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Examining Network Connectivity Patterns in Response to ‘Flow’: An fMRI Replication Study  
with Implications for the Synchronization Theory of Flow

A Thesis submitted in partial satisfaction of the  
Requirements for the degree Master of Arts  
in Communication

by

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December 2022

The thesis of Paula Ting Wang is approved.

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## ABSTRACT

Examining Network Connectivity Patterns in Response to ‘Flow’: An fMRI Replication Study  
with Implications for the Synchronization Theory of Flow

by

Paula Ting Wang

The need to develop a robust neurological measure of flow increases as the practical applications of flow become more apparent within the broader communication literature. The Synchronization Theory of Flow (Sync Theory; Weber et al., 2009) offers a neurological perspective of the ‘flow’ state (Csikszentmihalyi, 1990), hypothesizing that flow co-occurs with the synchronization of specific attention and reward networks in the brain. As a small step towards better understanding the neurological correlates of flow within the attentional network, we attempt to replicate Weber et al. (2018) using a sample size with increased power. The results from this study emphasize three primary findings that altogether have implications for Sync Theory and our understanding of the neurological basis of flow. First, Weber’s original distraction measure is shown to be a better indicator of flow compared to reaction time measures. Second, functional connectivity between attentional regions is nonlinearly dependent on distraction. Third, Sync Theory’s predictions are demonstrated across some attentional regions, but not others. Results from this study are used to supplement our understanding of the neurological correlates of flow, extend the findings from Weber et al (2018), and comment on the current state of Sync Theory.

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## Introduction

'Flow' is an experiential state characterized by attentional immersion, high productivity, and emotional gratification (Csikszentmihalyi, 1990). Flow offers a renewed perspective on how individuals maintain attentional focus on challenging tasks for long periods of time, with particular emphasis on its positive psychological outcomes. Practical applications of flow have provided meaningful contribution to a variety of communication research areas. For instance, flow has been used as a theoretical framework to understand the selection and enjoyment of entertainment-oriented media such as online gaming (Hsu & Lu, 2004), video games (Triberti & Argenton, 2013), and web-surfing (Pace, 2004; Skadberg & Kimmel, 2004). It has also been used to explain academic performance in e-learning tools for education (Bassi & Delle Fave, 2012; Davis & Wong, 2007), performance in workplace settings (Csikszentmihalyi & LeFevre, 1989; Engeser & Baumann, 2014; Schallberger & Pfister, 2001), cooperation between groups (Ghani & Deshpande, 1994; Magyaródi & Oláh, 2015), and as an emotional regulation tool in psychiatric rehabilitation (Delle Fave & Massimini, 1992; Massimini et al., 1987).

Efforts to triangulate a measure of flow using psychophysiological and neuroimaging techniques have been driven by concerns surrounding the validity of relying on self-report measures alone (Finneran & Zhang, 2002; Nakamura & Csikszentmihalyi, 2002). Subsequent research on physiological correlates of flow have demonstrated some valuable findings, such as how flow compares to related states of stress, relaxation, and meditation (e.g., Brefczynski-Lewis et al., 2007; de Manzano et al., 2010; Keller et al., 2011; Peifer et al. 2014), and how subjective experiences of 'effortlessness' during flow relate to physiological measures of effort (e.g., Austin, 2010).

The Synchronization Theory of Flow (Sync Theory; Weber et al., 2009) offers a

neurological perspective of flow. At a neurological level, understanding what flow looks like with a dynamic, real-time measure in the brain has implications for a variety of research questions, such as testing the length, depth, and stability of flow episodes across various conditions and types of distractors. Sync Theory operationalizes flow as the synchronization of attention and reward neural networks, which allows for flow to be measured using functional magnetic resonance imaging (fMRI) techniques. Recently, Weber et al. (2018) found evidence for a distraction-connectivity relationship in attentional components of the brain, which offered some critical support for the hypotheses of Sync Theory. However, given their low sample size and subsequent low statistical power, it calls to question the replicability of their final results. As functional magnetic resonance imaging (fMRI) methods gain traction within the communication sciences (Turner et al., 2018; Weber et al., 2015), it becomes increasingly important to likewise emphasize good practice in methodological applications of fMRI in communication neuroscience. As a burgeoning field, communication neuroscience sits in a unique position that allows it to observe and learn from the experiences of its predecessors (Turner et al., 2018) and to avoid the pitfalls currently plaguing fMRI studies in neighboring fields (e.g., Francis, 2012; Ioannidis, 2005). In particular, the proliferation of underpowered fMRI studies (i.e., with low sample size) has contributed to high Type-I error and overestimation of effect sizes in reported results (Button et al., 2013).

This paper therefore serves as a test of Weber and colleagues' (2018) distraction-connectivity relationship by replicating their method using a new dataset with a higher sample size. Results from this study will be used to supplement our understanding of the neurological correlates of flow, extend the findings from Weber et al (2018), and comment on the current state of Sync Theory.

## **The Synchronization Theory of Flow**

Cortical neurons communicate via action potentials, which are electrical impulses generated by a sudden shift in the electrical charge of the neuronal membrane. Action potentials generated and propagated by groups of cortical neurons can align in frequency and spontaneously self-organize into a synchronized oscillatory state. Self-organization and spontaneous order are properties of complex systems, whereby individual units of a group coordinate their activity without the need for centralized planning. The brain is one of many naturally occurring complex systems (Strogatz, 2004), and demonstrates self-organizational properties via synchronization of neural oscillations. Neural synchrony has been shown to play an important functional role in attention-related outcomes such as stimuli selection and behavioral responses (Knudsen, 2007; Salinas & Sejnowski, 2001). For instance, when attending to a stimulus, relevant neurons in the V4 visual cortex both increased and synchronized their firing rate (Fries et al., 2001; Bichot et al., 2005; Taylor et al., 2005; Womelsdorf et al., 2006), which predicted decreased behavioral response times when attending to the target stimulus and increased behavioral response times when attending to a distractor stimulus. Moreover, synchronization has been shown to be more sensitive than firing rate as a predictor for behavioral performance (Womelsdorf et al., 2006).

In 2009, Weber and colleagues theorized that neural network synchronization may be an explanation for the properties of flow. The first of the four hypotheses for the Synchronization Theory of Flow (Sync Theory; Weber et al., 2009) predicted that flow co-occurs with the synchrony of specific attention and reward networks.

*H1: If an individual is exposed to flow-inducing stimuli and flow occurs, then specific attentional and reward networks synchronize.*



The second hypothesis of Sync Theory asserts that when antecedent conditions for flow are satisfied, the synchronization of specified networks occurs as a discrete state change in time.

*H2: The synchronization of attentional and reward networks occurs in discrete states*

In this context, *discreteness* is a descriptor for how the sudden emergence of synchrony results in a dichotomous set of outcomes; neurons are either synchronized or they are not. Given that we cannot predict the time point at which spontaneous order emerges, it follows that we do not ‘approach synchronization’, and thus we cannot ‘approach flow’. At an undisclosed point in time we are in it, otherwise we simply are not. The logic behind discreteness as it is characterized in Sync Theory is rooted in complex systems theory, and can be best demonstrated via the “Bak Sand Pile Model” (Bak et al., 1987). In this demonstration, a sand pile is built one grain at a time. As each grain is added, some existing components of the pile are disrupted but the overall structure remains intact. However, at a critical time interval a single grain of sand is capable of triggering a sudden collapse in the structural integrity of the sand pile, fundamentally altering the dynamics of the sand system. Similarly, Sync Theory hypothesizes that there is an unpredictable and narrow window of time within which neural networks will spontaneously synchronize, prompting a discrete shift in the cognitive states between non-flow and flow.

The third and fourth hypotheses of Sync Theory relate flow’s experiential components of energetic efficiency and enjoyment with its neural dynamics.

*H3: Network synchronization corresponds to an energetically optimized state*

*H4: Network synchronization manifests as an enjoyable experience*

Properties of energetic optimization have found some early support (e.g., Huskey, Wilcox et al., 2018). However, the current study will primarily focus on H1 and H2.

### **The role of distraction and connectivity in flow**

In their 2018 paper, Weber and colleagues examined the executive attention network and found evidence for several claims, including that: (a) connectivity is dependent on distraction, (b) the distraction-connectivity relationship is bilinear, and that (c) the shape of the bilinear distraction-connectivity relationship differs based on whether the network components were related or unrelated to sensorimotor coordination.

Weber and colleagues (2018) did not intend to specifically test Sync Theory's predictions with their study; however, their findings about a distraction-connectivity relationship in attention networks managed to lend credence towards the first and second hypotheses of Sync Theory. Weber et al's (2018) finding that (a) synchronization in attention networks (which is driven by connectivity) indeed occurs at a critical level of distraction offers support for Sync Theory's *first* hypothesis. Moreover, Weber et al's (2018) finding that (b) the distraction-connectivity relationship is bilinear, meaning that connectivity sharply shifts when distraction falls below a certain threshold, offers support for Sync Theory's *second* hypothesis. Since Sync Theory does not speculate about the sensorimotor components of attention, Weber et al's (2018) finding about (c) the sensorimotor dependence of the distraction-connectivity relationship holds no bearing on Sync Theory's predictions.

However, Weber and colleagues' (2018) study used a dataset of 13 subjects from the University of Tübingen in Germany. Given rising concerns within the field regarding the replicability of fMRI studies with lower subject numbers (Turner et al., 2018), this study will aim to replicate the results of Weber et al. (2018) using a new dataset of 35 subjects recruited from

Ohio State University in the United States. The sections below will describe distraction, its relationship with connectivity, and situate all concepts within the realm of flow and Sync Theory. In the first section, we describe distraction as it was formulated by Weber et al. (2018), and then assert that distraction can be used as a proxy for flow, which was not hypothesized by Weber et al. (2018). In the second section, we contextualize Weber et al.'s (2018) original claims about distraction and connectivity within the realm of flow. Here, we aim to replicate all three claims from Weber et al. (2018), but we place greater importance on the claims that inform Sync Theory, and lesser importance on the claims that have no bearing to Sync Theory.

## **Distraction**

### *The distraction model*

Distraction ( $D$ ) is operationally defined as the demand on attentional capacity during a primary task activity. In Weber et al. (2018), participants were required to focus on a primary video game task while concurrently responding to a secondary distractor task. The distractor task involved the presentation of a laser light stimulus into the periphery of a participant's field of vision. Delays between stimulus presentations were randomized following a Poisson distribution with an average time delay of 10 seconds. Participants were instructed to respond as quickly as possible to the laser light stimulus using a button-press response with their non-dominant hand. The button-press ended a stimulus trial and reset the timer for a new delay.

$D$  is operationalized as a multiplicative distraction index calculated over a constant 10 second sliding (or overlapping) window ( $\Delta t$ ). The index is a function of the mean time interval between laser light presentations and mean response time to each presentation such that distraction increases when participants respond increasingly faster to increased presentation trials of the distractor task. Statistically, we calculate  $D$  as the inverse of the mean time interval

between laser light presentations ( $I_p$ ) multiplied by the mean response time to each presentation of the laser light ( $I_r$ ):

$$D_{\Delta t} = \frac{1}{I_p \times I_r} \quad (1)$$

The more laser light presentations ( $I_p \rightarrow 0$ ) and the faster participants' response to those laser light presentations ( $I_r \rightarrow 0$ ) the higher the distraction from the primary experimental task and the higher  $D$  is within sliding window  $\Delta t$ . Given that humans are resource capacity limited (Lang, 2000), an increase in distraction results in a strain on cognitive resources such that the participant is forced to divert attentional resources away from a primary task.

#### ***Flow co-occurs with a decrease in distraction***

Antecedent conditions for flow requires a balance between an individual's skill level and the demands of the task (Nakamura & Csikszentmihalyi, 2009), such that the individual is neither bored (i.e., task challenge < skill) nor frustrated (i.e., task challenge > skill). While studies have traditionally verified the skill-challenge balance using reaction time data, we aim to verify distraction as a better indicator for flow compared to traditional reaction time data.

We predict that distraction is highest when the primary task is both too boring (i.e., task challenge < skill) or too frustrating (i.e., task challenge > skill). Given excess attentional capacity within the boredom condition, the participant is likely to motivationally disengage from the primary task and redistribute attentional resources towards the secondary distractor task (Huskey, Craighead et al., 2018; Huskey et al., 2021). This would result in a relatively shorter mean response time ( $I_r$ ) and greater  $D$ . Within the frustration condition, as attentional capacity collapses due to cognitive overload, we likewise predict a shorter mean response time ( $I_r$ ) and greater  $D$ . However, when attentional capacity is maximally delegated to the primary task within

the balanced condition of flow, we predict a relatively longer mean response time ( $I_r$ ) to the distractor task and therefore smaller  $D$ . Following this logic, propensity for flow is high when distraction is low, and low when distraction is high.

*H1a: Distraction will be lowest during the flow condition and highest during the frustration and boredom conditions.*

Distraction as a flow indication method deviates from existing studies, which have typically predicted flow using reaction time (e.g., Huskey et al., 2021). As seen in Equation 1, the distraction model  $D$  is a function of response time with the added information of mean time interval between stimulus presentations. Given that the distraction takes the inverse of reaction time and stimulus presentation intervals, we expect that the relationship between reaction time and conditions is the inverse of the relationship between distraction and conditions. As yet, no comparison has been done that compares distraction and reaction time as predictors of flow. Therefore, the following two hypotheses identify reaction time as an alternative, but less powerful predictor for distraction.

*H1b: Reaction time will be highest during the flow condition and lowest during the frustration and boredom conditions.*

*H2: Distraction is a better predictor for flow compared to reaction time, such that the difference between conditions in H1a will be more significant compared to the difference between conditions in H1b.*

Having a continuous measure of distraction spanning the time series of the experimental paradigm allows us to calculate the statistical dependency between neural time series alongside a continuous distraction regressor.

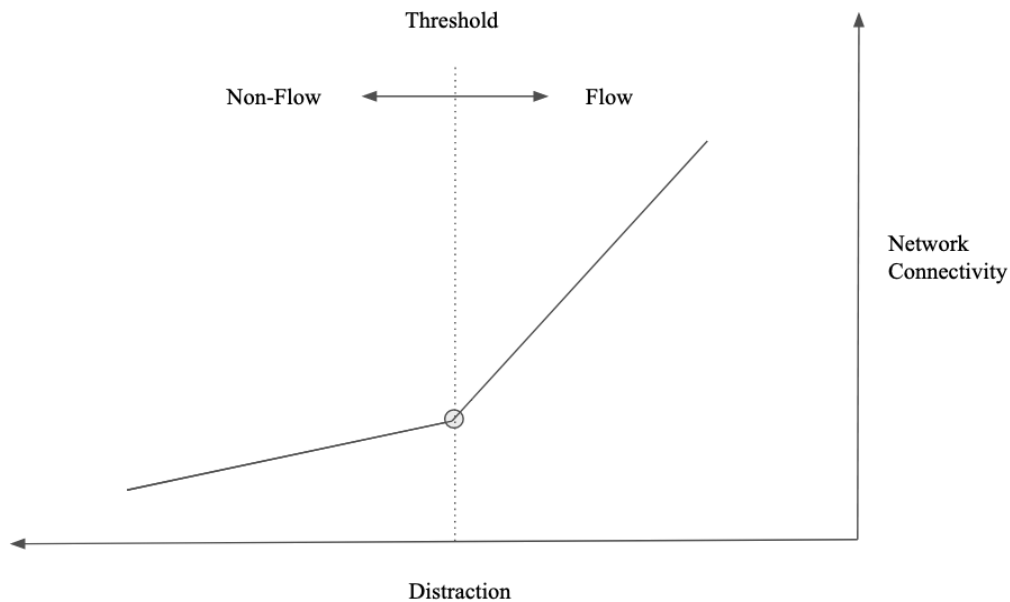
## The distraction-connectivity relationship

### *Synchrony expressed as a sudden acceleration of connectivity*

Sync Theory's second hypothesis asserts that at the point of entrance of flow, the synchronization of specified networks occurs as a discrete state change in time. As specified by Sync Theory, the discrete transition between cognitive states of non-flow to flow can be operationalized as an acceleration in connectivity strength within and across relevant neural networks. Figure 1 depicts Weber and colleague's (2018) hypothesized relationship between network connectivity and distraction, showing a bilinear graph that demonstrates nonlinearity at a critical parameter value.

### Figure 1

*The bilinear relationship between network connectivity and distraction from a primary task*



*Note.* The direction of the x-axis has been reversed for ease of interpretation. Distraction values decrease as we move from left to right along the axis. While Weber et al. (2018) hypothesized the distraction-connectivity relationship, annotations specifying the threshold between non-flow and flow were added for this study.

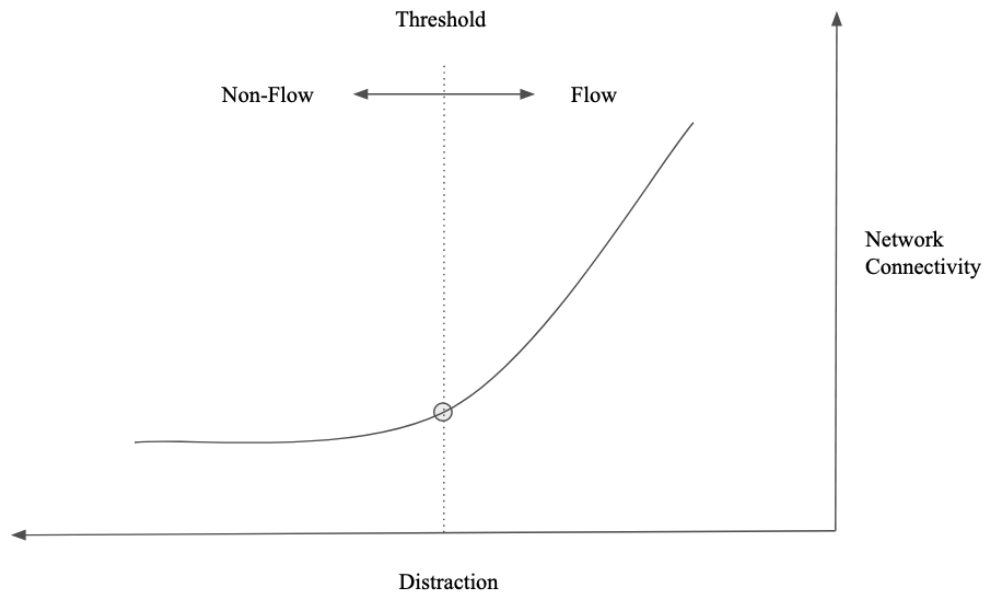
In Figure 1, as distraction decreases (i.e., propensity for flow increases), network

connectivity strength increases somewhat, then increases considerably more when distraction falls below a thresholded flow-induction point, triggering the spontaneous synchronization of neural networks and entrance into flow. Importantly, the time point and value of network connectivity strength at which the thresholded flow-induction point occurs is spontaneous and unpredictable.

Without a known value for the temporal parameter at which flow-induction occurs, it becomes difficult to utilize the model in Figure 1 for analysis purposes. We therefore turn to Figure 2, which aims to approximate the nature of the bilinear graph in Figure 1 using a nonlinear convex curve. Although the relationship hypothesized is that of a bilinear nature (Figure 1), we test the relationship using the nonlinear quadratic model (Figure 2). Henceforth, all mentions of the distraction-connectivity relationship will use the term ‘nonlinear’.

**Figure 2**

*The convex relationship between network connectivity and distraction from a primary task*



*Note.* The direction of the x-axis has been reversed for ease of interpretation. Distraction values decrease as we move from left to right along the axis. While Weber et al. (2018) hypothesized

the distraction-connectivity relationship, annotations specifying the threshold between non-flow and flow were added for this study.

### ***The psychophysiological interaction model***

To test for the sudden increase in functional connectivity acceleration strength (i.e., discrete transition into flow), we approximate the threshold model (Figure 1) using a nonlinear, quadratic form of a general linear regression model (Figure 2). This model is based on the original Psycho-Physiological Interactions model (PPI; Friston et al., 1997; O'Reilly et al., 2012), which is generalized as:

$$Y = (P_{sy})\beta1 + (P_{hy})\beta2 + (P_{sy} * P_{hy})\beta3 + e \quad (2)$$

The PPI model identifies brain regions whose activity depends on an interaction between a psychological context (a task) and physiological state (the time course of brain activity) of a particular seed region. It can therefore be considered an estimation of the context-dependent changes in functional connectivity between brain regions. In this equation,  $\beta1$  and  $\beta2$  are the parameter estimates for the main effects of the psychological ( $P_{sy}$ ) and physiological ( $P_{hy}$ ) variables respectively,  $\beta3$  is the parameter estimate for their interaction ( $P_{sy} * P_{hy}$ ), and  $Y$  is the dependent variable. If the interaction term can explain the brain activation of another brain region after taking into account the main effects of the psychological and physiological variables, then the existence of a task-dependent connectivity between the two brain regions is implied.

In line with the PPI model, our model of functional connectivity identifies the distraction parameter ( $D$ ) as a psychological regressor, a source region of interest ( $ROI_S$ ) as a physiological regressor, and a target region of interest ( $ROI_T$ ) as a dependent variable of interest. Replicating the method of Weber et al. (2018), the source and target regions that define the attentional network in this paper are theoretically rooted in the executive attention network from Posner and



Peterson's (1990) tripartite theory of attention, and are reliant on functions and localizations suggested a priori by Fan et al. (2002, 2005). The equation appears as follows:

$$ROI_T = a * ROI_S + b * D + (c * D + d * D^2) * ROI_S + \epsilon \quad (3)$$

This regression model links the blood-oxygen level dependent (BOLD) signal in the target region ( $ROI_T$ ) with that of the source region ( $ROI_S$ ), the distractor parameter ( $D$ ), as well as their linear ( $ROI_S * D$ ), and quadratic ( $ROI_S * D^2$ ) interactions. Of primary importance for our analysis are the  $c$  and  $d$  coefficients, which are the set of parameter estimates for the linear and quadratic interaction terms respectively. The  $c$  and  $d$  coefficients are used to measure the type and pattern of connectivity between  $ROI_T$  and  $ROI_S$  depending on  $D$ .

The following three hypotheses aim to verify the nature of the relationship between distraction and network connectivity for all pairs of target and source ROIs. The first of the three provides a validation that connectivity between these pre-defined regions indeed depends on the level of distraction. This hypothesis replicates Weber et al's (2018) first claim, and, if supported, provides further evidence for the first hypothesis of Sync Theory.

*H3 : Connectivity depends on distraction (i.e.,  $c \neq 0$ )*

The second and third hypotheses validate the convex shape of the curve as depicted in Figure 2. We divide these as two hypotheses, as we replicate Weber et al. (2018) by taking into account the activation of sensorimotor components of the attentional networks that are activated during the button-press distractor task. As distraction increases, participants are expected to engage in increased sensorimotor behavior to execute the button-press. Thus, attentional network components both related and unrelated to sensorimotor functioning will exhibit opposite responses to changing levels of distraction. While connectivity is predicted to *decrease* with

increasing distraction for attentional networks *unrelated* to sensorimotor coordination ( $c < 0$ ), connectivity should *increase* with increasing distraction for attentional networks *related* to sensorimotor coordination ( $c > 0$ ).

*H4 : For attentional network components unrelated to sensorimotor coordination, the curvature of an “decreasing distraction-increasing connectivity” relation is convex (i.e. if  $c < 0$  then  $d > 0$ )*

*H5 : For attentional network components related to sensorimotor coordination, the curvature of an “decreasing distraction-decreasing connectivity” relation is concave (i.e. if  $c > 0$  then  $d < 0$ )*

## Method

### Dataset

Huskey et al. (2021) collected functional magnetic resonance imaging (fMRI) data using a sample of  $n = 35$  participants recruited from Ohio State University and the surrounding community. Participants in the fMRI study were right-handed, had normal or corrected to normal vision, and did not demonstrate any contraindication to fMRI scanning. Both studies were approved by the host University’s Institutional Review Board. The data is organized in compliance with the Brain Imaging Data Structure (Gorgolewski et al., 2016) and is available on OpenNeuro<sup>1</sup>. Much like Weber et al. (2018), the Huskey et al. (2021) dataset utilizes a primary video game task along with a secondary distractor task.

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<sup>1</sup> <https://doi.org/10.18112/openneuro.ds003358.v1.0.0>

### ***Primary task***

Participants played *Asteroid Impact*<sup>2</sup>, a video game designed for experimental research that enables manipulation of in-game difficulty. Consistent with previously validated techniques for inducing flow using *Asteroid Impact* (Huskey, Craighead et al., 2018), participants engaged in low-difficulty (i.e., boredom), high-difficulty (i.e., frustration), and balanced challenge-skill conditions (i.e., flow). *Asteroid Impact* is a point-and-click style video game where subjects use a cursor to collect crystal-shaped targets located across the screen. At the same time, large asteroids bounce around the screen. If the participant's cursor collides with an asteroid, the current game ends. Parameters associated with asteroid size, speed, and target location can be seeded and manipulated to alter in-game difficulty, leaving all other conditions exactly constant. In the low-difficulty (boredom) condition, the asteroid speed was slow and did not change. In the high-difficulty (frustration) condition, asteroid speed was consistently fast. In the balanced-difficulty (flow) condition, the game started at a moderately high level of asteroid speed and an algorithm adjusted asteroid speed based on player performance.

### ***Distractor task***

Huskey et al.'s (2021) study utilized a similar distractor probe compared to Weber et al. (2018). In their study, Huskey and colleagues' participants were required to respond to an audiovisual red light stimulus appearing equally and randomly within one of the four quadrants of their screen. Delays in the presentation of the red light stimulus, measured as the inter-stimulus interval (*ISI*), were randomized using a truncated Gaussian probability distribution. Participants were required to do a button-press with their non-dominant hand. Secondary task reaction time (*STRT*) was determined as the period spanning the onset of a stimulus onset to the

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<sup>2</sup> [https://github.com/medianeuroscience/asteroid\\_impact](https://github.com/medianeuroscience/asteroid_impact)

subsequent key/button press.

The present study will use *STRT* and *ISI* as input variables within the distraction index (see Equation 1). This results in a distraction parameter ( $D$ ) that serves as a continuous regressor for the customized PPI model (see Equation 3). A mean value calculated for *STRT* will be used as the input variable for  $I_r$ , and a mean value for *ISI* will be used as the input variable for  $I_p$ . In line with Weber et al. (2018), the sliding time window for  $\Delta t$  will be set to 10-s.

## **Analysis**

### ***Preprocessing***

Dicoms were converted to NIfTI-1 format using `dcm2niix`, version v1.0.20190410 GCC6.3.0. Preprocessing was performed using `fMRIPrep` 21.0.0 (Esteban et al., 2018), which is based on `Nipype` 1.6.1 (Gorgolewski et al., 2011). T1-weighted structural MRI data were collected (256 slices, TR=1900ms, voxel size=1x1x1mm). For each subject, the T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with `N4BiasFieldCorrection` (Tustison et al. 2010), distributed with `ANTs` 2.3.3 (Avants et al. 2008), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a `Nipype` implementation of the `antsBrainExtraction.sh` workflow (from `ANTs`). Volume-based spatial normalization to one standard space was performed through nonlinear registration with `antsRegistration` (`ANTs` 2.3.3), using brain-extracted versions of both T1w reference and the T1w template.

Three functional runs were collected (72 slices in interleaved ascending order, TR=2000ms, voxel size=2x2x2mm), with 185 functional volumes acquired per run. For each of the three BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were

generated. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) were estimated before any spatiotemporal filtering). BOLD runs were slice-time corrected to 0.949s (0.5 of slice acquisition range 0s-1.9s). The BOLD time-series were resampled onto their original, native space by applying the transforms to correct for head-motion. Confound time-series were derived based on head motion parameters, global signal, white matter (WM) and cerebral spinal fluid (CSF). The BOLD reference was then co-registered to the T1w reference with boundary-based registration (Greve & Fischl, 2009) cost-function. Co-registration was configured with six degrees of freedom. The BOLD time-series were then resampled into standard space, generating preprocessed BOLD runs in MNI152 space.

### ***Distraction***

Distraction is calculated by the inverse of the product of the mean time interval between laser light presentations and the mean response time to laser light presentations (see Equation 1). We then applied a repeated measures ANOVA with condition as the within-subjects factor and distraction as the outcome variable. The same analysis was performed using reaction time as the outcome variable, and the two models were then compared.

### ***ROI Coordinates***

Replicating the method of Weber et al. (2018), the ROIs that define the attentional network in this paper are reliant on functions and localizations suggested a priori by Fan et al. (2002, 2005). Given that all of Huskey et al.'s (2021) and Weber et al.'s (2018) participants were right-handed and since visuospatial attention is right lateralized (Thiebaut de Schotten et al., 2011), the distractor task was universally conducted with the left hand. For this reason, the attentional network is biased toward executive attention components in the right hemisphere. The

ROIs are localized according to the suggested anatomical localization in Collins et al. (1994), and are represented as standardized Montreal Neurological Institute (MNI) coordinates: [22, -27, 3] mm for the thalamus (Thal); [16, 4, 44] mm for superior frontal gyrus (SFG); [36, 26, 15] mm for superior parts (IFGs) and [34, 20, 5] mm for inferior parts of the inferior frontal gyrus (IFGi); [44, -58, 1] mm for lateral parts (FFGI) and [36, -60, 1] mm for medial parts of the fusiform gyrus (FFGm); [0, -62, -32] mm for the cerebellum (Cere); [36, -5, 50] mm for middle frontal gyrus (MFG); and [6, 36, 26] mm for anterior cingulate cortex (ACC).

### ***Psychophysiological model***

The analytical model used in the present analysis follows is a customized form of the psychophysiological model and follows the standard logic of the general linear model. It includes a psychological regressor, a physiological regressor, a linear interaction predictor, and a non-linear interaction predictor (see Equation 3). All levels of the analyses were written using Nipype 1.6.1 (Gorgolewski et al., 2011) pipeline engine in Python.

**Level 1.** The preprocessed BOLD functional data was skull-stripped using the functional mask generated from fMRIPrep. In order to remain agnostic to any possible subsequent analysis, fMRIPrep does not perform any denoising (e.g., spatial smoothing) itself. Therefore, after skull-stripping, we applied spatial smoothing to all functional data with the full width at half maximum (FWHM) of the Gaussian kernel set to 6mm. The psychological distraction regressor was mean-centered and then squared to generate a hyperbolic regressor to be used as input for the nonlinear interaction term. Both the squared and non-squared distraction regressors were convolved with the canonical haemodynamic response function (HRF) from SPM<sup>3</sup>. Physiological time series for each of the ROI coordinates were extracted using the *NiftiSpheresMasker* function from Nilearn.

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<sup>3</sup> <https://www.fil.ion.ucl.ac.uk/spm/>

Spheres were extracted using a radius of 3mm and then mean-centered. Interaction regressors were then generated by multiplying the convolved form of the squared and non-squared distraction regressors with each of the physiological time series from each of the ROIs. For denoising, we went with a set of nine confound regressors, including six realignment parameters (three rotations and three translations), two physiological (white matter and cerebral spinal fluid), and global signal regression. This is a set of nuisance regressors that has been widely applied to functional connectivity studies (Ciric et al., 2017). Confounding regressors were mean-centered and then, along with the psychological distraction regressor, the physiological time series, and the interaction regressors, were fed into the level 1 design of the general linear model. Highpass filter cutoff was set to 100.

**Level 2.** The level 2 analysis combined the results from multiple runs of one subject into one statistical parametric map for all nine ROIs relevant for our study. Registered contrast parameter estimate files were merged and masked, and then fed into the level 2 design.

**Level 3.** The level 3 analysis combined the results from multiple runs of multiple subjects into one statistical parametric map for all nine ROIs relevant for our study. Like with the level 2 design, registered contrast parameter estimate files were merged and masked, and then fed into the level 3 design. Final parameter estimates for the interaction regressors across all nine ROIs were extracted from the t-statistic map. Significance was calculated using z-statistic values, controlling for multiple comparisons using FPR-correction and  $\alpha=0.05$ .

## **Results**

### **Distraction as an indicator of flow**

Hypotheses 1a and 1b predicted what distraction and reaction time would look like between the conditions of boredom, flow, and frustration. Hypothesis 2 predicted that the

differences observed in Hypothesis 1a and 1b would be more significant in the distraction model compared to the reaction time model. A repeated-measures ANOVA found that the effect of condition (within-subjects factor) was significant for both the distraction ( $F(2, 68)=15.70$ ,  $\eta^2_G=0.08$ ,  $p<0.01$ ) and reaction time models ( $F(2, 68)=3.42$ ,  $\eta^2_G=0.025$ ,  $p=0.04$ ). However, distraction exhibited greater effect size and significance ( $\eta^2_G=0.08$ ,  $p<0.01$ ) compared to reaction time ( $\eta^2_G=0.025$ ,  $p=0.04$ ), supporting Hypothesis 2.

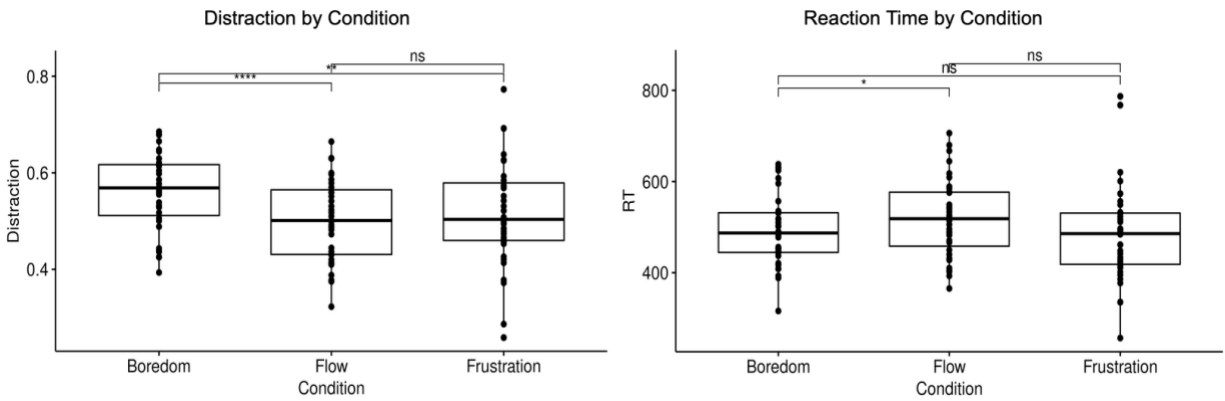
Descriptive statistics show that, across conditions, the mean distraction score from all repeated time points and all subjects follow the direction as predicted by Hypothesis 1a ( $M_{\text{Boredom}}=0.66$ ,  $M_{\text{Flow}}=0.59$ ,  $M_{\text{Frustration}}=0.60$ ), in which the mean distraction was *lowest* for flow compared to boredom and frustration. The mean reaction time score from all repeated time points and all subjects likewise followed the direction as predicted by Hypothesis 1b ( $M_{\text{Boredom}}=534.93$ ,  $M_{\text{Flow}}=588.85$ ,  $M_{\text{Frustration}}=588.12$ ), in which the mean reaction time was *highest* for flow compared to boredom and frustration. To test for significance in the difference between conditions, multiple pairwise paired t-tests were conducted between the levels of conditions using both distraction and reaction time as outcome variables. P-values were adjusted using the FDR correction method. Pairwise differences for distraction were significant between the flow-boredom ( $df=34$ ,  $t=6.20$ ,  $p_{\text{adj}}<0.01$ ) and boredom-frustration ( $df=34$ ,  $t=3.68$ ,  $p_{\text{adj}}<0.01$ ) conditions, but not for the flow-frustration condition ( $df=34$ ,  $t=-1.63$ ,  $p_{\text{adj}}=0.11$ ). Pairwise differences for reaction time were significant between the flow-boredom condition ( $df=34$ ,  $t=-2.58$ ,  $p_{\text{adj}}=0.04$ ), but not significant between the boredom-frustration ( $df=34$ ,  $t=0.40$ ,  $p_{\text{adj}}=0.69$ ) and flow-frustration ( $df=34$ ,  $t=2.19$ ,  $p_{\text{adj}}=0.05$ ) conditions, although the flow-frustration condition was closer to approaching significance in the reaction time model compared to the distraction model. Pairwise comparisons are visualized in Figure 3. Together, the means and



pairwise differences between conditions for distraction and reaction time support Hypotheses 1a and 1b, and provide additional support for Hypothesis 2.

### Figure 3

*Pairwise comparisons between conditions for distraction and reaction time*



### Psychophysiological interaction coefficients

Hypothesis 3, 4, and 5 together examine the linear and nonlinear interaction coefficients of the customized psychophysiological interaction model (Equation 3) used to examine the convex distraction-connectivity curve (Figure 2) hypothesized by Sync Theory. Results for the group level linear (*c*) and nonlinear (*d*) interaction coefficients are shown in Table 1.

**Table 1***Group-level interaction coefficients for this study*

Linear coefficients (c)									
	Thal	SFG	IFGs	FFGm	IFGi	Cere	MFG	FFGI	ACC
Thal		0.83	0.42***	0.61***	0.86	0.72	1.23	0.21***	1.15
SFG	0.43***		1.69	0.34***	-0.04***	0.12***	0.62***	-0.66***	0.98
IFGs	0.59***	0.56		-0.36***	1.01	1.26	1.15	-0.73***	0.95
FFGm	-0.38***	0.62***	0.21***		1.42	0.28***	1.18	0.48***	1.52
IFGi	-0.2***	0.62***	0.3***	1.24		1.08	1.37	0.62***	1.08
Cere	-0.27***	0.95	0.77	0.58***	-0.48***		1.3	0.03***	0.05***
MFG	-0.15***	0.47***	0.62	0.83***	-0.0***	0.45***		0.19***	1.27
FFGI	-0.72***	0.68***	0.3***	0.81	0.82***	0.1***	0.9***		1.35
ACC	0.03***	1.01	0.73	0.76***	0.58***	0.6***	1.14	0.04***	
Nonlinear coefficients (d)									
	Thal	SFG	IFGs	FFGm	IFGi	Cere	MFG	FFGI	ACC
Thal		0.91	-1.07***	0.57***	0.48***	-0.62***	0.62***	0.57***	0.56
SFG	-0.43*		-0.16***	-0.18***	0.86***	0.29	-0.33***	0.78	-0.83***
IFGs	0.48	0.44		-0.15***	0.44***	0.65***	-0.07***	0.73***	0.01***
FFGm	-1.41***	-0.27***	0.02***		0.7***	1.17	0.18***	-0.14***	0.31***
IFGi	-0.78***	1.61	-0.62***	0.1***		-0.13***	0.71***	-0.13***	0.53***
Cere	-0.82***	0.83***	-0.09***	-0.45***	-0.86***		0.94	0.41***	-0.53***
MFG	-1.78***	1.07	-0.03***	0.53***	-0.13***	-0.31***		0.8***	0.21***
FFGI	-1.32***	0.56***	0.32***	0.43***	1.11	-0.03***	0.67		0.4***
ACC	-0.11***	0.18***	-0.02***	0.58	0.89	0.03***	-0.03***	0.06***	

*Note.* Columns are predicted by rows. For example,  $ACC \sim (c \cdot D + d \cdot D^2) \cdot Thal = (0.03 \cdot D - 0.11 \cdot D^2) \cdot Thal$ , where 0.03 is the linear interaction coefficient and -0.11 is the nonlinear interaction coefficient. Coefficient pairs that exhibit significant opposite signs are colored in pairs of green/red, with green denoting sign > 0 and red denoting sign < 0. Thal, thalamus; SFG, superior frontal gyrus; IFGs, superior parts of the inferior frontal gyrus; FFGm, medial parts of the fusiform gyrus; IFGi, inferior parts of the inferior frontal gyrus; Cere, cerebellum; MFG, middle frontal gyrus; FFGI, lateral parts of the fusiform gyrus; ACC, anterior cingulate cortex. \*p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001.

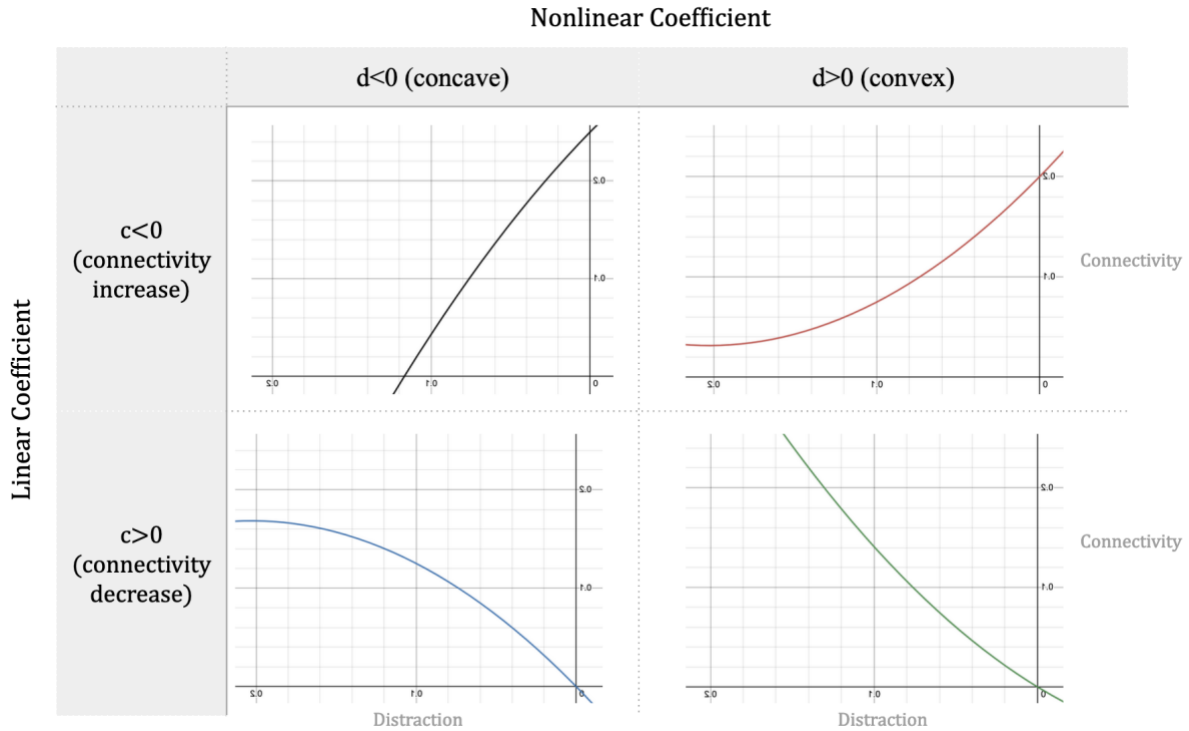
Hypothesis 3 predicted that connectivity was dependent on distraction ( $c \neq 0$ ). This was supported for all values of linear coefficient  $c$ . As predicted by Hypothesis 4, the increase in connectivity with decreasing distraction indicating a convex curve was found in frontal network areas such as SFG-iFGi ( $c=-0.04, p<0.01; d=0.86, p<0.01$ ) and IFGs-FFGI ( $c=-0.73, p<0.01; d=0.73, p<0.01$ ). Hypothesis 5 predicted that there would be a concave decreasing distraction-decreasing connectivity in sensorimotor networks, which found support in cerebellar-cortical connections reflecting sensorimotor networks such as Cere-FFGm ( $c=0.58, p<0.01; d=-0.45, p<0.01$ ) and Cere-ACC ( $c=0.05, p<0.01; d=-0.53, p<0.01$ ). These findings generally reflect the findings in the Weber et al. (2018) paper, which also indicated that the decreasing distraction-increasing connectivity model found support mainly in the frontal regions, whereas cerebellar connections showed an increase instead.

These findings lend some credence to the replicability for the decreasing distraction-increasing connectivity model. However, it must also be pointed out that other findings did not replicate the Weber et al. (2018) paper. For instance, Weber et al. (2018) found local frontal network connections (IFGs-IFGi, IFGi-IFGs, IFGi-MFG, SFG-MFG, ACC-MFG) and thalamo-frontal connections (Thal-SFG, Thal-MFG) showed a decrease in connectivity ( $c<0$ ) that revealed a significant convex relationship ( $d>0$ ), supporting Hypothesis 5. However our study did not find these effects. Instead, we found support for a concave decreasing distraction-decreasing connectivity ( $c>0, d<0$ ) in some local frontal connections (IFGi-IFGs, SFG-MFG) and thalamo-frontal connections (ACC-Thal, SFG-Thal, Thal-IFGs).

Figure 4 provides a visualization of the expected patterns between the possible combinations of positive and negative values for the  $c$  and  $d$  coefficients.

**Figure 4**

*Visualization of the possible combinations of positive and negative coefficients for the linear and the nonlinear interaction terms*



*Note.* The direction of the x-axis has been reversed for ease of interpretation. Distraction values decrease as we move from left to right along the axis. Weber et al. (2018) hypothesized  $c < 0$ ,  $d > 0$  for connections unrelated to sensorimotor coordination (red line), and  $c > 0$ ,  $d < 0$  for connections related to sensorimotor coordination (blue line).

Importantly, some findings of ours unrelated to Weber and colleague's (2018) hypotheses may lend some support to Sync Theory's predictions. Weber et al. (2018) did not hypothesize about a concave decreasing distraction-increasing connectivity relationship (black line), nor a convex decreasing distraction-decreasing connectivity relationship (green line). Sync Theory implies that there will be an increase in connectivity following decreasing distraction ( $c < 0$ ), but does not specify whether connectivity will increase at an increasing rate (convex,  $d > 0$ ) or increase at a decreasing rate (concave,  $d < 0$ ). We see that there is a significant increase in

connectivity ( $c < 0$ ) with a concave pattern ( $d < 0$ ) in many thalamic connections, which provides some further support for Sync Theory. This includes thalamo-frontal regions IFGi-Thal ( $c = -0.2$ ,  $p < 0.01$ ;  $d = -0.78$ ,  $p < 0.01$ ) and MFG-Thal ( $c = -0.15$ ,  $p < 0.01$ ;  $d = -1.78$ ,  $p < 0.01$ ), thalamo-occipitotemporal regions FFGm-Thal ( $c = -0.38$ ,  $p < 0.01$ ;  $d = -1.41$ ,  $p < 0.01$ ) and FFGl-Thal ( $c = -0.72$ ,  $p < 0.01$ ;  $d = -1.32$ ,  $p < 0.01$ ), and the thalamo-cerebellar connection Cere-Thal ( $c = -0.27$ ,  $p < 0.01$ ;  $d = -0.82$ ,  $p < 0.01$ ).

For comparison purposes, results for the group level linear ( $c$ ) and nonlinear ( $d$ ) interaction coefficients from the Weber et al. (2018) paper are shown in Table 2.

**Table 2***Group-level interaction coefficients for Weber et al., (2018)*

Linear coefficients (c)									
	Thal	SFG	IFGs	FFGm	IFGi	Cere	MFG	FFGI	ACC
Thal		-1.14**	-0.33	0.01	-0.05	-0.57	-2.34**	0.59	-0.20
SFG	-0.51		-0.26	0.13	-0.38	0.50	1.14*	-0.95	-0.22
IFGs	-0.55	-0.06		-0.28	-0.64**	1.03**	-0.38	0.73	-0.41*
FFGm	0.31	-0.81**	-0.38		0.83*	-0.35	-1.65	1.11	-0.28
IFGi	0.06	-0.89*	-1.38***	0.37		0.55	-2.51*	0.97	-0.33
Cere	-0.26	1.04***	1.79***	-0.22	0.67		2.41***	-1.1	0.41
MFG	-0.09	0.24	0.22	-0.01	-0.22	0.23		-0.38	-0.06
FFGI	0.24	-0.51	0.66	0.02	0.49	-0.71*	-0.40		0.64**
ACC	0.03	-0.73	-1.66**	-0.12	-0.13	0.67*	-2.20**	1.67	
Nonlinear coefficients (d)									
	Thal	SFG	IFGs	FFGm	IFGi	Cere	MFG	FFGI	ACC
Thal		2.64**	0.62	0.62	0.62	2.11	7.61**	0.61	0.73
SFG	0.41		-0.89	-1.38	0.19	-3.51	-5.50*	2.89	0.37
IFGs	0.50	-0.36		-0.21	1.41*	-2.43**	5.17	-2.61	0.54
FFGm	-1.14	2.60*	0.17		-2.05*	3.86	5.21*	-2.25	0.33
IFGi	-0.54	2.96	4.81***	0.07		1.33	11.59*	-3.47	0.66
Cere	-0.05	-3.53***	-5.57***	1.32	-2.61		-10.30	1.94	-0.93
MFG	-0.29	-0.30	-0.12	-0.24	0.94	-1.57		0.60	0.27
FFGI	-1.14	2.52**	-1.99	-0.65	-3.30	2.61*	1.79		-3.04
ACC	0.54	2.26	4.09***	0.37	0.48	1.43	11.57**	-4.66	

*Note.* Columns are predicted by rows. For example,  $ACC \sim (c \cdot D + d \cdot D^2) \cdot Thal = (0.03 \cdot D - 0.11 \cdot D^2) \cdot Thal$ , where 0.03 is the linear interaction coefficient and -0.11 is the nonlinear interaction coefficient. Coefficient pairs that exhibit significant opposite signs are colored in pairs of green/red, with green denoting  $sign > 0$  and red denoting  $sign < 0$ . Thal, thalamus; SFG, superior frontal gyrus; IFGs, superior parts of the inferior frontal gyrus; FFGm, medial parts of the fusiform gyrus; IFGi, inferior parts of the inferior frontal gyrus; Cere, cerebellum; MFG, middle frontal gyrus; FFGI, lateral parts of the fusiform gyrus; ACC, anterior cingulate cortex. \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .

## Discussion

In replicating Weber et al.'s (2018) paper, which had only a sample size of 13, this study aims to test the decreasing distraction-increasing connectivity relationship in the attentional system, using a higher powered sample size of 35. For this study, we situated the distraction-connectivity relationship within the context of flow and its implications for the hypotheses of Sync Theory. The results from our replication study emphasize three primary findings that altogether have implications for Sync Theory and our understanding of the neurological basis of flow. First, distraction is shown to be a better indicator of flow compared to reaction time. It is therefore recommended that those conducting behavioral analyses for flow using reaction time measures should adopt the distraction model in the analytical process. The distraction model requires two considerations in design and data collection: to be able to (1) collect reaction time data at a second-by-second rate, (2) and to collect second-by-second data on the interval period between stimulus presentations. Reaction time and stimulus interval can then be easily used as input for calculating distraction.

Second, our study successfully replicated the nonlinearity of the distraction-connectivity relationship, but the shape of the nonlinearity was different. Echoing Weber et al. (2018), our results indicate a significant dependence between attentional connectivity and distraction, which corroborates the existence of a connectivity shift given decreasing levels of distraction. Moreover, we found significant coefficients for the nonlinear interaction term, indicating the presence of nonlinearity in the distraction-connectivity dependence. However, the shape of the nonlinear connectivity shift – in terms of whether it increased/decreased given decreasing distraction and whether it exhibited a convex/concave nature – differed. Our replication was successful for a few frontal (SFG-IFGi, IFGs-FFGI) and cerebellar (Cere-ACC, Cere-FFGm)

connections; however, many more connections in the frontal and thalamo-frontal regions did not replicate. Interestingly, the implication of an opposite effect, as opposed to no effect, in the failed replication connections call into question the validity of the Weber et al. (2018) findings and re-emphasize the need and importance of replication.

Third, some but not all attentional network connections exhibit the connectivity pattern that we would expect from flow. According to Sync Theory's second hypothesis, the transition into flow is understood as the sudden, discrete synchronization of attentional and reward networks, which in our study is operationalized as a sudden, exponential shift in connectivity. We would therefore expect that decreasing distraction leads to increasing connectivity, regardless of whether it was convex or concave in nature. Figure 5 depicts the significant connections in our findings on the executive attention network, categorized by the sign of the coefficients of the linear and nonlinear interaction terms. It is clear from the distribution of these connections across the top ( $c < 0$ ) and bottom ( $c > 0$ ) rows that not all areas of the executive attention network follow the increasing-connectivity pattern as hypothesized by Sync Theory.



**Figure 5**

*Significant patterns of connectivity in the executive attention network categorized by their linear and nonlinear coefficient signs in response to decreasing distraction*

		Nonlinear coefficient	
		d<0 (concave)	d>0 (convex)
Linear coefficient	c<0 (increasing connectivity)	<b>Local frontal</b> (MFG-IFGi) <b>Thalamo-frontal</b> (IFGi-Thal, MFG-Thal) <b>Thalamo-occipitotemporal</b> (FFGm-Thal) <b>Occipitotemporal-frontal</b> (IFGs-FFGm) <b>Cerebellar</b> (Cere-Thal, Cere-IFGi)	<b>Local frontal</b> (SFG-iFGi) <b>Occipitotemporal-frontal</b> (IFGs-FFGI)
	c>0 (decreasing connectivity)	<b>Local frontal</b> (IFGi-IFGs, SFG-MFG) <b>Thalamo-frontal</b> (ACC-Thal, SFG-Thal, Thal-IFGs) <b>Local occipitotemporal</b> (FFGm-FFGI) <b>Occipitotemporal-frontal</b> (SFG-FFGm, FFGm-SFG, IFGi-FFGI) <b>Cerebellar</b> (Cere-FFGm, FFGL-Cere, Cere-ACC, MFG-Cere)	<b>Thalamo-occipitotemporal</b> (Thal-FFGm, Thal-FFGI) <b>Occipitotemporal-frontal</b> (MFG-FFGm, ACC-FFGI, MFG-FFGI, FFGL-SFG, FFGm-IFGs, FFGL-IFGs) <b>Cerebellar</b> (ACC-Cere, Cere-FFGI)

The expected pattern existed in some thalamic and frontal connections; however, many cerebellar and occipitotemporal connections found a decreasing connectivity pattern instead. Here we come to a critical flaw in Sync Theory.

Very little specificity was provided in Weber and colleagues' (2009) original conception of Sync Theory regarding the subcomponents of attention and reward networks that should or should not be implicated within flow. Attention network theory (Posner & Petersen, 1990) posits that there are three distinct forms of attention – alerting, orienting, and executive attention – that dissociate neuroanatomically into three independent “attention networks” (Posner & Rothbart, 2007). Research into the specific neural structures that make up attention (e.g., Corbetta & Shulman, 2002; Fox et al., 2006; Power et al., 2011; Thomas et al., 2011; Vincent et al., 2008;

Vossel et al., 2014) have localized attention across the extended fronto-parietal network (EFPN), which includes the dorsal network, the ventral network, and the control network. Attempts to integrate Posner and Petersen's tripartite classification of attention across the EFPN have led to assertions that each of the three attention networks correspond to activation within the sub-networks of the EFPN (Petersen & Posner, 2012; Xuan et al., 2016). It is currently unclear whether flow is implicated within all areas of some attention networks but not others, or only some areas of all three attention networks, or all areas of all attention networks.

A similar criticism can be made in relation to the reward system. Research on neural processing of rewards (e.g., Berridge & Kringelbach, 2015; Richard et al., 2013) has localized the reward system with robust consensus to areas across the cortex, basal ganglia and thalamus. These areas include the ventral tegmental area, the dorsal (i.e., caudate and putamen) and ventral (i.e. nucleus accumbens) stratum, substantia nigra, dorsal and ventral pallidum, hippocampus, hypothalamus, thalamus, amygdala, prefrontal cortex, anterior cingulate cortex, and insular cortex. Like with the attention system, it is unclear whether all or only some of these reward processing areas should be implicated within flow. Moreover, for both attention and reward areas, it is also unclear whether the theorized synchronization occurs only *within* existing networks, only *across* networks, or both *within and across* networks.

Moreover, while Sync Theory predicts that flow occurs at the discrete synchronization of attentional and reward networks, our study, as did Weber et al's (2018) study, only examined the *executive attention* network. We therefore do not yet know whether the decreasing distraction-increasing connectivity curve may be replicated within-and-between *orienting* and *alerting* regions of attention, as well as other reward structures in the brain. To clarify the ambiguities

surrounding Sync Theory, future research should aim to specify a network in which the decreasing distraction-increasing connectivity pattern holds true for all flow situations.

Researchers should utilize new regions of interest that correspond to other areas of the extended fronto-parietal network (EFPN), distinguishing the patterns of connectivity within-and-across the dorsal network, ventral network, and the control network. Furthermore, research should uncover the connectivity pattern within-and-across attention and reward networks with an overall goal to implicate a specific flow-attention-reward network that can be used to measure length, depth, and stability of flow depending on its network connectivity strength.

Recently, Huskey et al. (2021) called for a revision of Sync Theory that also takes into account evidence for high flexibility in attentional connectivity during flow. In their paper, flexibility was defined as the ability for neural networks to be functionally reconfigured during psychological states. The evidence for high flexibility during flow suggests that functional connectivity during flow is dynamic, and not relegated to a single, static functional structure. Research that maps the temporally-dependent changes in network connectivity strength - beyond the initial transition as tested by our study - may also provide further insight into the dynamic role of attentional activation during flow.

### **Limitations**

Despite the fact that distraction, compared to reaction time, was able to unveil greater difference between flow-boredom and boredom-frustration conditions, it was not able to demonstrate significant difference between the flow-frustration conditions. In fact, distraction found less of a difference between flow-frustration compared to reaction time. However, this finding should not be attributed to a fault of the model and is more likely due to experimental error. Given increasing use in media-based technology, increasing complexity in modern gaming

architecture, and overall increased exposure and normalization of gaming as a pastime, people have become more proficient at coordinating movements on a computer. Video gaming has become a core part of the developmental experience in the United States, with 91-99% of children and adolescents playing video games for at least one hour per day<sup>4</sup>. Even individuals who may not identify gaming as a common pastime, will still spend upwards of eight hours on digital media per day<sup>5</sup>. Asteroid Impact is a simple point-and-click style video game that harkens back to the asteroids-type arcade style of gaming that was popular in the 80s. While difficulty in Asteroid Impact can be manipulated via asteroid speed, an argument can be made that due to the inflated proficiency towards navigating interactive media for both gaming and non-gaming individuals, it can be difficult to create a truly challenging experience using gaming architecture that appears too simplistic.

Secondly, there were small differences in Huskey et al.'s (2021) and Weber et al.'s (2018) operationalization of the distractor tasks. Huskey et al. (2021) had an audiovisual red light stimulus appearing equally and randomly within one of the four quadrants of the participants' screens. On the other hand, Weber and colleagues (2018) distractor task was a visual-only light point projected by a red laser, which always appeared on the upper right corner of the screen. Therefore, Huskey et al.'s (2021) distractor task – which became the dataset for this study – may have induced greater distraction for two reasons: (1) the involvement of an audio component may have invoked a stronger orienting response, and (2) the randomness of the quadrant in which the stimulus appeared may have reduced spatial predictability, thereby requiring greater cognitive resources in order to respond.

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<sup>4</sup> <https://www.statista.com/statistics/189582/age-of-us-video-game-players/>

<sup>5</sup> <https://www.insiderintelligence.com/insights/us-time-spent-with-media/>

## Conclusion

The need to develop a robust neurological measure of flow increases as the practical applications of flow become more apparent within the broader communication literature. As a small step towards better understanding the neurological correlates of flow within the attentional network of the brain, we attempt to replicate Weber et al. (2018) using a sample size with increased power. Our replication was partially successful, as we found that there is indeed a significant exponential shift in connectivity given changes in an individual's level of distraction, and that the shape of the connectivity shift is mostly nonlinear. However, results demonstrating the direction and nature of the connectivity shift did not replicate, which calls into question the validity of Weber et al's (2018) findings. Our study further discussed the implications of our findings on Sync Theory's hypotheses. In demonstrating that only some network connections exhibited an increasing-connectivity shift, we lend only partial support for Hypothesis 2 of Sync Theory. We call for further clarification and specificity as to which connective areas should follow the increasing-connectivity pattern of a discrete transition into flow, and which should not.

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