sensitive to the inclusion of a task. For instance, Mediano and colleagues (2024) show that the LSD vs. placebo difference in Lempel-Ziv entropy is greatest with eyes-closed rest and progressively attenuated by listening to music, followed by eyes-open rest, and then followed by silent video viewing. In related work, a separate study administered low-dose psilocybin (so-called "microdoses") and did not find increases in the experience of flow, creativity, or entropy rate (Cavanna et al., 2022). Together, these studies suggest that both dose and task modulate the entropic brain and its experiential correlates (Carhart-Harris, 2018;

Carhart-Harris et al., 2014). Based on our results, we could speculate that psychedelic usage would enhance creative flow experiences such as music improvisation, but might inhibit non-creative flow experiences such as solving simple arithmetic problems (for a discussion, see e.g., van der Linden et al., 2021).

#### *4.1.2 Synchronization and Metastability*

Synchronization between brain networks (i.e., attention and reward, fronto-parietal and reward) has been proposed to underlie the flow experience (Huskey et al., 2018; Weber et al., 2009), and more recent theorizing has speculated that metastable brain dynamics may underlie flow (Kotler et al., 2022). Network neuroscience results supporting these hypotheses are mixed, and appear dependent on, among other things, analytical approach. When examined in the time domain, averaged across task, and linearly modeled using psychophysiological interaction analysis (PPI; Friston et al., 1997), it appears that flow is associated with functional connections between the nucleus accumbens (ventral striatum) and dorsolateral prefrontal cortex (Huskey et al., 2018). However, more recent work using instantaneous phase analyses shows that both synchronous and metastable connections between fronto-parietal and reward networks are lowest during flow, particularly when compared to frustration (Huskey et al., 2022).[3]

In this analysis, we find more complicated results linking connectivity between subcortical reward structures and attentional/fronto-parietal structures. In Mode 2, we observe connectivity between the bilateral caudate nucleus (dorsal striatum) and left cingulum mid (ventral attention), although we note that this connection is observed across all three conditions,

[3] We remind readers that the current manuscript re-analyzes a dataset previously reported in Huskey et al., (2022). That project also evaluated global signatures of synchrony and metastability using a slightly different data cleaning technique and analytical pipeline. Nevertheless, global synchrony and metastability results reported in that manuscript (i.e., Table 3 in Huskey et al., 2022) are largely aligned with the findings reported in this manuscript (i.e., Figure 1). We take this as evidence that this (null) result at the global level is not sensitive to analytical approach.

therefore it does not appear unique to flow (see Supplementary figures SF5-SF7). Additionally, in Mode 2, the bilateral caudate (dorsal striatum) is broadly connected with the default mode network, limbic system, and ventral attention network for flow, boredom, and frustration. Similarly, in Mode 3, the right pallidum (basal ganglia) shows widespread connectivity with ventral attention, visual, somatomotor, and frontal-parietal structures for both flow and boredom. In Mode 3, we also see that the right putamen (dorsal striatum) shows widespread connectivity with dorsal and ventral attention, visual, somatomotor, and frontal-parietal structures for flow, boredom, and frustration. These findings demonstrate that connectivity between fronto-parietal and reward, or attention and reward networks is associated with, but not unique to, flow. This undermines a core premise of synchronization theory (Weber et al., 2009).

Similarly, when examining brain-phenomenology (i.e., self-report) or brain-behavior (i.e., reaction time) relationships, we do not see evidence that synchrony or metastability explains variance in phenomenology or behavior during the flow condition. Instead, and surprisingly, our linear regression models show that Mode 3 synchronization is detrimental to both flow and enjoyment during the boredom condition. By comparison, increases in Mode 3 metastability are associated with increased flow and enjoyment. For the frustration condition, we find that Mode 2 decreases in synchronization are associated with increased enjoyment, whereas increases in metastability contribute positively to enjoyment. It is important to contextualize these relationships between phenomenology across conditions. Self-reported flow and enjoyment are highest in the flow condition, followed by the boredom and then frustration conditions (see Table 2 in Huskey et al., 2023). The implication is that synchrony and metastability only explain variance in phenomenology during conditions that do not elicit high levels of flow; a finding that

undermines theories that strongly implicate synchrony (Weber et al., 2009) or metastability (Kotler et al., 2022) in flow.

Nevertheless, the complexity signature patterns observed in the boredom and frustration conditions raise intriguing questions. Both synchronization and metastability explain flow and enjoyment in these states, but the Modes engaged were distinct. In boredom, both synchronous and metastable signatures were associated with flow and enjoyment specifically in Mode 3—a pattern linked to movement, working memory, and response inhibition. This may reflect the fact that, although participants reported boredom, they remained engaged in the task with a high degree of self-control, enabling seamless cognitive control. Flow has been linked to reward-modulated cognitive control (Huskey et al., 2018), and this condition may have offered just enough demand to generate a subjectively enjoyable experience, even if that experience was less enjoyable than the flow condition. Although the negative relationship we observe stands in contrast to prior work showing that increased functional connectivity between the caudate and orbitofrontal cortex (connections we observed in Mode 2 for boredom and flow) is associated with increases in self-reported pleasure (Y. Wang et al., 2023).

Frustration, alternatively, was characterized by synchronization and metastability in Mode 2, a mode associated with emotion, decision making, and anticipation. The frustration condition may be eliciting low flow and enjoyment scores via Mode 2, possibly because of its highly-arousing and negatively valenced nature, which may require participant's active emotional regulation in order to maintain affective control. This result may be in line with prior work linking flow with the biopsychosocial model of challenge and threat (Blascovich, 2008), which demonstrates that task challenges that exceed participant skills elicit physiological signatures of threat, and low self-reported flow (Scheepers & Keller, 2022).

Overall, this pattern of results suggests that synchrony and metastability may play more important roles in the phenomenological experiences of boredom and frustration, relative to flow. Future research may more carefully interrogate the positive relationship between metastability and phenomenological markers during conditions of boredom or frustration. Notably, these phenomenological experiences are often experienced as aversive (K. A. Mathiak et al., 2013; Scheepers & Keller, 2022; Westgate, 2020). It could be that metastable brain dynamics that facilitate flexibility in neural coupling (Tognoli & Kelso, 2014) help prepare the brain to transition out of (rather than being locked into) these aversive experiences.

#### *4.1.3 Dynamical Agility & Complexity*

We previously noted that entropy rate explained variance in self-reported flow during the flow condition. As a convergent validity measure, we also evaluated self-reported enjoyment. The best explanatory model for self-reported enjoyment in the flow condition included dynamical agility in Mode 5 such that increases in dynamical agility were associated with increases in enjoyment. Switching between brain-network configurations with different dynamic alignment reflects the brain's flexibility to form coalitions of varying sizes (de Alteriis et al., 2024; Lombardo et al., 2020). This reconfiguration may help facilitate shifting functional demands of flow-inducing tasks; in our case, playing a video game. Indeed, prior research shows that flexibly organized function brain networks (i.e., connectivity between nodes reconfigures during task) are implicated in the successful deployment of cognitive control (Cole et al., 2013) as well as flow (Huskey et al., 2022).

At the whole-brain level, we see that dynamical complexity is lowest—an indicator of increased integration (Hancock et al., 2023)—in the flow condition (Supplementary Figure SF8), although this is only statistically different from rest. Similarly, our explanatory modeling shows

that, in the flow condition, longer reaction times are associated with decreases in dynamical complexity in Mode 2. Previous research shows that longer reaction times to task-irrelevant audiovisual probes are a behavioral correlate of flow (Huskey et al., 2018, 2022). The rationale draws on the relationship between attentional capacity limitations and motivation (Fisher, Huskey, et al., 2018; Fisher, Keene, et al., 2018; Lang, 2006). Briefly, if a task is highly motivating and has high attentional demand (e.g., it elicits flow), then people will focus their attention on that task, which should slow reaction times to task-irrelevant stimuli (in our case, an audiovisual probe).

How then might we understand the dynamical complexity results? Remember that Mode 2 was associated with emotion, anticipation, and decision-making. As connectivity within Mode 2 becomes more integrated, it may become more difficult to interrupt in order to switch to other modes implicating movement, attention, and coordination (Modes 3, 4, and 5, respectively), and respond to a secondary task. Simply put, when emotions and decisions are tightly coupled, redirecting attention to a new stimulus in the gaming environment may take longer and require greater cognitive effort. Our efforts to examine this (e.g., Figure 4) showcase substantial heterogeneity in switches between modes for each participant during task. This appears, at least partially, explained by changes in game difficulty over time. Future research might resolve this issue by more carefully annotating the gameplay dynamics, and linking them with brain dynamics (Schmälzle & Huskey, 2023a).

More broadly, these findings offer a new perspective on theories implicating either synchrony (Weber et al., 2009) or metastability in flow experiences (Kotler et al., 2022), notably one that is only possible thanks to new perspectives on complex signatures of brain dynamics (Hancock et al., 2025). Synchronization is estimated as a ‘mean-field’ variable—in-phase values

cancel out anti-phase values—which results in the loss of information captured by the anti-phase values. A high estimate for synchronization implies that a set of brain regions are trapped in a phase and frequency locked state—a state of absolute coordination (Hancock et al., 2025; Kelso, 1995). The variability of this synchronization has been proposed to estimate metastability (Shanahan, 2010).

In contrast, metastable dynamics refer to patterns of transient coordination, where brain regions that are 'almost in sync' intermittently lose and regain synchrony before shifting into new, similarly coordinated configurations (Hancock et al., 2025; Kelso, 1995). Metastability captures the brain's simultaneous tendencies toward both integration—where subsets of regions transiently couple to support specific functions—and segregation—where other regions remain functionally independent. Synchronization implies a strongly integrated configuration and metastability, as in Shanahan (2010), reflects the stability or lack of flexibility of this configuration. This balance between integration and segregation can be quantified using measures of dynamical complexity (Hancock, 2025). In our case, the dynamical complexity results clarify the inherent tension between previous complexity explanations for flow (i.e., synchronization, metastability)—that is, both signatures are estimated from a mean phase (mean-field phase) which cancels out the contribution of of regions that are in anti-phase alignment, our modes—the exact communities that are of interest during rest or task. In contrast, dynamical complexity captures the simultaneous tendency for integration and segregation both at whole brain level and in the modes, that is, metastability as defined by Kelso (Kelso, 1995; Hancock et al., 2025), and we have shown that the tendency for integration in a specific mode is higher during flow.

#### *4.1.4 Cerebellar Phase Alignment*

Across conditions, cerebellar phase alignment was most prevalent in Mode 5. Our findings are in line with previous literature that strongly implicates the cerebellum in flow (Gold & Ciorciari, 2021). The cerebellum is known to play a key role in fine-tuning motor-movements (Ito, 2008) that are necessary during flow-inducing tasks (e.g., like playing a video game). Consistent with this finding, our analysis demonstrates that Mode 5 during flow is characterized by brain regions involved in navigation and coordination. More broadly, the cerebellum uses predictive sequencing and a feed-forward movement loop to compare predicted motor command patterns to learned environmental responses (Wolpert et al., 1998), which helps explain why the cerebellum contributes the most to Mode 5.

We observed less cerebellar contribution in the flow condition compared to both the boredom and frustration conditions. This is evidence against theorizing (Gold & Ciorciari, 2021) that strongly implicates the cerebellum in flow. In fact, cerebellar involvement was lowest during flow, followed by boredom, with frustration showing the highest levels. Given the cerebellum's role in refining motor behavior for successful task execution (Molinari et al., 2008), this pattern is consistent with the phenomenology of flow—an experience marked by perceived effortlessness. When in flow, individuals often feel they are performing with minimal conscious effort. The reduced cerebellar phase alignment during flow may reflect diminished demands on motor control and spatial navigation relative to the other conditions. As the motor or navigational demands of the task vary, cerebellar activation may scale accordingly.

### 4.2 The Utility of a Complexity Science Approach

Within the framework of complexity science, we found that 1 (i.e., entropy rate) out of 15 global, and 2 (i.e., dynamical alignment, dynamical agility, both in Mode 4) out of 7 local

complexity signatures distinguished flow from other phenomenological experiences. These results were further refined in our brain-phenomenology analyses that linked complexity signatures with self-reported flow. This point is particularly worth emphasizing as few papers explicitly link brain response to phenomenological experience (a longstanding limitation in this research area). In doing so, we gain new insights into the brain-network dynamics associated with flow. More broadly, these results support not only the dynamic nature of brain functioning, but also reject both locationist and simple connectionist models of brain function (for an extended argument, see Noble et al., 2024) by recognizing that individual brain regions repeatedly align to form a set of communities (modes) rather than exclusively belonging to a single network. This means that the contribution of each brain region within a mode changes over time, thereby enabling endless configurations both spontaneously (Hancock, Cabral, et al., 2022; Hancock et al., 2023) and now, in response to a task.

**4.3 Implications for Theories of Flow**

Our findings challenge and extend existing theories of flow by demonstrating that no single, localized brain structure or connectionist model can fully account for the complexity of this phenomenological experience. Prior models of flow have emphasized mechanisms such as prefrontal deactivation (Dietrich, 2004), synchronization of attentional and reward networks (Weber et al., 2009), or cerebellar contributions to internal models of motor control (Gold & Ciorciari, 2021). Our results, however, show that these accounts capture only fragments of the full picture. By applying complexity metrics to whole-brain dynamics, we reveal that flow involves a distributed, metastable coordination of neural processes that cannot be reduced to static network configurations or regional activity patterns. This suggests that existing models

might benefit from integration under a broader framework that explicitly incorporates the nonlinear, emergent properties of the brain as a complex system.

The complexity science perspective also offers a way to reconcile apparent contradictions across prior studies of flow. For example, while some studies have emphasized localized hypo-frontality as central to flow, our data indicate that prefrontal contributions fluctuate dynamically depending on the dominant spatiotemporal mode. Similarly, rather than supporting rigid synchronization between specific networks, our results point to dynamical complexity and dynamical agility as key features of flow, enabling the brain to flexibly navigate between configurations suited to the task at hand. This fluidity may help explain why flow appears across such a wide range of activities, from athletic performance to creative work, each requiring different constellations of cognitive, affective, and sensorimotor dynamics. In this way, complexity metrics provide a unifying lens that can accommodate the diversity of empirical findings on flow.

Finally, our work highlights the potential of complexity science to advance a more neurophenomenological account of flow—one that directly links subjective experience with the dynamic interplay of large-scale brain systems. By capturing the temporal evolution of neural coordination patterns, complexity metrics move us closer to characterizing how the felt sense of effortlessness, absorption, and intrinsic reward in flow arises from underlying brain dynamics. This opens the door for future studies to more precisely map individual variations in flow experience to distinct patterns of brain organization and to explore how these dynamics shift across different contexts and forms of expertise. Ultimately, such an approach can help bridge gaps between theory, phenomenology, and neuroscience in the study of flow.

**4.4 Limitations**

The results reported within this manuscript represent a novel analysis of a pre-existing dataset (Huskey et al., 2022). Limitations associated with the dataset and experimental procedure are already well-discussed in that previous publication. We have also noted additional limitations in various subsections of this manuscript's discussion section. Nevertheless, our new analyses introduce new limitations deserving of consideration. Notably, the myriad of complexity signatures in the neuroimaging literature may actually be limiting for their use. Many are correlated, and as demonstrated here, not all are sensitive to phenomenological or behavioral experiences. However, different signatures have been shown to be sensitive to aging populations, neo-natals, psychiatric conditions, and neurodegenerative disorders (see Hancock et al., 2025 for a review). Although it is relatively easy to estimate the signatures when, as here, the code is provided, it may be more challenging to conceptually understand the signatures and interpret the results appropriately. Moreover, we examined a vast array of complexity signatures in a data driven (rather than a priori) way. Although we took careful analytical steps to minimize the chance of false positive results, it is still important to understand these as exploratory findings requiring subsequent confirmation in a new, preferably preregistered, project (Dienlin et al., 2021).

Finally, our analysis relies on the AAL anatomical parcellation to define regions of interest. This is a deviation from prior work on this dataset that has used an atlas defined by Seitzman and colleagues (2020). This decision was made to allow for more direct comparisons with other work using measures drawn from complexity science (e.g., Hancock, Cabral, et al., 2022; Hancock et al., 2023), although this makes comparison with prior flow research more difficult. To bridge this gap, we worked to landmark commonalities between atlases. We also

note that, at a global level, measures of synchrony and metastability yield common results for both the AAL and Seitzman atlas. Nevertheless, prior work shows that some network measures are sensitive to atlas (Craddock et al., 2012; Fisher et al., 2021), and therefore future work might seek to examine these results across a multitude of atlases (Kong et al., 2025), being sure to use those that include cortical, subcortical, and cerebellar nodes (as is true for both the AAL and Seitzman atlases).

## 5. Conclusion: Flow, Media, and Wellbeing

Flow is an intrinsically rewarding and attentionally absorbing phenomenological experience that is linked with a wide variety of wellbeing outcomes (Csikszentmihalyi, 1990). In a TED talk that has attracted more than 7.8 million views, Csikszentmihalyi calls flow "the secret to happiness" (Csikszentmihalyi, 2004). A vast array of daily activities can elicit flow, including media use (Sherry, 2004), although not all media are likely to elicit flow. Low-challenge and passive media (e.g., TV viewing) rarely elicit flow, whereas as interactive media that elicit high challenge and demand high levels of player skill (e.g., video games) are much more likely to elicit flow and corresponding increases in wellbeing (for an extended discussion, see Kubey & Csikszentmihályi, 1990). Our study uses a video game to examine brain dynamics during flow. In doing so, we observe a complex system characterized by efficient information dynamics (entropy rate), rapid brain-network reconfiguration (dynamical agility), and balanced integration and segregation (dynamical complexity). Critically, these brain dynamics also explain variance in flow, enjoyment, and behavior, respectively. Accordingly, we gain new insights into the ways media elicit flow, brain dynamics during flow, and linkages with wellbeing outcomes.

At the same time, we consider our work in light of high-quality evidence demonstrating that flow can be elicited from low-difficulty tasks (Melnikoff et al., 2022, 2025). This

substantially contradicts long-standing theorizing that a balance between task-difficulty and individual skill is a causal precursor of flow (Csikszentmihalyi, 1990)—a theoretical framework that motivated our study design. These findings raise important questions. If flow can be elicited during low-difficulty tasks, is it flow, or more active (compared to passive) and difficult (compared to easy) media that are required for wellbeing outcomes? Considering recent findings demonstrating that high-effort tasks are perceived as valuable (Inzlicht et al., 2018) and elicit increases in wellbeing (Campbell et al., 2025), and the uncertain causal pathway between task→flow→wellbeing outcomes (Huskey & Schmälzle, 2025), it is unclear if it is flow or effort during media use that elicits wellbeing. Answering this question will help explain results showing that time (overall) spent playing video games is associated with either no (Vuorre et al., 2022) or modest increases in wellbeing (Johannes et al., 2021). Ultimately, clarifying these relationships will require careful experimentation capable of elucidating explanation at multiple levels (Huskey et al., 2020; Schmälzle & Huskey, 2023b).

Finally, there are substantial concerns about media, particularly video games, and linkages with video gaming disorder, a behavioral addiction (Weber et al., 2016; Woodman & Weber, 2025). Some evidence suggests that experiencing flow while playing video games may be a precursor to gaming disorder (Hull et al., 2013; Tokunaga, 2013), although the evidence for this claim is fairly limited (P. T. Wang et al., 2023; Weber et al., 2016). Regrettably, our study offers limited insight into this as our design is not longitudinal, and only includes healthy participants. Although, preliminary evidence demonstrates clear differences in complexity signatures between healthy and addicted video game players during passive (resting state) and active (working memory) tasks (Hosseini et al., 2021). Therefore, it seems likely that individuals

experiencing gaming disorder would show different complexity signatures than the ones we observed. Fully addressing this question remains an important direction for future research.

## 6. Author Contributions

**Fran Hancock:** Conceptualization; Formal analysis; Methodology; Software; Visualization; Writing - original draft; Writing - review and editing

**Rachael Kee:** Writing - review and editing

**Fernando Rosas:** Writing - review and editing

**Manesh Girn:** Writing - review and editing

**Steven Kotler:** Writing - review and editing

**Michael Maninno:** Writing - review and editing

**Richard Huskey:** Conceptualization, Data Curation, Investigation, Writing - original draft, Writing - review and editing

All authors participated in the discussion of the ideas, read and approved the submitted version.

### 6.1 Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## 7. References

Abrams, D. M., & Strogatz, S. H. (2004). Chimera States for Coupled Oscillators. *Physical Review Letters*, *93*(17), 174102. https://doi.org/10.1103/PhysRevLett.93.174102

Alonso Martínez, S., Marsman, J.-B. C., Kringelbach, M. L., Deco, G., & ter Horst, G. J. (2020). Reduced spatiotemporal brain dynamics are associated with increased depressive symptoms after a relationship breakup. *NeuroImage: Clinical*, *27*, 102299. https://doi.org/10.1016/j.nicl.2020.102299

Aquino, K. M., Fulcher, B., Oldham, S., Parkes, L., Gollo, L., Deco, G., & Fornito, A. (2022). On the intersection between data quality and dynamical modelling of large-scale fMRI signals. *NeuroImage*, *256*, 119051. https://doi.org/10.1016/j.neuroimage.2022.119051

Barrett, L. F. (2017). *How Emotions Are Made: The Secret Life of the Brain*. HarperCollins.

Bassett, D. S., & Gazzaniga, M. S. (2011). Understanding complexity in the human brain. *Trends in Cognitive Sciences*, *15*(5), 200–209. https://doi.org/10.1016/j.tics.2011.03.006

Battaglia, D., Boudou, T., Hansen, E. C. A., Lombardo, D., Chettouf, S., Daffertshofer, A., McIntosh, A. R., Zimmermann, J., Ritter, P., & Jirsa, V. (2020). Dynamic Functional Connectivity between order and randomness and its evolution across the human adult lifespan. *NeuroImage*, *222*, 117156. https://doi.org/10.1016/j.neuroimage.2020.117156

Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, *57*(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Benjamini, Y., & Yekutieli, D. (2001). The Control of the False Discovery Rate in Multiple Testing under Dependency. *The Annals of Statistics*, *29*(4), 1165–1188.

Bernecker, K., & Becker, D. (2021). Beyond Self-Control: Mechanisms of Hedonic Goal Pursuit

and Its Relevance for Well-Being: *Personality and Social Psychology Bulletin*, *47*(4), 627–642. https://doi.org/10.1177/0146167220941998

Blascovich, J. (2008). Challenge, threat, and health. In *Handbook of motivation science* (pp. 481–493). The Guilford Press.

Bonnelle, V., Feilding, A., Rosas, F. E., Nutt, D. J., Carhart-Harris, R. L., & Timmermann, C. (2024). Autonomic nervous system activity correlates with peak experiences induced by DMT and predicts increases in well-being. *Journal of Psychopharmacology*, *38*(10), 887–896. https://doi.org/10.1177/02698811241276788

Bowman, N. D., Weber, R., Tamborini, R., & Sherry, J. (2013). Facilitating game play: How others affect performance at and enjoyment of video games. *Media Psychology*, *16*(1), 39–64. https://doi.org/10.1080/15213269.2012.742360

Cabral, J., Vidaurre, D., Marques, P., Magalhães, R., Silva Moreira, P., Miguel Soares, J., Deco, G., Sousa, N., & Kringelbach, M. L. (2017). Cognitive performance in healthy older adults relates to spontaneous switching between states of functional connectivity during rest. *Scientific Reports*, *7*(1), 5135. https://doi.org/10.1038/s41598-017-05425-7

Cacioppo, J. T., Gardner, W. L., & Berntson, G. G. (1999). The affect system has parallel and integrative processing components: Form follows function. *Journal of Personality and Social Psychology*, *76*(5), 839–855. https://doi.org/10.1037/0022-3514.76.5.839

Calcagnotto, L., Huskey, R., & Kosicki, G. M. (2021). The Accuracy and Precision of Measurement: Tools for Validating Reaction Time Stimuli. *Computational Communication Research*, *3*(2), 133–151. https://doi.org/10.5117/CCr2021.2.001.CALC

Campbell, A. V., Wang, Y., & Inzlicht, M. (2025). Experimental evidence that exerting effort increases meaning. *Cognition*, *257*, 106065.

https://doi.org/10.1016/j.cognition.2025.106065

Carhart-Harris, R. L. (2018). The entropic brain—Revisited. *Neuropharmacology*, *142*, 167–178. https://doi.org/10.1016/j.neuropharm.2018.03.010

Carhart-Harris, R. L., & Friston, K. J. (2019). REBUS and the Anarchic Brain: Toward a Unified Model of the Brain Action of Psychedelicss. *Pharmacological Reviews*, *71*(3), 316–344. https://doi.org/10.1124/pr.118.017160

Carhart-Harris, R. L., Leech, R., Hellyer, P. J., Shanahan, M., Feilding, A., Tagliazucchi, E., Chialvo, D. R., & Nutt, D. (2014). The entropic brain: A theory of conscious states informed by neuroimaging research with psychedelic drugs. *Frontiers in Human Neuroscience*, *8*. https://doi.org/10.3389/fnhum.2014.00020

Carson, J. R. (1922). The Heaviside operational calculus. *The Bell System Technical Journal*, *1*(2), 43–55. https://doi.org/10.1002/j.1538-7305.1922.tb00388.x

Cavanna, F., Muller, S., de la Fuente, L. A., Zamberlan, F., Palmucci, M., Janeckova, L., Kuchar, M., Pallavicini, C., & Tagliazucchi, E. (2022). Microdosing with psilocybin mushrooms: A double-blind placebo-controlled study. *Translational Psychiatry*, *12*(1), 307. https://doi.org/10.1038/s41398-022-02039-0

Chiang, Y.-T., Lin, S. S. J., Cheng, C.-Y., & Liu, E. Z.-F. (2011). Exploring Online Game Players' Flow Experiences and Positive Affect. *Turkish Online Journal of Educational Technology - TOJET*, *10*(1), 106–114.

Ciric, R., Rosen, A. F. G., Erus, G., Cieslak, M., Adebimpe, A., Cook, P. A., Bassett, D. S., Davatzikos, C., Wolf, D. H., & Satterthwaite, T. D. (2018). Mitigating head motion artifact in functional connectivity MRI. *Nature Protocols*, *13*(12), 2801–2826. https://doi.org/10.1038/s41596-018-0065-y

Cole, M. W., Reynolds, J. R., Power, J. D., Repovs, G., Anticevic, A., & Braver, T. S. (2013). Multi-task connectivity reveals flexible hubs for adaptive task control. *Nature Neuroscience*, *16*(9), 1348–1355. https://doi.org/10.1038/nn.3470

Craddock, R. C., James, G. A., Holtzheimer, P. E., Hu, X. P., & Mayberg, H. S. (2012). A whole brain fMRI atlas generated via spatially constrained spectral clustering. *Human Brain Mapping*, *33*(8), 1914–1928. https://doi.org/10.1002/hbm.21333

Csikszentmihalyi, M. (1975). *Beyond boredom and anxiety: The experience of play in work and games*. Jossey-Bass, Inc.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. HarperCollins Publishers.

Csikszentmihalyi, M. (Director). (2004, February). *Flow, the secret to happiness* [Video]. https://www.ted.com/talks/mihaly_csikszentmihalyi_flow_the_secret_to_happiness

Davison, E. N., Schlesinger, K. J., Bassett, D. S., Lynall, M.-E., Miller, M. B., Grafton, S. T., & Carlson, J. M. (2015). Brain network adaptability across task states. *PLoS Computational Biology*, *11*(1), e1004029. https://doi.org/10.1371/journal.pcbi.1004029

de Alteriis, G., MacNicol, E., Hancock, F., Ciaramella, A., Cash, D., Expert, P., & Turkheimer, F. E. (2024). EiDA: A lossless approach for dynamic functional connectivity; application to fMRI data of a model of ageing. *Imaging Neuroscience*, *2*, 1–22. https://doi.org/10.1162/imag_a_00113

Deco, G., & Kringelbach, M. L. (2016). Metastability and Coherence: Extending the Communication through Coherence Hypothesis Using A Whole-Brain Computational Perspective. *Trends in Neurosciences*, *39*(3), 125–135. https://doi.org/10.1016/j.tins.2016.01.001

Deco, G., & Kringelbach, M. L. (2017). Hierarchy of Information Processing in the Brain: A Novel 'Intrinsic Ignition' Framework. *Neuron*, *94*(5), 961–968. https://doi.org/10.1016/j.neuron.2017.03.028

Demirtaş, M., Burt, J. B., Helmer, M., Ji, J. L., Adkinson, B. D., Glasser, M. F., Essen, D. C. V., Sotiropoulos, S. N., Anticevic, A., & Murray, J. D. (2019). Hierarchical Heterogeneity across Human Cortex Shapes Large-Scale Neural Dynamics. *Neuron*, *101*(6), 1181-1194.e13. https://doi.org/10.1016/j.neuron.2019.01.017

Dienlin, T., Johannes, N., Bowman, N. D., Masur, P. K., Engesser, S., Kumpel, A. S., Lukito, J., Bier, L. M., Zhang, R., Johnson, B. K., Huskey, R., Schneider, F. M., Breuer, J., Parry, D. A., Vermeulen, I., Fisher, J. T., Banks, J., Weber, R., Ellis, D. A., … Vreese, C. D. (2021). An Agenda for Open Science in Communication. *Journal of Communication*, *71*(1), 1–26. https://doi.org/10.1093/joc/jqz052

Dietrich, A. (2004). Neurocognitive mechanisms underlying the experience of flow. *Consciousness and Cognition*, *13*(4), 746–761. https://doi.org/10.1016/j.concog.2004.07.002

Dolan, D., Jensen, H. J., Mediano, P. A. M., Molina-Solana, M., Rajpal, H., Rosas, F., & Sloboda, J. A. (2018). The Improvisational State of Mind: A Multidisciplinary Study of an Improvisatory Approach to Classical Music Repertoire Performance. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.01341

Doucet, G. E., Lee, W. H., & Frangou, S. (2019). Evaluation of the spatial variability in the major resting-state networks across human brain functional atlases. *Human Brain Mapping*, *40*(15), 4577–4587. https://doi.org/10.1002/hbm.24722

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J.

D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., & Gorgolewski, K. J. (2019). fMRIPrep: A robust preprocessing pipeline for functional MRI. *Nature Methods*, *16*(1), 111–116. https://doi.org/10.1038/s41592-018-0235-4

Falk, E. B., O'Donnell, M. B., Cascio, C. N., Tinney, F., Kang, Y., Lieberman, M. D., Taylor, S. E., An, L., Resnicow, K., & Strecher, V. J. (2015). Self-affirmation alters the brain's response to health messages and subsequent behavior change. *Proceedings of the National Academy of Sciences*, *112*(7), 1977–1982. https://doi.org/10.1073/pnas.1500247112

Figueroa, C. A., Cabral, J., Mocking, R. J. T., Rapuano, K. M., van Hartevelt, T. J., Deco, G., Expert, P., Schene, A. H., Kringelbach, M. L., & Ruhé, H. G. (2019). Altered ability to access a clinically relevant control network in patients remitted from major depressive disorder. *Human Brain Mapping*, *40*(9), 2771–2786. https://doi.org/10.1002/hbm.24559

Finn, E. S., Glerean, E., Hasson, U., & Vanderwal, T. (2022). Naturalistic imaging: The use of ecologically valid conditions to study brain function. *NeuroImage*, *247*, 118776. https://doi.org/10.1016/j.neuroimage.2021.118776

Fisher, J. T., Hopp, F. R., & Weber, R. (2021). A Practical Introduction to Network Neuroscience for Communication Researchers. *Communication Methods and Measures*, *15*(1), 60–79. https://doi.org/10.1080/19312458.2020.1860206

Fisher, J. T., Huskey, R., Keene, J. R., & Weber, R. (2018). The limited capacity model of motivated mediated message processing: Looking to the future. *Annals of the International Communication Association*, *42*(4), 291–315. https://doi.org/10.1080/23808985.2018.1534551

Fisher, J. T., Keene, J. R., Huskey, R., & Weber, R. (2018). The limited capacity model of motivated mediated message processing: Taking stock of the past. *Annals of the International Communication Association*, *42*(4), 270–290. https://doi.org/10.1080/23808985.2018.1534552

Fornito, A., Zalesky, A., & Bullmore, E. (2016). *Fundamentals of Brain Network Analysis*. Academic Press.

Friston, K. J., Buechel, C., Fink, G. R., Morris, J., Rolls, E., & Dolan, R. J. (1997). Psychophysiological and modulatory interactions in neuroimaging. *NeuroImage*, *6*(3), 218–229. https://doi.org/10.1006/nimg.1997.0291

Gabor, D. (1946). Theory of communication. Part 1: The analysis of information. *Journal of the Institution of Electrical Engineers - Part III: Radio and Communication Engineering*, *93*(26), 429–441. https://doi.org/10.1049/ji-3-2.1946.0074

Girn, M., Rosas, F. E., Daws, R. E., Gallen, C. L., Gazzaley, A., & Carhart-Harris, R. L. (2023). A complex systems perspective on psychedelic brain action. *Trends in Cognitive Sciences*, *0*(0). https://doi.org/10.1016/j.tics.2023.01.003

Gold, J., & Ciorciari, J. (2021). A neurocognitive model of flow states and the role of cerebellar internal models. *Behavioural Brain Research*, *407*, 113244. https://doi.org/10.1016/j.bbr.2021.113244

Grall, C., Tamborini, R., Weber, R., & Schmälzle, R. (2021). Stories Collectively Engage Listeners' Brains: Enhanced Intersubject Correlations during Reception of Personal Narratives. *Journal of Communication*, *jqab004*. https://doi.org/10.1093/joc/jqab004

Hancock, F., Cabral, J., Luppi, A. I., Rosas, F. E., Mediano, P. A. M., Dipasquale, O., & Turkheimer, F. E. (2022). Metastability, fractal scaling, and synergistic information

processing: What phase relationships reveal about intrinsic brain activity. *NeuroImage*, *259*, 119433. https://doi.org/10.1016/j.neuroimage.2022.119433

Hancock, F., Rosas, F. E., Luppi, A. I., Zhang, M., Mediano, P. A. M., Cabral, J., Deco, G., Kringelbach, M. L., Breakspear, M., Kelso, J. A. S., & Turkheimer, F. E. (2025). Metastability demystified—The foundational past, the pragmatic present and the promising future. *Nature Reviews Neuroscience*, *26*(2), 82–100. https://doi.org/10.1038/s41583-024-00883-1

Hancock, F., Rosas, F. E., McCutcheon, R. A., Cabral, J., Dipasquale, O., & Turkheimer, F. E. (2023). Metastability as a candidate neuromechanistic biomarker of schizophrenia pathology. *PLOS ONE*, *18*(3), e0282707. https://doi.org/10.1371/journal.pone.0282707

Hancock, F., Rosas, F. E., Mediano, P. A. M., Luppi, A. I., Cabral, J., Dipasquale, O., & Turkheimer, F. E. (2022). May the 4C's be with you: An overview of complexity-inspired frameworks for analysing resting-state neuroimaging data. *Journal of The Royal Society Interface*, *19*(191), 20220214. https://doi.org/10.1098/rsif.2022.0214

Hansen, E. C. A., Battaglia, D., Spiegler, A., Deco, G., & Jirsa, V. K. (2015). Functional connectivity dynamics: Modeling the switching behavior of the resting state. *NeuroImage*, *105*, 525–535. https://doi.org/10.1016/j.neuroimage.2014.11.001

Hansen, J. Y., Markello, R. D., Vogel, J. W., Seidlitz, J., Bzdok, D., & Misic, B. (2021). Mapping gene transcription and neurocognition across human neocortex. *Nature Human Behaviour*, *5*(9), 1240–1250. https://doi.org/10.1038/s41562-021-01082-z

Hasson, U., Landesman, O., Knappmeyer, B., Vallines, I., Rubin, N., & Heeger, D. J. (2008). Neurocinematics: The Neuroscience of Film. *Projections*, *2*(1), 1–26. https://doi.org/10:3167/proj.2008.020102

Hellyer, P. J., Scott, G., Shanahan, M., Sharp, D. J., & Leech, R. (2015). Cognitive Flexibility through Metastable Neural Dynamics Is Disrupted by Damage to the Structural Connectome. *Journal of Neuroscience*, *35*(24), 9050–9063. https://doi.org/10.1523/JNEUROSCI.4648-14.2015

Holland, J. H. (2014). *Complexity: A Very Short Introduction*. OUP Oxford.

Honari, H., Choe, A. S., & Lindquist, M. A. (2021). Evaluating phase synchronization methods in fMRI: A comparison study and new approaches. *NeuroImage*, *228*, 117704. https://doi.org/10.1016/j.neuroimage.2020.117704

Horga, G., & Abi-Dargham, A. (2019). An integrative framework for perceptual disturbances in psychosis. *Nature Reviews Neuroscience*, *20*(12), 763–778. https://doi.org/10.1038/s41583-019-0234-1

Hosseini, Z., Delpazirian, R., Lanjanian, H., Salarifar, M., & Hassani-Abharian, P. (2021). Computer Gaming and Physiological Changes in the Brain: An Insight from QEEG Complexity Analysis. *Applied Psychophysiology and Biofeedback*, *46*(3), 301–308. https://doi.org/10.1007/s10484-021-09518-y

Hull, D. C., Williams, G. A., & Griffiths, M. D. (2013). *Video game characteristics, happiness and flow as predictors of addiction among video game players: A pilot study*. https://doi.org/10.1556/jba.2.2013.005

Huskey, R., Bue, A. C., Eden, A., Grall, C., Meshi, D., Prena, K., Schmälzle, R., Scholz, C., Turner, B. O., & Wilcox, S. (2020). Marr's Tri-Level Framework Integrates Biological Explanation Across Communication Subfields. *Journal of Communication*, *70*(3), 356–378. https://doi.org/10.1093/joc/jqaa007

Huskey, R., Craighead, B., Miller, M. B., & Weber, R. (2018). Does intrinsic reward motivate

cognitive control? A naturalistic-fMRI study based on the Synchronization Theory of Flow. *Cognitive, Affective & Behavioral Neuroscience*, *18*(5), 902–924. https://doi.org/10.3758/s13415-018-0612-6

Huskey, R., Keene, J. R., Wilcox, S., Gong, X. (Jason), Adams, R., & Najera, C. J. (2022). Flexible and Modular Brain Network Dynamics Characterize Flow Experiences During Media Use: A Functional Magnetic Resonance Imaging Study. *Journal of Communication*, *72*(1), jqab044. https://doi.org/10.1093/joc/jqab044

Huskey, R., & Schmälzle, R. (2025). Finding Middle Ground In Cognitive Media Psychology. In K. Shackleford & N. D. Bowman (Eds.), *Oxford Handbook of Media Psychology* (2nd ed.). Oxford University Press.

Insel, T. R. (2010). Rethinking schizophrenia. *Nature*, *468*(7321), 187–193. https://doi.org/10.1038/nature09552

Inzlicht, M., Shenhav, A., & Olivola, C. Y. (2018). The effort paradox: Effort is both costly and valued. *Trends in Cognitive Sciences*, 1–13. https://doi.org/10.1016/j.tics.2018.01.007

Ito, M. (2008). Control of mental activities by internal models in the cerebellum. *Nature Reviews Neuroscience*, *9*(4), 304–313. https://doi.org/10.1038/nrn2332

Jackson, S. A., & Eklund, R. C. (2004). *The flow scales manual*. Fitness Information Technology, Inc.

James, W. (1890). *The principles of psychology, Volume 1*. Dover Publications.

Jensen, H. J. (1998). *Self-Organized Criticality: Emergent Complex Behavior in Physical and Biological Systems*. Cambridge University Press.

Johannes, N., Vuorre, M., & Przybylski, A. K. (2021). Video game play is positively correlated with well-being. *Royal Society Open Science*, *8*(2), 202049.

https://doi.org/10.1098/rsos.202049

Kang, Y., Cooper, N., Pandey, P., Scholz, C., O'Donnell, M. B., Lieberman, M. D., Taylor, S. E., Strecher, V. J., Dal Cin, S., Konrath, S., Polk, T. A., Resnicow, K., An, L., & Falk, E. B. (2018). Effects of self-transcendence on neural responses to persuasive messages and health behavior change. *Proceedings of the National Academy of Sciences*, *115*(40), 9974–9979. https://doi.org/10.1073/pnas.1805573115

Kee, R., & Huskey, R. (in press). Neurobiology of Flow and Optimal Performance. In *Performance Neuroscience*. Springer Natur.

Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior*. MIT press.

Kong, R., Spreng, R. N., Xue, A., Betzel, R. F., Cohen, J. R., Damoiseaux, J. S., De Brigard, F., Eickhoff, S. B., Fornito, A., Gratton, C., Gordon, E. M., Holmes, A. J., Laird, A. R., Larson-Prior, L., Nickerson, L. D., Pinho, A. L., Razi, A., Sadaghiani, S., Shine, J. M., … Uddin, L. Q. (2025). A network correspondence toolbox for quantitative evaluation of novel neuroimaging results. *Nature Communications*, *16*(1), 2930. https://doi.org/10.1038/s41467-025-58176-9

Kotler, S., Mannino, M., Kelso, S., & Huskey, R. (2022). First few seconds for flow: A comprehensive proposal of the neurobiology and neurodynamics of state onset. *Neuroscience & Biobehavioral Reviews*, *143*, 104956. https://doi.org/10.1016/j.neubiorev.2022.104956

Kubey, R., & Csikszentmihályi, M. (1990). *Television and the quality of life: How viewing shapes everyday experience* (pp. xvii, 287). Lawrence Erlbaum Associates, Inc.

Kuhn, M. (2008). Building Predictive Models in R Using the caret Package. *Journal of*

*Statistical Software*, *28*, 1–26. https://doi.org/10.18637/jss.v028.i05

Kuhn, M., & Johnson, K. (2013). *Applied Predictive Modeling*. Springer Science & Business Media.

Ladyman, J., Lambert, J., & Wiesner, K. (2013). What is a complex system? *European Journal for Philosophy of Science*, *3*(1), 33–67. https://doi.org/10.1007/s13194-012-0056-8

Lang, A. (2006). Using the limited capacity model of motivated mediated message processing to design effective cancer communication messages. *Journal of Communication*, *56*(1), S57–S80. https://doi.org/10.1111/j.1460-2466.2006.00283.x

Lang, A., Bradley, S. D., Park, B., Shin, M., & Chung, Y. (2006). Parsing the resource pie: Using STRTs to measure attention to mediated messages. *Media Psychology*, *8*(4), 369–394. https://doi.org/10.1207/s1532785xmep0804_3

Limb, C. J., & Braun, A. R. (2008). Neural Substrates of Spontaneous Musical Performance: An fMRI Study of Jazz Improvisation. *PLOS ONE*, *3*(2), e1679. https://doi.org/10.1371/journal.pone.0001679

Lombardo, D., Cassé-Perrot, C., Ranjeva, J.-P., Le Troter, A., Guye, M., Wirsich, J., Payoux, P., Bartrés-Faz, D., Bordet, R., Richardson, J. C., Felician, O., Jirsa, V., Blin, O., Didic, M., & Battaglia, D. (2020). Modular slowing of resting-state dynamic functional connectivity as a marker of cognitive dysfunction induced by sleep deprivation. *NeuroImage*, *222*, 117155. https://doi.org/10.1016/j.neuroimage.2020.117155

López-González, A., Panda, R., Ponce-Alvarez, A., Zamora-López, G., Escrichs, A., Martial, C., Thibaut, A., Gosseries, O., Kringelbach, M. L., Annen, J., Laureys, S., & Deco, G. (2021). Loss of consciousness reduces the stability of brain hubs and the heterogeneity of brain dynamics. *Communications Biology*, *4*(1), 1037. https://doi.org/10.1038/s42003-

021-02537-9

Lord, L.-D., Expert, P., Atasoy, S., Roseman, L., Rapuano, K., Lambiotte, R., Nutt, D. J., Deco, G., Carhart-Harris, R. L., Kringelbach, M. L., & Cabral, J. (2019). Dynamical exploration of the repertoire of brain networks at rest is modulated by psilocybin. *NeuroImage*, *199*, 127–142. https://doi.org/10.1016/j.neuroimage.2019.05.060

Lutz, A., & Thompson, E. (2003). Neurophenomenology Integrating Subjective Experience and Brain Dynamics in the Neuroscience of Consciousness. *Journal of Consciousness Studies*, *10*(9–10), 31–52.

Mathiak, K. A., Klasen, M., Zvyagintsev, M., Weber, R., & Mathiak, K. (2013). Neural networks underlying affective states in a multimodal virtual environment: Contributions to boredom. *Frontiers in Human Neuroscience*, *7*(820). https://doi.org/10.3389/fnhum.2013.00820

Mathiak, K., & Weber, R. (2006). Toward brain correlates of natural behavior: fMRI during violent video games. *Human Brain Mapping*, *27*(12), 948–956. https://doi.org/10.1002/hbm.20234

Mediano, P. A. M., Rosas, F. E., Timmermann, C., Roseman, L., Nutt, D. J., Feilding, A., Kaelen, M., Kringelbach, M. L., Barrett, A. B., Seth, A. K., Muthukumaraswamy, S., Bor, D., & Carhart-Harris, R. L. (2024). Effects of External Stimulation on Psychedelic State Neurodynamics. *ACS Chemical Neuroscience*, *15*(3), 462–471. https://doi.org/10.1021/acschemneuro.3c00289

Melnikoff, D. E., Carlson, R. W., & Stillman, P. E. (2022). A computational theory of the subjective experience of flow. *Nature Communications*, *13*(1), Article 1. https://doi.org/10.1038/s41467-022-29742-2

Melnikoff, D. E., Carlson, R. W., & Stillman, P. E. (2025). *Optimal Task Representations for Engagement, Enjoyment, and Performance*. OSF. https://doi.org/10.31219/osf.io/v93cp_v1

Molinari, M., Chiricozzi, F. R., Clausi, S., Tedesco, A. M., De Lisa, M., & Leggio, M. G. (2008). Cerebellum and Detection of Sequences, from Perception to Cognition. *The Cerebellum*, *7*(4), 611–615. https://doi.org/10.1007/s12311-008-0060-x

Mosing, M. A., Butkovic, A., & Ullén, F. (2018). Can flow experiences be protective of work-related depressive symptoms and burnout? A genetically informative approach. *Journal of Affective Disorders*, *226*, 6–11. https://doi.org/10.1016/j.jad.2017.09.017

Nagel, T. (1974). What is it like to be a bat? *The Philosophical Review*, *83*(4), 435–450.

Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, *103*(23), 8577–8582. https://doi.org/10.1073/pnas.0601602103

Noble, S., Curtiss, J., Pessoa, L., & Scheinost, D. (2024). The tip of the iceberg: A call to embrace anti-localizationism in human neuroscience research. *Imaging Neuroscience*, *2*, 1–10. https://doi.org/10.1162/imag_a_00138

Pachaud, C., Gerber, T., Firla, M., Martin, N., & Mailhes, C. (2013, June). Consequences of non-respect of the Bedrosian theorem when demodulating. *CM 2013 - MFPT 2013 - 10th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies*. https://hal.science/hal-00844834

Pàmies-Vilà, R., Fabregat-Sanjuan, A., Ros-Alsina, A., Rigo-Vidal, A., & Pascual-Rubio, V. (2023). Analysis of the Dorsolateral Prefrontal Cortex MNI Coordinates. In A. Vizán Idoipe & J. C. García Prada (Eds.), *Proceedings of the XV Ibero-American Congress of*

*Mechanical Engineering* (pp. 132–138). Springer International Publishing. https://doi.org/10.1007/978-3-031-38563-6_20

Pang, J. C., Aquino, K. M., Oldehinkel, M., Robinson, P. A., Fulcher, B. D., Breakspear, M., & Fornito, A. (2023). Geometric constraints on human brain function. *Nature*, *618*(7965), 566–574. https://doi.org/10.1038/s41586-023-06098-1

Pereda, E., Quiroga, R. Q., & Bhattacharya, J. (2005). Nonlinear multivariate analysis of neurophysiological signals. *Progress in Neurobiology*, *77*(1), 1–37. https://doi.org/10.1016/j.pneurobio.2005.10.003

Pessoa, L. (2022). *The Entangled Brain: How Perception, Cognition, and Emotion Are Woven Together*. The MIT Press. https://doi.org/10.7551/mitpress/14636.001.0001

Petkoski, S., Ritter, P., & Jirsa, V. K. (2023). White-matter degradation and dynamical compensation support age-related functional alterations in human brain. *Cerebral Cortex*, *33*(10), 6241–6256. https://doi.org/10.1093/cercor/bhac500

Poldrack, R. A., Kittur, A., Kalar, D., Miller, E., Seppa, C., Gil, Y., Parker, D. S., Sabb, F. W., & Bilder, R. M. (2011). The Cognitive Atlas: Toward a Knowledge Foundation for Cognitive Neuroscience. *Frontiers in Neuroinformatics*, *5*. https://doi.org/10.3389/fninf.2011.00017

Quian Quiroga, R., Kraskov, A., Kreuz, T., & Grassberger, P. (2002). Performance of different synchronization measures in real data: A case study on electroencephalographic signals. *Physical Review E*, *65*(4), 041903. https://doi.org/10.1103/PhysRevE.65.041903

Rankin, K., Walsh, L. C., & Sweeny, K. (2019). A better distraction: Exploring the benefits of flow during uncertain waiting periods. *Emotion*, *19*(5), 818–828. https://doi.org/10.1037/emo0000479

Rosen, D., Oh, Y., Chesebrough, C., Zhang, F. (Zoe), & Kounios, J. (2024). Creative flow as optimized processing: Evidence from brain oscillations during jazz improvisations by expert and non-expert musicians. *Neuropsychologia*, *196*, 108824. https://doi.org/10.1016/j.neuropsychologia.2024.108824

Schartner, M. M., Carhart-Harris, R. L., Barrett, A. B., Seth, A. K., & Muthukumaraswamy, S. D. (2017). Increased spontaneous MEG signal diversity for psychoactive doses of ketamine, LSD and psilocybin. *Scientific Reports*, *7*(1), 46421. https://doi.org/10.1038/srep46421

Scheepers, D., & Keller, J. (2022). On the physiology of flow: Bridging flow theory with the biopsychosocial model of challenge and threat. *International Journal of Psychophysiology*, *182*, 119–128. https://doi.org/10.1016/j.ijpsycho.2022.10.007

Schirner, M., Kong, X., Yeo, B. T. T., Deco, G., & Ritter, P. (2022). Dynamic primitives of brain network interaction. *NeuroImage*, *250*, 118928. https://doi.org/10.1016/j.neuroimage.2022.118928

Schmälzle, R. (2022). Theory and Method for Studying How Media Messages Prompt Shared Brain Responses Along the Sensation-to-Cognition Continuum. *Communication Theory*, qtac009. https://doi.org/10.1093/ct/qtac009

Schmälzle, R., & Grall, C. (2020). The Coupled Brains of Captivated Audiences: An Investigation of the Collective Brain Dynamics of an Audience Watching a Suspenseful Film. *Journal of Media Psychology: Theories, Methods, and Applications*. https://doi.org/10.1027/1864-1105/a000271

Schmälzle, R., & Huskey, R. (2023a). Integrating media content analysis, reception analysis, and media effects studies. *Frontiers in Neuroscience*, *17*.

https://www.frontiersin.org/articles/10.3389/fnins.2023.1155750

Schmälzle, R., & Huskey, R. (2023b). Skyhooks, Cranes, and the Construct Dump: A Comment on and Extension of Boster (2023). *Asian Communication Research*, 5–15. https://doi.org/10.20879/acr.2023.20.016

Schmälzle, R., Liu, H., Delle, F. A., Lewin, K. M., Jahn, N. T., Zhang, Y., Yoon, H., & Long, J. (2024). Moment-by-moment tracking of audience brain responses to an engaging public speech: Replicating the reverse-message engineering approach. *Communication Monographs*, *91*(1), 31–55. https://doi.org/10.1080/03637751.2023.2240398

Seguin, C., Sporns, O., & Zalesky, A. (2023). Brain network communication: Concepts, models and applications. *Nature Reviews Neuroscience*, *24*(9), Article 9. https://doi.org/10.1038/s41583-023-00718-5

Seitzman, B. A., Gratton, C., Marek, S., Raut, R. V., Dosenbach, N. U. F., Schlaggar, B. L., Petersen, S. E., & Greene, D. J. (2020). A set of functionally-defined brain regions with improved representation of the subcortex and cerebellum. *NeuroImage*, *206*, 116290. https://doi.org/10.1016/j.neuroimage.2019.116290

Shanahan, M. (2010). Metastable chimera states in community-structured oscillator networks. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *20*(1), 013108. https://doi.org/10.1063/1.3305451

Sherry, J. (2004). Flow and media enjoyment. *Communication Theory*, *14*(4), 328–347. https://doi.org/10.1111/j.1468-2885.2004.tb00318.x

Solms, M. (2021). *The Hidden Spring: A Journey to the Source of Consciousness*. W. W. Norton & Company.

Sonkusare, S., Breakspear, M., & Guo, C. (2019). Naturalistic Stimuli in Neuroscience:

Critically Acclaimed. *Trends in Cognitive Sciences*, *23*(8), 699–714. https://doi.org/10.1016/j.tics.2019.05.004

Sporns, O. (2011). *Networks of the brain*. The MIT Press.

Sweeny, K., Rankin, K., Cheng, X., Hou, L., Long, F., Meng, Y., Azer, L., Zhou, R., & Zhang, W. (2020). Flow in the time of COVID-19: Findings from China. *PLOS ONE*, *15*(11), e0242043. https://doi.org/10.1371/journal.pone.0242043

Tabibnia, G. (2020). An affective neuroscience model of boosting resilience in adults. *Neuroscience & Biobehavioral Reviews*, *115*, 321–350. https://doi.org/10.1016/j.neubiorev.2020.05.005

Telesford, Q. K., Lynall, M.-E., Vettel, J., Miller, M. B., Grafton, S. T., & Bassett, D. S. (2016). Detection of functional brain network reconfiguration during task-driven cognitive states. *NeuroImage*, *142*, 198–210. https://doi.org/10.1016/j.neuroimage.2016.05.078

Tepper, S. J., & Lewis, N. A. (2021). When the Going Gets Tough, How Do We Perceive the Future? *Social Cognition*, *39*(4), 526–541. https://doi.org/10.1521/soco.2021.39.4.526

Thurner, S., Hanel, R., & Klimek, P. (2018). *Introduction to the Theory of Complex Systems*. Oxford University Press.

Timmermann, C., Roseman, L., Schartner, M., Milliere, R., Williams, L. T. J., Erritzoe, D., Muthukumaraswamy, S., Ashton, M., Bendrioua, A., Kaur, O., Turton, S., Nour, M. M., Day, C. M., Leech, R., Nutt, D. J., & Carhart-Harris, R. L. (2019). Neural correlates of the DMT experience assessed with multivariate EEG. *Scientific Reports*, *9*(1), 16324. https://doi.org/10.1038/s41598-019-51974-4

Tognoli, E., & Kelso, J. A. S. (2014). The Metastable Brain. *Neuron*, *81*(1), 35–48. https://doi.org/10.1016/j.neuron.2013.12.022

Toker, D., Pappas, I., Lendner, J. D., Frohlich, J., Mateos, D. M., Muthukumaraswamy, S., Carhart-Harris, R., Paff, M., Vespa, P. M., Monti, M. M., Sommer, F. T., Knight, R. T., & D'Esposito, M. (2022). Consciousness is supported by near-critical slow cortical electrodynamics. *Proceedings of the National Academy of Sciences*, *119*(7), e2024455119. https://doi.org/10.1073/pnas.2024455119

Tokunaga, R. S. (2013). Engagement with Novel Virtual Environments: The Role of Perceived Novelty and Flow in the Development of the Deficient Self-Regulation of Internet Use and Media Habits. *Human Communication Research*, *39*(3), 365–393. https://doi.org/10.1111/hcre.12008

Turkheimer, F. E., Rosas, F. E., Dipasquale, O., Martins, D., Fagerholm, E. D., Expert, P., Váša, F., Lord, L.-D., & Leech, R. (2022). A Complex Systems Perspective on Neuroimaging Studies of Behavior and Its Disorders. *The Neuroscientist*, *28*(4), 382–399. https://doi.org/10.1177/1073858421994784

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., Mazoyer, B., & Joliot, M. (2002). Automated Anatomical Labeling of Activations in SPM Using a Macroscopic Anatomical Parcellation of the MNI MRI Single-Subject Brain. *NeuroImage*, *15*(1), 273–289. https://doi.org/10.1006/nimg.2001.0978

Ulrich, M., Keller, J., & Grön, G. (2016a). Dorsal raphe nucleus down-regulates medial prefrontal cortex during experience of flow. *Frontiers in Behavioral Neuroscience*, *10*, 169. https://doi.org/10.3389/fnbeh.2016.00169

Ulrich, M., Keller, J., & Grön, G. (2016b). Neural signatures of experimentally induced flow experiences identified in a typical fMRI block design with BOLD imaging. *Social Cognitive and Affective Neuroscience*, *11*(3), 496–507.

https://doi.org/10.1093/scan/nsv133

Ulrich, M., Niemann, F., & Grön, G. (2022). The neural signatures of the psychological construct "flow": A replication study. *Neuroimage: Reports*, *2*(4), 100139. https://doi.org/10.1016/j.ynirp.2022.100139

Van Dam, N. T., van Vugt, M. K., Vago, D. R., Schmalzl, L., Saron, C. D., Olendzki, A., Meissner, T., Lazar, S. W., Kerr, C. E., Gorchov, J., Fox, K. C. R., Field, B. A., Britton, W. B., Brefczynski-Lewis, J. A., & Meyer, D. E. (2018). Mind the Hype: A Critical Evaluation and Prescriptive Agenda for Research on Mindfulness and Meditation. *Perspectives on Psychological Science*, *13*(1), 36–61. https://doi.org/10.1177/1745691617709589

van der Linden, D., Tops, M., & Bakker, A. B. (2021). Go with the flow: A neuroscientific view on being fully engaged. *European Journal of Neuroscience*, *53*(4), 947–963. https://doi.org/10.1111/ejn.15014

Vella, K., Johnson, D., & Hides, L. (2013). Positively playful: When videogames lead to player wellbeing. *Proceedings of the First International Conference on Gameful Design, Research, and Applications*, 99–102. https://doi.org/10.1145/2583008.2583024

Vivot, R. M., Pallavicini, C., Zamberlan, F., Vigo, D., & Tagliazucchi, E. (2020). Meditation Increases the Entropy of Brain Oscillatory Activity. *Neuroscience*, *431*, 40–51. https://doi.org/10.1016/j.neuroscience.2020.01.033

Vohryzek, J., Deco, G., Cessac, B., Kringelbach, M. L., & Cabral, J. (2020). Ghost Attractors in Spontaneous Brain Activity: Recurrent Excursions Into Functionally-Relevant BOLD Phase-Locking States. *Frontiers in Systems Neuroscience*, *14*. https://doi.org/10.3389/fnsys.2020.00020

Vuorre, M., Johannes, N., Magnusson, K., & Przybylski, A. K. (2022). Time spent playing video games is unlikely to impact well-being. *Royal Society Open Science*, *9*(7), 220411. https://doi.org/10.1098/rsos.220411

Waldrop, M. M. (1993). *Complexity: The Emerging Science at the Edge of Order and Chaos*. Simon and Schuster.

Wang, P. T., Woodman, K., & Weber, R. (2023). Flow Experiences and Media. In *Oxford Research Encyclopedia of Communication*. https://doi.org/10.1093/acrefore/9780190228613.013.1474

Wang, Y., Han, B., Li, M., Li, J., & Li, R. (2023). An efficiently working brain characterizes higher mental flow that elicits pleasure in Chinese calligraphic handwriting. *Cerebral Cortex*, *33*(12), 7395–7408. https://doi.org/10.1093/cercor/bhad047

Weber, R., Alicea, B., Huskey, R., & Mathiak, K. (2018). Network dynamics of attention during a naturalistic behavioral paradigm. *Frontiers in Human Neuroscience*, *12*(182), 1–14. https://doi.org/10.3389/fnhum.2018.00182

Weber, R., Eden, A., Huskey, R., Mangus, J. M., & Falk, E. B. (2015). Bridging media psychology and cognitive neuroscience: Challenges and opportunities. *Journal of Media Psychology*, *27*(3), 146–156. https://doi.org/10.1027/1864-1105/a000163

Weber, R., Hopp, F. R., Eden, A., Fisher, J. T., & Lee, H.-E. (2024). Vicarious punishment of moral violations in naturalistic drama narratives predicts cortical synchronization. *NeuroImage*, *292*, 120613. https://doi.org/10.1016/j.neuroimage.2024.120613

Weber, R., Huskey, R., & Craighead, B. (2016). Flow experiences and well-being: A media neuroscience perspective. In M. B. Oliver & L. Reinecke (Eds.), *Handbook of media use and well-being: International perspectives on theory and research on positive media*

*effects* (pp. 183–196). Routledge.

Weber, R., Ritterfeld, U., & Mathiak, K. (2006). Does playing violent video games induce aggression? Empirical evidence of a functional magnetic resonance imaging study. *Media Psychology*, *8*(1), 39–60. https://doi.org/10.1207/S1532785XMEP0801_4

Weber, R., Tamborini, R., Westcott-Baker, A., & Kantor, B. (2009). Theorizing flow and media enjoyment as cognitive synchronization of attentional and reward networks. *Communication Theory*, *19*(4), 397–422. https://doi.org/10.1111/j.1468-2885.2009.01352.x

Westgate, E. C. (2020). Why Boredom Is Interesting. *Current Directions in Psychological Science*, *29*(1), 33–40. https://doi.org/10.1177/0963721419884309

Westlin, C., Theriault, J. E., Katsumi, Y., Nieto-Castanon, A., Kucyi, A., Ruf, S. F., Brown, S. M., Pavel, M., Erdogmus, D., Brooks, D. H., Quigley, K. S., Whitfield-Gabrieli, S., & Barrett, L. F. (2023). Improving the study of brain-behavior relationships by revisiting basic assumptions. *Trends in Cognitive Sciences*, *27*(3), 246–257. https://doi.org/10.1016/j.tics.2022.12.015

Wolpert, D. M., Miall, R. C., & Kawato, M. (1998). Internal models in the cerebellum. *Trends in Cognitive Sciences*, *2*(9), 338–347. https://doi.org/10.1016/S1364-6613(98)01221-2

Woodman, K., & Weber, R. (2025). Cracking the Code of Gaming Disorder. In M. C. Yzer & J. T. Siegel (Eds.), *The Handbook of Mental Health Communication* (pp. 167–180). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781394179909.ch12

Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *Nature Methods*, *8*(8), 665–670. https://doi.org/10.1038/nmeth.1635

Zhou, D., Kang, Y., Cosme, D., Jovanova, M., He, X., Mahadevan, A., Ahn, J., Stanoi, O., Brynildsen, J. K., Cooper, N., Cornblath, E. J., Parkes, L., Mucha, P. J., Ochsner, K. N., Lydon-Staley, D. M., Falk, E. B., & Bassett, D. S. (2023). Mindful attention promotes control of brain network dynamics for self-regulation and discontinues the past from the present. *Proceedings of the National Academy of Sciences*, *120*(2), e2201074119. https://doi.org/10.1073/pnas.2201074119

**Table 1**

A summary of the 15 complexity signatures assessed in the present study. More details are provided in *methods.* PHM: phase matrix; PALM: phase alignment matrix; LEiDA: leading eigenvector dynamic analysis.

| Name | Brief Description | Relevant Citations |
|---|---|---|
| Synchronization (PHM) | Degree of synchronization between brain regions, calculated as the average of the Kuramoto Order Parameter.(Shanahan, 2010) | Shanahan, 2010 |
| Metastability (PHM) | Variability in synchronization, reflecting switching between communities, a signature of metastability. | Shanahan, 2010 |
| Coalition Diversity (PHM) | Diversity of synchronised communities, calculated as variance or standard deviation of synchronization over spacetime. | Shanahan, 2010 |
| Dynamical Complexity (LEiDA) | Balance between integration and segregation of brain regions, reflecting a metastability signature. | Hancock et al., 2023 |
| Dynamical Alignment (PALM) | Number of regions in anti-phase alignment, calculated using spectral decomposition. | Alteriis et al., 2024 |
| Dynamical Agility (PALM) | Switching between connectivity configurations (in-phase and anti-phase) measured via spectral decomposition. | Alteriis et al., 2024; Lombardo et al., 2020 |
| Reconfiguration Speed (PHM) | Speed of smooth flow across morphing connectivity configurations, measured as correlation distance between matrices. | Battaglia et al., 2020 |
| Ignition Flexibility (PALM) | Flexibility to trigger varying sizes of ignitions from spontaneous activity, | Alonso Martínez et al., 2020; Deco & Kringelbach, 2017 |

| | | |
|---|---|---|
| | measured by connected component size. | |
| Ignition Hierarchy (PALM) | Hierarchy in the ignition triggered by spontaneous activity across regions, measured by the largest connected component. | Alonso Martínez et al., 2020; Deco & Kringelbach, 2017 |
| Integration (PALM) | Capacity of the brain to maintain connectivity between regions, calculated by scanning and binarizing phase alignment matrices. | López-González et al., 2021 |
| Segregation (PALM) | Modularity or breakdown of brain systems into subcomponents, measured using the Louvain algorithm on phase alignment matrices. | López-González et al., 2021 |
| Dynamical Criticality | Proximity to criticality, measured using a modified 0-1 chaos test | Toker et al., 2022 |
| Global Entropy Rate | Complexity estimator of time series, measuring the unpredictability of the next value based on Lempel-Ziv complexity. | Mediano et al., 2024 |
| Functional Connectivity Dynamics | Spatiotemporal statistics of resting-state activity based on phase-lagged coupling structures over time. | Aquino et al., 2022; Pang et al., 2023 |
| Global Fluidity (PALM) | Standard deviation of the Functional Connectivity Dynamics, reflecting fluctuating internal coalitions. | Petkoski et al., 2023 |
| Occurrence | A measure of the amount of time a mode occurred during a scanning session. | Cabral et al., 2017 |
| Duration | The average of all consecutive time periods spent in a particular mode. | Cabral et al., 2017 |

**Table 2**

Significant contributions of complexity signatures in linear modes.

| Experimental Condition: Flow | | | | | |
|---|---|---|---|---|---|
| Global/Local | Outcome Variable | $R^2$ | $R^{2\ Adj}$ | p-value | Explanatory Terms |
| *Global* | | | | | |
| | Flow | .19 | .16 | .011 | Entropy rate |
| | Enjoyment | .13 | .10 | .039 | Entropy rate |
| *Cerebellum* | | | | | |
| | Enjoyment | .15 | .12 | .025 | CB_7b_L |
| *Local* | | | | | |
| Mode 2 | | | | | |
| | RT | .14 | .11 | .029 | Dynamical complexity |
| Mode 3 | | | | | |
| | Flow | .04 | .01 | .011 | Dynamical alignment |
| | Enjoyment | .01 | -.03 | .025 | Dynamical agility |
| Mode 5 | | | | | |
| | Enjoyment | .15 | .12 | .026 | Dynamical agility |
| Experimental Condition: Boredom | | | | | |
| Global/Local | Outcome Variable | $R^2$ | $R^{2\ Adj}$ | p-value | Explanatory Terms |
| *Global* | | | | | |
| | Flow | .19 | .14 | .035 | Metastability, Coalition diversity |
| *Cerebellum* | | | | | |
| | RT | .36 | .32 | .001 | CB_3_R, CB_8_R |
| *Local* | | | | | |
| Mode 3 | | | | | |
| | Flow | .44 | .34 | .011 | Synchronization, Metastability, Dynamical complexity, Duration, Dynamical agility |
| | Enjoyment | .38 | .32 | .025 | Synchronization, Metastability, Dynamical agility |
| Mode 4 | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | Enjoyment | .24 | .16 | .041 | Metastability, Duration, Dynamical alignment |
| Experimental Condition: Frustration | | | | | |
| Global/Local | Outcome Variable | $R^2$ | $R^{2\ Adj}$ | p-value | Explanatory Terms |
| *Global* | | | | | |
| | Enjoyment | .24 | .16 | .041 | Synchronization, Ignition flexibility, Recognition speed |
| *Cerebellum* | | | | | |
| | Flow | .29 | .27 | .001 | CB_3_R |
| | RT | .40 | .34 | .002 | CB_3_L, CB_7b_R, CB_8_L |
| *Local* | | | | | |
| Mode 1 | | | | | |
| | Flow | .16 | .13 | .019 | Duration |
| | Enjoyment | .14 | .11 | .028 | Duration |
| Mode 2 | | | | | |
| | Enjoyment | .44 | .38 | .001 | Synchronization, Metastability, Dynamical agility |
| Mode 3 | | | | | |
| | Flow | .24 | .17 | .011 | Dynamical complexity, Occurrence, Dynamical agility |
| | Enjoyment | .04 | .01 | .025 | Dynamical agility |
| Mode 4 | | | | | |
| | Flow | .12 | .10 | .042 | Dynamical alignment |
| | RT | .13 | .11 | .034 | Dynamical alignment |

**Table 3**

Mapping of AAL116 ROIs to MNI coordinates.

| MNI Subregion | MNI Region | AAL116 Region | YEO | Limb & Braun (2008) |
|---|---|---|---|---|
| Medial DLPFC L | DLPFC | Frontal_Mid_L | FPA | Deactivation |
| Medial DLPFC R | DLPFC | Frontal_Inf_Tri_R | FPA | Deactivation |
| Lateral DLPFC L | DLPFC | Frontal_Mid_L | FPA | Deactivation |
| Lateral DLPFC R | DLPFC | Frontal_Mid_R | FPA | Deactivation |
| Superior DLPFC L | DLPFC | Frontal_Mid_L | FPA | Deactivation |
| Superior DLPFC R | DLPFC | Frontal_Mid_R | FPA | Deactivation |

**Figure 1**

Differences in Global Complexity Signatures. A) Synchronization. B) Metastability. C) Coalition diversity. D) Dynamical complexity. E) Dynamical alignment. F) Dynamical agility. G) Ignition flexibility. H) Ignition hierarchy. I) Reconfiguration speed. J) Integration. K) Segregation. L) Dynamical criticality. M) Entropy rate. N) Global functional connectivity dynamics. O) Global fluidity.*p< 0.05; **p<0.01; ***p<0.001.

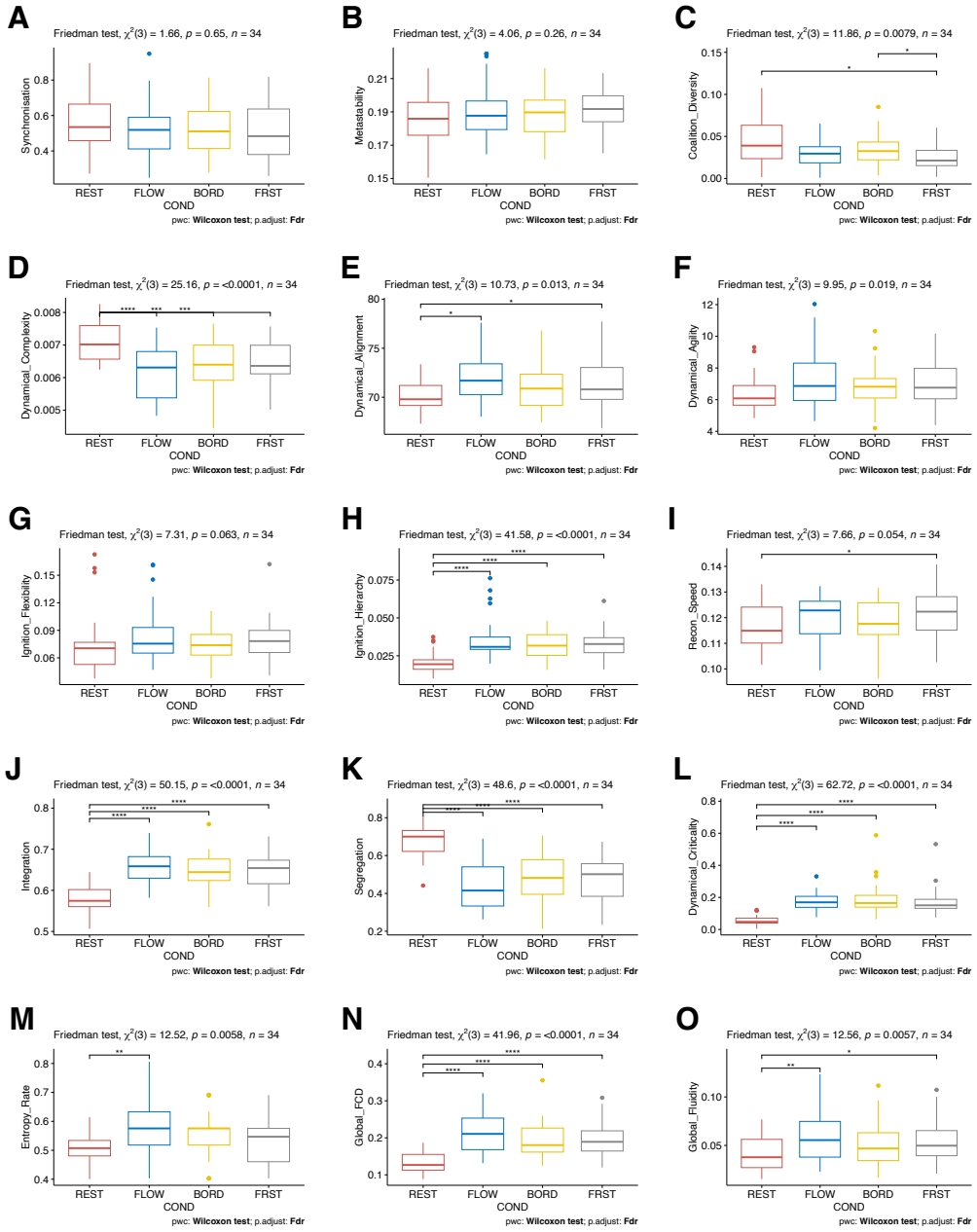

**Figure 2**

Spatiotemporal modes of phase alignment. VIS, visual network; SMT, somatomotor network; DAT, dorsal attention network; VAT, ventral attention network; LBC, limbic network; FPA, frontoparietal; DMN, default mode network; SC, subcortical; CB, cerebellum.

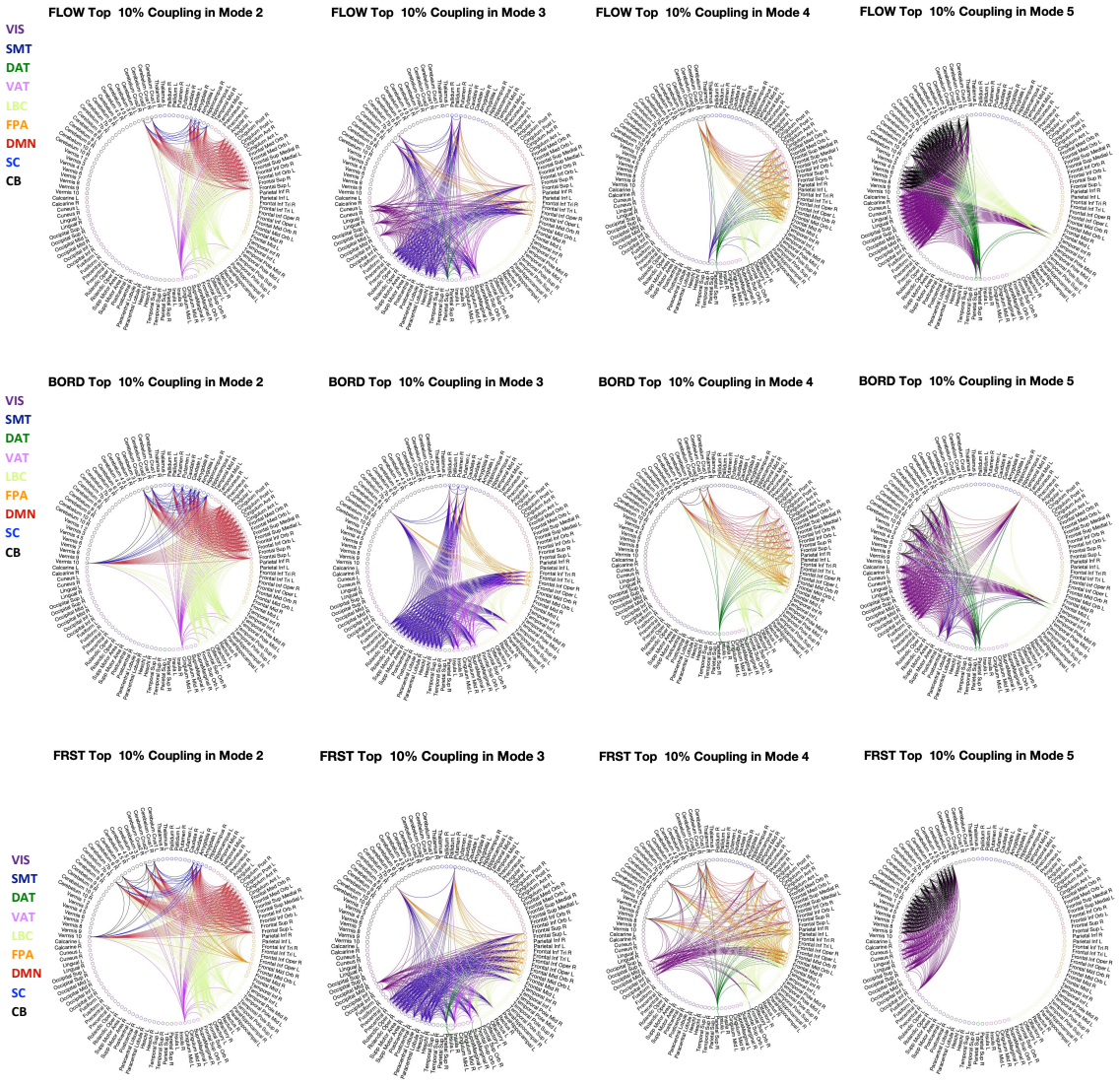

**Figure 3**

Neurosynth meta-analysis of the spatiotemporal modes. The psychological concepts associated with the brain regions in each mode are presented here in a word-cloud format. Word size is proportional to the region's contribution to the phase alignment of the mode.

**Figure 4**

Spatiotemporal modes and mode dynamics. The sequence of modes for all subjects during the flow condition. The grey-line plot indicates the difficulty level of the video game. VIS, visual network; SMT, somatomotor network; DAT, dorsal attention network; VAT, ventral attention network; LBC, limbic network; FPA, frontoparietal; DMN, default mode network; SC, subcortical; CB, cerebellum.

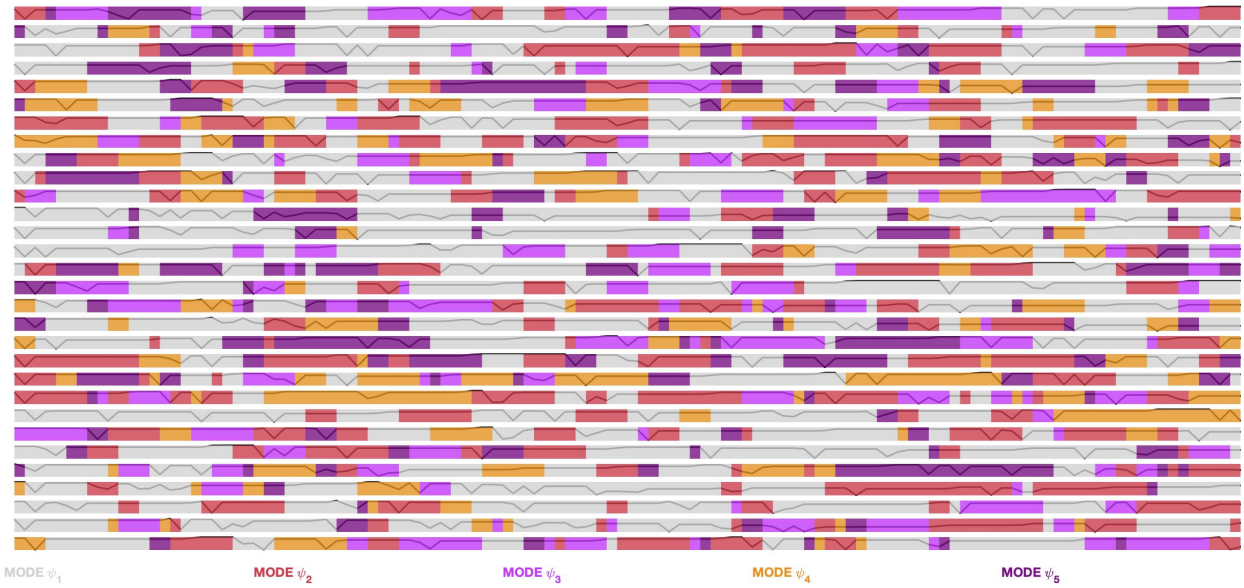

**Figure 5**

Differences in local complexity signatures and cerebellar contributions. A) Synchronization. B) Metastability. C) Dynamical Complexity. D) Occurrence. E) Duration. F) Dynamical alignment. G) Dynamical Agility. H) BR_Crus2_R. I) CB_Crus1_R. FLOW, flow condition; BORD, boredom condition; FRST, frustration condition. *p< 0.05; **p<0.01; ***p<0.001.

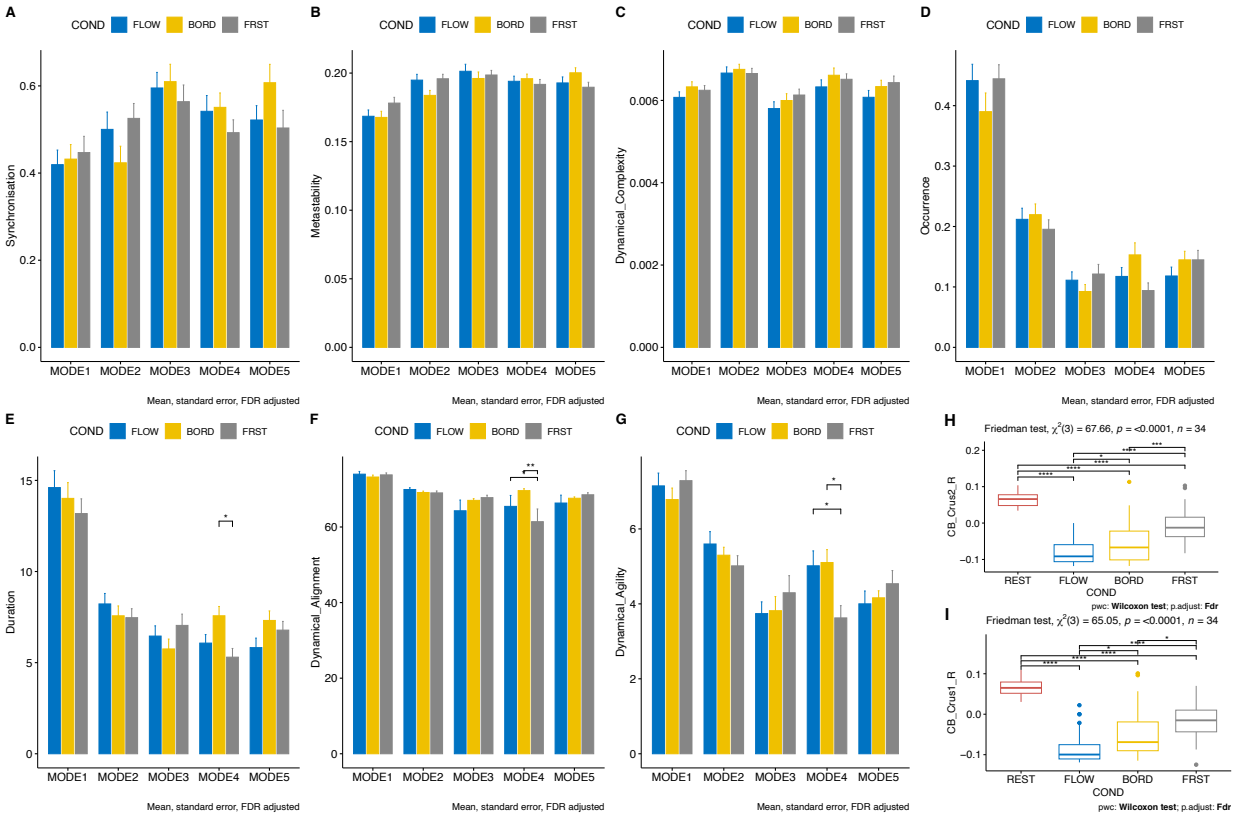

**Figure 6**

Partial hypo-frontality in the flow, boredom, and frustration conditions. Details of the leading eigenvectors phase orientation for the Frontal Parietal Network in all three conditions.