

ORIGINAL ARTICLE

Flexible and Modular Brain Network Dynamics Characterize Flow Experiences During Media Use: A Functional Magnetic Resonance Imaging Study

Richard Huskey^{1,2}, Justin Robert Keene³, Shelby Wilcox⁴,
Xuanjun (Jason) Gong¹, Robyn Adams⁵, & Christina J. Najera^{3,6}

¹Cognitive Communication Science Lab, Department of Communication, University of California Davis, Davis, CA, USA

²Center for Mind and Brain, University of California Davis, Davis, CA, USA

³Cognition and Emotion Lab, College of Media and Communication, Texas Tech University, Lubbock, TX, USA

⁴Neuroscience of Messages Lab, Department of Communication, Michigan State University, East Lansing, MI, USA

⁵Department of Advertising and Public Relations, Michigan State University, East Lansing, MI, USA

⁶School of Advertising and Public Relations, University of Tennessee Knoxville, Knoxville, TN, USA

Flow is thought to occur when both task difficulty and individual ability are high. Flow experiences are highly rewarding and are associated with well-being. Importantly, media use can be a source of flow. Communication scholars have a long history of theoretical inquiry into how flow biases media selection, how different media content results in flow, and how flow influences media processing and effects. However, the neurobiological basis of flow during media use is not well understood, limiting our explanatory capacity to specify how media contribute to flow or well-being. Here, we show that flow is associated with a flexible and modular brain-network topology, which may offer an explanation for why flow is simultaneously perceived as high-control and effortless, even when the task difficulty is high. Our study tests core predictions derived from synchronization theory, and our results provide qualified support for the theory while also suggesting important theoretical updates.

Keywords: Flow, Synchronization Theory, Media, Network Neuroscience, Open Science

<https://doi.org/10.1093/joc/jqab044>

Communication has long been interested in the biological and psychological processes that contribute to well-being. Today, researchers study media contributions to numerous well-being outcomes, such as recovery from fatigue

Corresponding author: Richard Huskey; e-mail: rwhuskey@ucdavis.edu

(Reinecke, Hartmann, & Eden, 2014), goal-attainment (Prestin & Nabi, 2020), and enjoyment (Tamborini, Bowman, Eden, Grizzard, & Organ, 2010). A related line of research studies flow (Csikszentmihalyi, 1990) during media use. Flow is an *autotelic* experience that emerges when task difficulty and individual ability are both high and balanced. *Autos* (self) *telos* (end or goal) experiences are hedonically marked, intrinsically rewarding, and contribute to well-being via successful goal-pursuit (Bernecker & Becker, 2020; Tepper & Lewis, 2021) and resilience (Tabibnia, 2020). Flow also facilitates well-being during periods of uncertainty (Rankin, Walsh, & Sweeny, 2019) and even during the COVID-19 pandemic (Sweeny et al., 2020). Finally, there is evidence indicating that flow is protective against depression and burnout (Mosing et al., 2018).

Although the contribution of media to flow experiences and well-being has been extensively investigated, the cognitive and neural mechanisms that underpin flow processes remain unclear. Addressing this gap is a necessary first-step that will enable subsequent research linking neural responses associated with flow to specific well-being outcomes. We draw on synchronization theory (Weber, Tamborini, Westcott-Baker, & Kantor, 2009), which specifies a neurobiological model for how media content contributes to flow experiences. In two studies, we show that a balance between media difficulty and individual ability results in high self-reported flow, high levels of motivated attention, and a flexible and modular brain network topology. We will show how this brain network topology may explain several phenomenological characteristics of flow experiences. Our results offer a more complete explanation (Huskey et al., 2020) of media contributions to flow while also providing insights into the neural basis of flow.

In what follows, we articulate what is currently known about flow during media use and how it is possible to empirically determine when media use results in flow. We then describe the synchronization theory of flow during media use and explain the brain network properties associated with flow experiences. Finally, we use classic criteria for evaluating theoretical contributions to communication as a framework for considering how our study advances flow theory and research.

Flow and Media Use

Flow theory (Csikszentmihalyi, 1990) proposes that individuals can find high levels of intrinsic reward in everyday experiences and that regularly experiencing flow is central to well-being. Flow is characterized by intense concentration, a loss of self-consciousness, a merging of action and awareness, a strong sense of control, a distorted sense of time, perceived effortlessness, and high levels of intrinsic reward. These outcomes result from three causal antecedents: clear and distinguishable goals, immediate performance feedback, and a balance between high task difficulty and high levels of individual ability at the task.

Media content varies in difficulty, and individuals vary in cognitive ability. Accordingly, Sherry (2004) argues that media can result in flow and that individuals

select flow-inducing media. Empirical results support these assertions. Expecting to feel flow motivates media selection (Liu, Liao, & Pratt, 2009), balanced difficulty and ability are necessary to experience flow during media use (Jin, 2012), autotelic personality (flow propensity) modulates flow during media use (Keller & Blomann, 2008), and flow modulates media effects (Matthews, 2015). Experimental research shows an inverted-U shaped pattern where self-reported flow is highest when task difficulty \approx individual ability and lowest when task difficulty \neq individual ability (Huskey, Craighead, Miller, & Weber, 2018). We seek to replicate this finding:

H1: Self-reported flow will show an inverted-U shaped pattern with self-reported flow highest when task difficulty \approx ability and lowest when task difficulty \neq ability.

Harris, Vine, and Wilson (2017) show a dissociation between objective and subjective measures of effort during flow-inducing media use. Subjectively, participants perceive that effort increases linearly with task difficulty, whereas eye tracking and psychophysiological measures show the greatest cognitive effort when difficulty \approx ability. Behavioral results using secondary task reaction times (STRT; Lang, Bradley, Park, Shin, & Chung, 2006) also show this inverted-U shaped pattern. Secondary task reaction times are longest when task difficulty \approx individual ability (Huskey, Craighead et al., 2018; Castellar, Antons, Marinazzo, & Van Looy, 2019). Clearly, flow requires motivated attention. We will replicate this finding:

H2: STRTs will show an inverted-U shaped pattern where STRTs will be longest when task difficulty \approx ability and fastest when task difficulty \neq ability.

These replication hypotheses function as a manipulation check. Given that replication is also foundational to cumulative communication science (McEwan, Carpenter, & Westerman, 2018), these hypotheses provide critical information about the replicability of core findings in the flow literature.

The Synchronization Theory of Flow During Media Use

Scholars are beginning to probe the cognitive and neurobiological foundations of flow with a growing number of studies testing synchronization theory (Weber et al., 2009). Synchronization theory's key proposition is that flow experiences during media use are underpinned by a discrete and energetically efficient pattern of functional brain connectivity (synchrony) between cognitive control and reward networks (RNs) when media difficulty (e.g., how challenging the media is to use) and individual ability at using the media are both high and balanced. Empirical results support synchronization theory's core tenets (Harris, Vine, & Wilson, 2017). Flow is associated with neural activity in cognitive control and RNs (Klasen, Weber, Kircher, Mathiak, & Mathiak, 2012; Ulrich, Keller, & Grön, 2016), and structures in these networks are functionally connected during flow (Huskey, Craighead et al., 2018). Moreover, research shows a U-shaped pattern where the brain is more

energetically efficient when task difficulty \approx individual ability (Huskey, Wilcox, & Weber, 2018). We now turn our attention to two as-of-yet untested predictions: flow is associated with a modular and discrete brain network architecture.

Modularity and Brain Network Organization

Modularity is a widely used indicator of the extent to which local intra-module connections in the network are denser than global inter-module connections (Rubinov & Sporns, 2010). Dense local intra-module connections and sparse global inter-module connections indicate a more segregated network, whereas sparse local intra-module connections and dense global inter-module connections indicate a more integrated network. Importantly, more modular brain networks optimally balance the tradeoff between network segregation-integration and energetic efficiency (Bullmore & Sporns, 2012). Previous research has shown that the brain network topology associated with flow is energetically efficient (Huskey, Wilcox et al., 2018). If modularity and metabolic efficiency are positively related, then:

H3: Modularity will show an inverted-U shaped pattern where modularity is highest when task difficulty \approx ability and lowest when task difficulty \neq ability.

Synchronization as a Discrete State

Synchronization theory predicts that brain structures implicated in cognitive control and reward are functionally connected during flow. What are the properties of this connectivity? Two or more brain structures are considered functionally connected when their neural responses oscillate at the same frequency. When this happens, these brain structures are described as being synchronized. When two or more structures are in sync, they are thought to be working together and this synchrony process can be expanded beyond two structures to understand how a constellation of brain structures work together as a network (Bassett & Gazzaniga, 2011). Brain-network topologies are discrete network states and correspond with discrete psychological states (Davison et al., 2015). Notably, the brain shifts between different brain-network topologies to execute various behavioral and psychological responses (Gu et al., 2015). Synchronization theory predicts a discrete brain network organization among cognitive control and RNs that is synchronized and highly stable (Fisher, Lonergan, Hopp, & Weber, 2020), which means that structures within these networks should be least flexible (reconfigure the least) during flow. Therefore:

H4: Flexibility will show a U shaped pattern where flexibility is lowest when task difficulty \approx ability and highest when task difficulty \neq ability.

Importantly, synchronization is just one possible brain-network state (Tognoli & Kelso, 2014). During synchrony, strong coupling means nodes in the network are trapped in states of phase and frequency locking and therefore cannot leave the

attractor without some external force. The second state is fully uncoupled nodes that are segregated from one another and oscillate at different frequencies. In this state, nodes in the system will never be drawn toward a stable attractor. Synchronization theory is built on this logic. Nodes in a network either are, or are not, synchronized (Weber et al., 2009, pp. 409–410). However, the theory of Coordination Dynamics argues that persistently synchronized (or unsynchronized) brain-network states are rare because the brain more commonly shifts in and out of sync, a term called *metastability* (Tognoli & Kelso, 2014). When the brain is in a metastable state, it will show a transiently synchronized and unsynchronized state. This is called metastability because the system is attracted by the synchronized and unsynchronized states, but will not be trapped by either. Metastability offers a potential alternative explanation for the neural basis of flow. Evidence shows metastable brain dynamics for a variety of perceptual, cognitive, and social tasks and that metastability can be energetically efficient (Tognoli & Kelso, 2014). This leads to competing hypotheses, the first drawn from synchronization theory, the second drawn from coordination dynamics theory:

H5a: Synchrony will show an inverted-U shaped pattern where synchrony is highest when task difficulty \approx ability and lowest when task difficulty \neq ability.

H5b: Metastability will show an inverted-U shaped pattern where metastability is highest when task difficulty \approx ability and lowest when task difficulty \neq ability.

Given that synchronization theory implicates cognitive control and RNs in flow, hypotheses 4, 5a, and 5b will be tested among subnetworks containing nodes within the fronto-parietal control network (FPCN; implicated in cognitive control), the reward network (RN), and a combined fronto-parietal and reward network (FPRN). We will also conduct our analysis on the whole-brain to clarify how specific our results are to a given subnetwork.

Implications for Communication Theory

Communication scientists have long theorized about how a balance between high task difficulty and high individual ability can cause flow during media use (Sherry, 2004). We articulate our study's contributions to these endeavors using criteria common to communication science (DeAndrea & Holbert, 2017). Our first two hypotheses *replicate* important findings in the flow literature and provide confidence in our understanding of how media content induces flow. Our hypotheses specify specific U or inverted-U shaped patterns of results; a formalization that *elucidates contingency* by specifying exactly when media content should, or should not, contribute to self-reported, behavioral, and neural markers of flow. Finally, our multilevel approach provides a more complete explanation of communication processes (Huskey et al., 2020).

Possibly most important is our study's capacity to *elucidate the mechanisms* by which media contribute to flow. We do this in multiple ways. First, we test the precise conditions when media content causes flow. Second, our study illuminates the cognitive and biological processes that underpin flow. In doing so, we clarify by what mechanisms media content contributes to flow.

Methods

We report results from two studies: (i) a lab-based behavioral experiment, and (ii) a direct replication that also gathered functional magnetic resonance imaging (fMRI) data.

Open Science Practices

Consistent with recent calls for open science in communication research (Bowman & Keene, 2018; Dienlin et al., 2020), the project includes open data and materials (OSF <https://osf.io/bxvhr/>; GitHub <https://github.com/cogcommscience-lab/flow-dynamic>). The fMRI data are organized in compliance with the Brain Imaging Data Structure (Gorgolewski et al., 2019) and are available on OpenNeuro (<https://doi.org/10.18112/openneuro.ds003358.v1.0.0>).

Power Analysis

An *a priori* power analysis was conducted for the behavioral study using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007). We used the smallest effect size reported in Huskey, Craighead et al. (2018) to estimate a repeated measures analysis of variance (ANOVA) with $\alpha = .05$, power $(1 - \beta) = .95$, and $f(V) = .39$, which returned $n = 104$. There is no known procedure for calculating a power analysis for network neuroscience studies, although our sample size is consistent with other published research.

Participants

Five participants were excluded from the behavioral study for non-compliance. This resulted in a final $n = 107$ undergraduate students recruited from Texas Tech University. Three participants were excluded from the fMRI study, one for an abnormal radiological reading, two who requested to terminate their participation during fMRI scanning. This resulted in a total of $n = 35$ participants recruited from The 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 (Table 1). Both studies were approved by the host University's Institutional Review Board.

Table 1 Summary Statistics Describing the Participants Samples in Each Study

Experiment	Final <i>n</i>	Mean Age (Standard Deviation)	% Female	Mean Self- Reported Video Game Ability ^a	% Student	% Caucasian/ White
Behavioral Experiment	107	20.61 (1.72)	56.00	3.95 (1.92)	100	46.67
fMRI Experiment	35	25.00 (6.40)	45.71	4.11 (1.68)	71.43	48.57

^aSelf-reported video game ability was using a seven-point single item measure (as validated in Huskey, Craighead et al., 2018).

Stimulus and Experimental Manipulation

Participants in both studies played *Asteroid Impact* (Supplementary Data, Section 1). Consistent with previously validated techniques for inducing flow using *Asteroid Impact* (Huskey, Craighead et al., 2018), we manipulated three experimental conditions: low-difficulty or *boredom* (difficulty < ability), high-difficulty or *frustration* (difficulty > ability), and balanced-difficulty or *flow* (difficulty ≈ ability). In the low-difficulty condition, the asteroid speed was slow and did not change. In the high-difficulty condition, asteroid speed was consistently fast. In the balanced-difficulty condition, the game started at a moderately high level of asteroid speed (difficulty) and an algorithm adjusted asteroid speed based on player performance. Asteroid speed was the only thing that differed between conditions.

Dependent Measures

Behavioral and self-report measures were collected in both studies; neuroimaging data were collected in the fMRI study. Dependent fMRI measures are drawn from network science.

Self-Reported Flow and Enjoyment

Self-reported flow was measured using the Autotelic Experience subscale of the Event Experience Scale (FFS-2; Jackson & Eklund, 2004). For convergent validity purposes, we also measured self-reported video game enjoyment (Bowman, Weber, Tamborini, & Sherry, 2013).

Secondary Task Reaction Time

Participants responded to an audiovisual STRT probe while playing *Asteroid Impact*. Previous research shows that *Asteroid Impact* accurately measures STRTs (Calcagnotto, Huskey, & Kosicki, 2021). The probe was a semi-opaque red circle along with a tone (sine waveform, 440.0 Hz). Probes were shown equally in one of four game corners. A total of 68 probes were shown during each condition. The

interstimulus interval was drawn from a truncated Gaussian probability distribution (lower bound = 3000 ms; upper bound = ∞). Interstimulus interval and probe locations varied between experimental conditions but were identical within conditions. Participants were told to respond to probes as quickly as possible by pressing the spacebar key (behavioral study) or a button box (fMRI study) using their non-dominant hand. Secondary task reaction time was calculated as the latency between probe onset and the subsequent key/button press.

Modularity and Flexibility

Modularity is the extent that nodes in a network have dense intra-module connections but sparse inter-module connections. Following the latest guidelines (Yang et al., 2020), we applied a generalized Louvain community detection algorithm that assigns nodes to putative communities and generates modularity metrics based on community assignment (Supplementary Data, Section 2). Nodal flexibility, defined as changes in community membership for each node, is calculated by counting the number of times a node switches its community membership over time normalized by the total possible number of changes (Bassett et al., 2011). Flexibility averages these changes over nodes within a network (Supplementary Data, Section 2).

Synchrony and Metastability

Synchrony and metastability capture neural phase oscillations (Tognoli & Kelso, 2014) and are calculated from the instantaneous phasic neural time series data (Supplementary Data, Section 3). Synchrony measures the strength of phase-coupling between all nodes in a network with values ranging between one (pure synchronization) and zero (pure independence). Metastability measures the variability of the collective coupling strength.

Experimental Procedure Behavioral Study

Participants were seated at an individual cubicle with a desktop computer, a 23-inch monitor, and a pair of over-ear headphones. Participants first completed a brief demographic questionnaire before completing three 60 s training rounds (respond to STRT probes, play *Asteroid Impact* without STRT probes, play *Asteroid Impact* with STRT probes). Participants were then randomly assigned to one of six orders where they completed each experimental condition (low-difficulty, high-difficulty, balanced-difficulty). Each experimental condition lasted 240 s. At the end of each experimental condition, participants completed the self-reported flow and enjoyment measures. The procedure lasted about 30 min.

fMRI Study

The fMRI study followed all the same procedures as the behavioral study with three minor changes. Participants: (i) completed a training session outside of the scanner

using a 15-inch laptop and a trackball, (ii) completed a training session, also using a trackball, once they were positioned in the fMRI scanner, and (iii) were paid \$45.00. Each session lasted 2 h.

STRT Data Cleaning

The STRT analysis was determined *a priori* based on previous research (Huskey, Craighead et al., 2018). Reaction times were capped at 1500 ms, and the harmonic mean was calculated. It is possible that our results are contingent on the analytical procedure employed (Witt, Kemmerer, Linkenauger, & Culham, 2020). To test this, we also conducted a multiverse analysis (Steege, Tuerlinckx, Gelman, & Vanpaemel, 2016), where we systematically varied 24 different cleaning procedures as described by Ratcliff (1993).

Self-Report Data Cleaning

Missing data (behavioral study =.97%, fMRI study =1.55%) were imputed with a classification and regression trees approach using the *mice* package (Buuren & Groothuis-Oudshoorn, 2011) for R (R Core Team, 2020). The self-report data were then averaged for each scale for each condition. Following Hayes and Coutts (2020), reliability was evaluated using McDonald's omega (ω) using the *psych* package (Revelle, 2018) for R.

Statistical Modeling of Self-Report and STRT Data

Repeated measures ANOVAs were modeled using the *rstatix* package (Kassambara, 2020) for R. Variables of interest (STRT, self-reported flow, self-reported enjoyment) were entered as within-subjects factors. In instances where the sphericity assumption was violated, Greenhouse-Geisser corrected degrees of freedom are reported, noting that Greenhouse-Geisser corrected degrees of freedom can include decimals in the numerator and denominator. Two-tailed paired-samples *t*-tests were used to evaluate pairwise comparisons. Familywise error rate was controlled by false discovery rate (FDR) correction at the model level.

fMRI Acquisition and Preprocessing

The fMRI data were preprocessed using *fmripiprep* (Esteban et al., 2019) and denoised using XCP engine (Ciric et al., 2018). For complete details, see [Supplementary Data, Section 4](#).

fMRI Analysis

Defining the Network

We defined brain network nodes using a recently published brain atlas that augments the canonical Power atlas (Power et al., 2011) with newly identified nodes in subcortical structures (Seitzman et al., 2020). This atlas consists of

300 functionally-defined nodes from cortical and subcortical brain regions. Next, we used *NiLearn*'s (Abraham et al., 2014) *fit_transform* function to extract time series from the preprocessed and denoised functional images, which resulted in 120 (TR) \times 300 (nodes) time series for each experimental condition and each participant. To capture the dynamic properties of functional connectivity between nodes in the network, we applied a non-overlapping sliding window technique (Telesford et al., 2016) and separated each time series into four sequential 30 TR (60 s) windows.

Time series within each window were then correlated using a Ledoit–Wolf estimator (Supplementary Data, Section 2). Off-diagonal entries were set to zero. Correlation matrices were then group-level averaged, which resulted in 3 (experimental condition) \times 4 (time window) 300×300 adjacency matrices, where each row/column represents a given node defined by the brain atlas (Figure 1). The adjacency matrices were then thresholded such that only the strongest 30% of connections were retained, and these connections were then binarized (Rubinov & Sporns, 2010). Finally, for each condition, we constructed a multilayer network by linking the adjacency matrix for each window with the adjacency matrix in the window before and after, by adding edges from nodes to themselves in the neighboring window (Figure S2; Sizemore & Bassett, 2018). Modularity and nodal flexibility were then calculated on this multi-layer network.

Null Model Construction for Modularity and Flexibility Analysis

To determine if the observed flexibility and modularity for each experimental condition differed significantly, we constructed a dynamic null network model using a *randomly permuted times* approach (Sizemore & Bassett, 2018). This approach randomly permutes the time when a connection between two nodes occurs while preserving the overall number of connections. We used the empirically observed temporal adjacency matrices to generate 1000 randomly permuted null models for each experimental condition and each time window. Then we applied the multilayer network community detection algorithm described above and computed flexibility and modularity statistics for each null model which resulted in a null distribution for inferential testing using a paired-samples *t*-test approach as described by Snijders and Borgatti (1999). Flexibility was calculated for the global brain network (GB), FPCN, RN, and a subgraph that included FPCN and RN nodes (FPRN).

Frequency Domain Analysis

Synchrony and metastability were evaluated in the frequency domain for the dense graph (Supplementary Data, Section 4). We calculated the *Kuramoto order parameter* (Acebrón, Bonilla, Pérez Vicente, Ritort, & Spigler, 2005) for each TR for each participant and each experimental condition within the GB, FPCN, RN, and FPRN. Synchrony was computed by averaging the Kuramoto order parameter over all time points and metastability is the standard deviation of the Kuramoto order parameter (Alderson, Bokde, Kelso, Maguire, & Coyle, 2020). This procedure lends itself to standard inferential testing using repeated measures ANOVA. Variables of interest

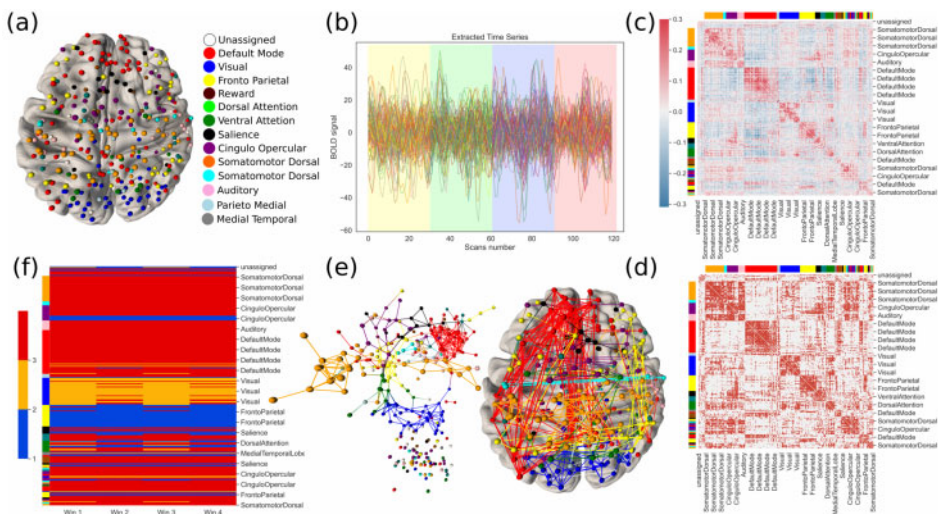


Figure 1 Network neuroscience analysis pipeline. (A) Define 300 nodes (10 mm diameter binary spheres for cortical nodes and 8 mm diameter binary spheres for subcortical nodes) across 14 brain networks in standard MNI152 brain space. (B) For each preprocessed participant for each experimental condition, use the `fit_transform` function in `nilearn` toolbox to extract the BOLD signal. The time series data were then sliced into four non-overlapping time windows. (C) The time series data were correlated to construct adjacency matrices, which were used to construct the brain networks. The adjacency metrics define the undirected edges between any two nodes. The brain networks were averaged across participants to generate group-level networks. (D) The group-level adjacency matrices were thresholded and binarized. (E) Using the adjacency matrices, we can visualize the brain network in standard brain space or in a network space. (F) A community assignment algorithm applied to the multilayer network returned the community assignment for each node at each time window for each experimental condition.

(metastability, synchrony) for the GB, RN, FPCN, and FPRN were entered as within-subjects factors. Paired-samples t-tests (two-tailed) were FDR corrected.

Results

Self-Reported Flow and Enjoyment

The self-reported flow scale was reliable (ω 's $>.81$; [Supplementary Data, Section 5](#)). The repeated measures ANOVA, testing the effect of condition on self-reported flow, was significant for the behavioral ($F(1.81, 191.84) = 46.936, p <.0001, \eta^2_G = .157$) and fMRI ($F(2, 68) = 22.931, p <.0001, \eta^2_G = .288$) studies. In both studies, the flow $>$ boredom pairwise comparison was not significant, although the flow $>$ frustration pairwise comparison was ([Table 2](#)). H1 is partially supported for self-reported flow.

Table 2 Means and Standard Deviations for Secondary Task Reaction Times, Self-Reported Flow, and Self-Reported Enjoyment fMRI Study

Dependent Variable	(a) Boredom Mean (Standard Deviation)	(b) Flow Mean (Standard Deviation)	(c) Frustration Mean (Standard Deviation)
	STRT		
Behavioral Study	519.617 (117.597) ^b	556.629 (131.230) ^a	526.227 (204.254)
fMRI Study	491.270 (77.5612) ^b	518.396 (85.540) ^a	485.571 (107.580)
	Self-Reported Flow		
Behavioral Study	3.171 (1.063) ^c	3.222 (.964) ^c	2.250 (1.086) ^{ab}
fMRI Study	2.936 (.856) ^c	3.164 (.754) ^c	2.057 (.659) ^{ab}
	Self-Reported Enjoyment		
Behavioral Study	4.028 (1.786) ^{bc}	4.404 (1.781) ^{ac}	2.918 (1.843) ^{ab}
fMRI Study	3.493 (1.561) ^{bc}	4.214 (1.432) ^{ac}	2.521 (1.375) ^{ab}

Note: For each row, superscripted text indicates statistically significant pairwise comparisons (two-tailed) after FDR correction for multiple comparisons at the $p < .05$ level.

The self-reported enjoyment scale was reliable (ω 's $> .88$; [Supplementary Data, Section 5](#)). The repeated-measures ANOVA model, testing the effect of condition on self-reported enjoyment, was significant for the behavioral ($F(1.84, 194.98) = 35.552, p < .0001, \eta^2_G = .11$) and fMRI ($F(2, 68) = 15.711, p < .0001, \eta^2_G = .189$) studies. Pairwise comparisons were significant for flow $>$ boredom and flow $>$ frustration ([Table 2](#)). To the extent that self-reported enjoyment is convergently valid with self-reported flow, H1 is supported.

STRT Results

After Greenhouse-Geisser correction, the repeated measures ANOVA, testing the effect of condition on STRT, was not significant for the behavioral study ($F(1.49, 157.7) = 3.053, p = .065, \eta^2_G = .011$). However, the model was significant for the fMRI study ($F(2, 68) = 3.427, p = .038, \eta^2_G = .025$). In both, STRTs were significantly longer in the flow $>$ boredom pairwise comparison. Secondary task reaction times were not significantly different for the flow $>$ frustration pairwise comparison for both the behavioral and fMRI studies ([Table 2](#)). Therefore, H2 is partially supported.

Multiverse analyses revealed a consistent pattern of results ([Supplementary Data, Sections 6–7](#)). Of the 24 models for each study, 21 were significant for the behavioral and 11 were significant for the fMRI studies. Even after FDR correction at the model level, STRTs were significantly longer for the flow $>$ boredom comparison for all 24 of the behavioral and 22 of the fMRI models. After FDR correction, STRTs were significantly longer in the flow $>$ frustration comparison for just two of the

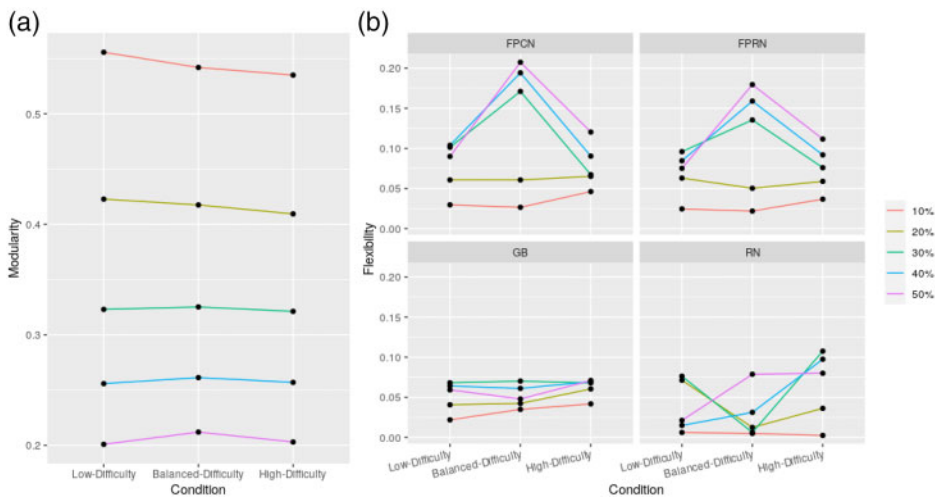


Figure 2 Modularity and flexibility at different thresholds. (A) Modularity for different thresholds (ranging from 10% to 50%). (B) Flexibility across different brain systems (GB, FPCN, RN, and FPRN) at different thresholds (ranging from 10% to 50%).

behavioral and two of the fMRI models. These results show strong support for the flow > boredom comparison, but marginal support for the flow > frustration comparison.

Modularity and Flexibility

FDR -corrected two-tailed paired-sample *t*-tests show that the flow condition is more modular than the frustration ($t = 2.948$; $p = .008$) but not the boredom condition ($t = 1.731$; $p = .118$; Figure 2A; Supplementary Data, Section 8). H3 is partially supported.

The flexibility analysis partially supports H4 (Figure 2B; Supplementary Data, Section 8). Within the RN, the flow condition is significantly less flexible than the frustration ($t = -3.135$, $p = .008$) and boredom conditions ($t = -4.065$; $p < .001$). However, opposite to H4, the FPCN has the highest flexibility during the flow condition compared to the frustration condition ($t = 3.059$; $p = .008$), although the comparison to the boredom condition was not significant ($t = 2.001$; $p = .076$). Similarly, flexibility within the combined FPRN is not statistically different when comparing the flow >frustration contrast ($t = 2.154$; $p = .063$) or the flow >boredom contrast ($t = 1.428$; $p = .192$). Finally, at the GB level, flexibility in the flow condition is not significantly different from the frustration condition ($t = .259$; $p = .811$) or the low-difficulty condition ($t = .239$; $p = .811$).

Network measures can vary at different thresholds. Thus, we conducted a sensitivity analysis on sparse binary graphs retaining between 10% and 50% of the strongest connections. The results are reported in Figure 2. At most thresholds, we see

the identical inverted U-shaped pattern for modularity, although we note that this pattern disappears at very low thresholds (Figure 2A). A similar pattern of results is also observed for the flexibility analyses (Figure 2B).

Synchrony and Metastability

For synchrony, repeated measures ANOVA models testing the effect of condition on synchrony showed that, for the GB ($F(2, 68) = 4.001; p = .023; \eta^2_G = .041$), FPCN ($F(2, 68) = 3.840; p = .026; \eta^2_G = .055$), and FPRN ($F(2, 68) = 5.347; p = .007; \eta^2_G = .079$) were all significant. The RN ($F(2, 68) = 2.141; p = .125; \eta^2_G = .042$) was not significant. Global brain network showed the predicted inverted-U shaped pattern of results, although only the flow >boredom comparison was significant. Unexpectedly, the FPCN and FPRN showed a U-shaped pattern of results where synchrony in the flow condition was lowest, although only the pairwise comparison between the frustration and flow condition was significant. Therefore, only the GB results partially support H5a.

For metastability, repeated measures ANOVA models testing the effect of condition on metastability showed that the FPCN ($F(2, 68) = 1.961; p = .149; \eta^2_G = .029$) and RN ($F(2, 68) = 2.421; p = .096; \eta^2_G = .051$) were not significant, as were all pairwise comparisons. Only the GB ($F(2, 68) = 2.104; p = .013; \eta^2_G = .024$) and FPRN ($F(2, 68) = 3.643; p = .031; \eta^2_G = .056$) models were significant. For the FPRN, metastability was lowest in the flow condition compared to the frustration condition. None of these results matches the pattern predicted in H5b (Table 3 and Supplementary Data, Section 9).

Discussion

This study investigated how task difficulty modulates self-reported, behavioral, and neural responses associated with flow. We used a naturalistic video game to experimentally manipulate three conditions: boredom (low-difficulty), frustration (high-difficulty), and flow (balanced-difficulty). This decision let us replicate previous self-report and behavioral findings in the flow literature, examine the brain network topology associated with flow, and test alternate mechanistic explanations for the neural basis of flow. We consider each of these in turn while also discussing broader implications and next steps for communication theory.

Replicating Key Findings in the Flow Literature

Do previous findings replicate? Yes, but with some caveats. For both the behavioral and fMRI studies, we observed the predicted inverted-U shaped pattern of results where self-reported flow, self-reported enjoyment, and STRTs were highest in the flow condition. However, not every predicted relationship was statistically

Table 3 Means and Standard Deviations for Synchrony and Metastability by Experimental Condition

Dependent Variable	(a) Boredom Mean (Standard Deviation)	(b) Flow Mean (Standard Deviation)	(c) Frustration Mean (Standard Deviation)
Synchrony			
Global	.0953 (.0197) ^{bc}	.1070 (.0312) ^a	.1060 (.0257) ^a
Frontal-parietal	.3920 (.0654)	.3640 (.0511) ^c	.3950 (.0597) ^b
Reward	.4460 (.0519)	.4350 (.0506)	.4210 (.0481)
Frontal-parietal and reward	.3010 (.0512)	.2800 (.0393) ^c	.3130 (.0498) ^b
Metastability			
Global	.0495 (.0115)	.0549 (.0168)	.0527 (.0144)
Frontal-parietal	.1650 (.0198)	.1580 (.0184)	.1650 (.0216)
Reward	.2000 (.0212)	.0202 (.0202)	.1890 (.0209)
Frontal-parietal and reward	.1320 (.0175)	.1250 (.0160) ^c	.1340 (.0168) ^b

Note: For each row, superscripted text indicates statistically significant pairwise comparisons (two-tailed) after FDR correction for multiple comparisons at the $p < .05$ level.

significant. As we will show, instances where a result failed to replicate, are just as illuminating as successful replications.

Self-Reported Flow

Self-reported flow showed the predicted inverted-U shaped pattern (H1); however, the flow condition was only significantly different from the frustration condition for both the behavioral and fMRI studies. As a form of convergent validity, we also measured self-reported enjoyment, which did show the predicted inverted-U shaped pattern in both studies.

Why were we unable to perfectly replicate previous findings related to self-reported flow? Previous research using *Asteroid Impact* to manipulate flow experimentally (Huskey, Craighead, et al., 2018) allowed the number of asteroids and targets to vary between experimental conditions. These studies also allowed participants to advance between multiple levels, provided moment-by-moment feedback on progress toward advancing to a new level, and made it clear when a participant advanced to a new level. These manipulations reinforced causal flow antecedents: clear and distinguishable goals and immediate performance feedback.

Unfortunately, these differences muddied interpretation of the earlier fMRI results (Huskey, Craighead et al., 2018). Accordingly, the present study replaced levels with an “endless” play-mode while also holding the number of asteroids and targets constant. As a result, we maintained just one causal flow antecedent: the high task difficulty and high individual ability balance. Removing two causal flow antecedents may have weakened our manipulation.

We also note that the pairwise comparison between the flow and boredom conditions in study three by [Huskey, Craighead, et al. \(2018\)](#) also showed a small (but statistically significant) effect using the same self-reported flow scale. We observed the expected pattern of results for both the behavioral and fMRI studies reported in this manuscript; however, the absolute difference between these conditions was small. We may have been underpowered to detect the effect. Supporting this interpretation, self-reported flow effect sizes observed in our study are approximately one-third the magnitude of those observed in [Huskey, Craighead et al. \(2018\)](#).

The second potential issue relates to the FSS-2 Autotelic Experience subscale's ([Jackson & Eklund, 2004](#)) measurement validity. Measurement validity is the extent to which a measure assesses what it purports to measure and nothing else. Presumably, this subscale measures intrinsic reward. However, the "I loved the feeling of performance and want to capture it again" item may capture something that is not uniquely about intrinsic reward. Therefore, participants in the boredom condition may have also rated this item highly. Paired samples *t*-tests show no significantly different responses to this item between the boredom and flow conditions for the behavioral ($t(106) = -.985, p = .327$) and fMRI ($t(34) = -1.18, p = .245$) studies. The FSS-2 was validated on observational data, and therefore, might be suboptimal for capturing self-reported flow in experimental contexts that include a boredom comparison condition.

As a final consideration, our boredom condition was designed to elicit boredom, and it could be that our task was suboptimal. Experimentally inducing boredom using active tasks is non-trivial, and some of the best inductions are considerably more mundane than playing a video game ([Markey, Chin, Vanepps, & Loewenstein, 2014](#)). There is also debate about what causes boredom. Our study drew on [Csikszentmihalyi's \(1990\)](#) conceptualization that boredom occurs when individual ability exceeds task difficulty. Others have conceptualized boredom as a negative affective state that lacks goal-oriented behavior ([Mathiak et al., 2013](#)) or instances where a task requires but does not elicit executive control ([Danckert & Merrifield, 2018](#)). Our task was goal-oriented (collect targets, avoid asteroids). Nevertheless, our results indicate that participants allocated attentional resources away from the task and self-reported low enjoyment for the boredom condition. Together, these suggest a successful, albeit imperfect, manipulation. Future research should design better boredom-inducing tasks and rely on modern conceptualizations that treat boredom as resulting from different combinations of attentional demand and task value ([Westgate, 2020](#)).

Replicating STRTs

We also expected STRTs to show an inverted U-shaped pattern with the longest STRTs in the flow condition (H2). This prediction was based on limited capacity models of motivated attention ([Lang et al., 2006](#); [Fisher, Huskey, et al., 2018](#); [Fisher, Keene, et al., 2018](#)). When more attentional resources are allocated to *Asteroid*

Impact, fewer attentional resources should be available, thus resulting in longer STRTs.

Both the behavioral and fMRI studies showed the predicted inverted-U shaped pattern of results. Secondary task reaction times were significantly longer in the flow compared to boredom conditions. However, STRTs were not significantly longer in the flow condition compared to the frustration condition. This pattern of results was confirmed in the multiverse analysis. The flow condition had significantly longer STRTs compared to the boredom condition in all 24 models for the behavioral and 22 models for the fMRI studies. By comparison only two of the behavioral and two of the fMRI models showed that STRTs were significantly longer in the flow compared to frustration conditions. Clearly there is strong support that the flow condition was more motivationally relevant than the boredom condition. Support is less robust when comparing the flow condition to the frustration condition. One interpretation is that the results are sensitive to cleaning procedure.

A second interpretation is that some cleaning procedures are more (or less) powerful depending on the distribution of the STRT data (Ratcliff, 1993). Our power analysis suggested that $n = 104$ participants were necessary to achieve 95% power when $\alpha = .05$. Therefore, our behavioral study was properly powered, but our fMRI study could have been underpowered.

A third explanation for the mixed STRT results is that our study assumes that motivation, and therefore attentional allocation and STRTs, are stationary across time within each experimental condition. An analysis of the STRTs by trial indicates that this assumption is violated for the frustration conditions (Supplementary Data, Section 10). Secondary task reaction times are significantly and negatively correlated with trial in the frustration condition for the behavioral ($r = -.349$) and fMRI ($r = -.486$) studies. Inspection of the results (Figures S14–S15) shows that STRTs start off slow early on, but drop and somewhat stabilize after ~ 10 trials (approximately 30 s) into the frustration condition. This interpretation is shown by a temporal autocorrelation analysis. For the frustration condition, some lags for the first ~ 10 STRT trials are positively correlated (Figures S14–S15). Moreover, a Ljung-Box test (Ljung & Box, 1978) reveals that the frustration, and to a lesser extent, the flow conditions do not meet stationarity assumptions.

It seems that participants are motivated to allocate substantial attentional resources early on in the frustration condition, but this motivated attentional allocation quickly subsides over time. If so, our frustration induction is less than ideal because it takes some time (30 s–60 s) for participants to allocate attentional resources away from *Asteroid Impact* as would be expected based on previous research (Castellar et al., 2019; Huskey et al., 2018). Ultimately, participants self-reported low levels of flow and enjoyment in the frustration condition, which suggests that the manipulation eventually induces the expected psychological response, just that this response takes time to occur. One possible explanation is that participants expect video games to be enjoyable (Liu et al., 2009). Accordingly, participants may be biased to allocate more attentional resources early on when playing a video game.

In sum, both our behavioral and fMRI studies replicate the inverted-U shaped pattern of STRT results observed in previous research (Castellar, Antons, Marinazzo, & Van Looy, 2019; Huskey *et al.*, 2018). Our multiverse analysis and investigation of the STRT time series data suggest there is opportunity for a stronger experimental manipulation. It is worth pointing out that we were unable to identify empirical or methodological suggestions for cleaning reaction time data that violate stationarity assumptions. This represents an opportunity for future methodological inquiry and advancement.

Modularity and Flexibility

We predicted an inverted-U shaped pattern of results where the brain would show the most modular network topology during the flow condition (H3). The flow condition was significantly more modular compared to the frustration condition. However, modularity in the flow condition was not different from boredom. A consensus-based community assignment analysis of the brain network modules (Figure S12) shows that the flow condition is modular with a brain-network where most FPCN nodes exist within communities containing reward-network nodes.

However, our synchrony results also show that synchrony is lowest between nodes in the FPCN in the flow condition compared to the boredom and frustration conditions. Previous theorizing (Fisher *et al.*, 2020) as well as empirical results (Huskey, Craighead *et al.*, 2018) have implicated the salience network in flow. The consensus-based community assignment analysis (Figure S12) shows that nodes in the salience network are most commonly grouped in communities with nodes in the FPCN and reward subnetworks during the flow condition. We interpret this as further, albeit data-driven, evidence that the salience subnetwork plays an important, but as of yet underspecified, role in flow.

More broadly, modular brain-network topologies serve several important functions, including: increasing robustness and resilience to sudden perturbation, reducing wiring cost, thus making the cognitive processes more metabolically efficient, and promoting information processing through a hierarchical organization (Bullmore & Sporns, 2012; Sporns & Betzel, 2016). This maps directly onto core sync theory assumptions (Weber *et al.*, 2009). Moreover, evidence suggests that brain segregation (indicated by larger modularity) enhances performance and learning in various tasks (Bassett *et al.*, 2011). This might explain why flow is associated with perceptions of a merging of action and awareness, a sense of control, and effortlessness.

We also note, however, that the relationship between modularity, cognitive control, and task performance is not completely resolved. For instance, previous research using n-back tasks shows that more GB integration (lower modularity) is associated with increased task performance (Shine *et al.*, 2016) and increased brain segregation (increased modularity) is associated with automatic task performance (Finc *et al.*, 2020). Clarifying the extent to which the brain is integrated or

segregated during flow and the contribution of integration and segregation to task performance and subjective experience is a vital next step for synchronization theory.

We also expected that flexibility would show a U-shaped pattern where flexibility was lowest during the flow condition (H4). Instead, we see a more complex pattern of results. Previous research shows that lower-level cognitive control tasks are associated with fairly low flexibility in the FPCN (Telesford et al., 2016). In our study, we see the lowest FPCN flexibility during the frustration condition. One interpretation, given the sharp drop-off in STRTs after 30 s of gameplay in the frustration condition (Figure S15), is that participants motivationally disengaged from the primary task (playing *Asteroid Impact*) and instead focused their attention on the STRTs, which is consistent with Huskey, Craighead et al. (2018). In that case, and over time, the STRT task in the frustration condition became primary and conceptually similar to a lower-level cognitive control task.

What then are we to make of the increased flexibility in the FPCN during the flow condition? Control-theoretic approaches to understanding brain-network organization during demanding cognitive control tasks argue that the FPCN is flexible and that this flexibility maintains performance during tasks (Dosenbach, Fair, Cohen, Schlaggar, & Petersen, 2008). Empirical research supports this theoretical proposition showing that fast and flexible network connections in the FPCN are critical for adaptive control deployment during learned tasks and novel tasks (Cole et al., 2013). Computational models of empirical data suggest a control circuit where the insula tracks control volatility, the caudate nucleus estimates the amount of control necessary, and this estimate feeds forward to the FPCN for control deployment (Jiang, Beck, Heller, & Egner, 2015). Theoretical updates have implicated the salience network in flow (Fisher et al., 2020); however, our results suggest additional updates are necessary. Future theorizing and empirical efforts should examine if and how sync theory intersects with the latest control theory developments. Such efforts would help account for the high level of FPCN flexibility observed in the flow condition.

Finally, it is worth noting the low flexibility in the reward network during the flow condition. Given that most nodes in this network were constrained to one community in our consensus analysis and reward nodes typically show low flexibility during cognitive control (Cole et al., 2013), we interpret this as evidence that the reward network shows sustained and stable connections during flow, consistent with synchronization theory.

Synchrony and Metastability

Lastly, we tested two competing hypotheses for the mechanistic processes underlying flow. We predicted an inverted-U-shaped pattern for synchrony (H5a) and metastability (H5b), where each was highest in the flow condition. Overall, support for the metastability hypothesis is relatively weak. Two of the four models were not

significant. For the significant GB and FPRN metastability models, the overall effect sizes were lower than the GB and FPRN synchrony models, which indicates that the synchrony model better explains the data. By comparison, only the RN synchrony model was *not* significant. Contrary to our predictions, only the GB synchrony model showed the predicted inverted-U shaped pattern of results. Although, only the flow > boredom pairwise comparison was significant. At best, this offers qualified support for sync theory. We say “qualified support” because an examination of the subnetworks shows significant results in the opposite direction from our predictions.

Our results show that the FPCN and FPRN have the lowest synchrony during the flow condition when compared to the frustration condition. Given the flexibility results described above, we should (post hoc) expect low synchrony in the FPCN and FPRN since synchrony and flexibility measure two sides of the same coin (synchrony in the frequency domain, flexibility in the time domain). If flexibility goes up within a subnetwork, this means that nodes within that subnetwork are changing their modular assignment more frequently over time. Therefore, we should expect that synchrony within that subnetwork goes down. This is what we see for the FPCN and FPRN.

The State of Synchronization Theory

Synchronization theory was first published in 2009. Since then, empirical research into reward-modulated cognitive control has substantially outpaced research investigating the neural basis of flow. More recent formulations of synchronization theory (e.g., Fisher *et al.*, 2020) have kept pace with these developments and have even implicated the salience network in flow experiences, although the core prediction of a synchronization between FPCN and reward subnetworks has prominently remained in each explication of the theory.

Consistent with synchronization theory, and replicating previous results, our STRT data demonstrate that flow requires high levels of attentional resources and that participants are motivated to allocate attention to the flow-inducing task. By elucidating contingent predictions derived from synchronization theory, we show that the brain has a more modular organization during flow compared to frustration. Finally, we show that nodes in the reward subnetwork exhibit the least flexibility during flow compared to boredom or frustration.

We also see results that contradict synchronization theory. Most notably, synchronization theory predicts high levels of synchrony between FPCN and reward subnetworks. Contrary to this prediction, we show that nodes in the FPCN are most flexible during flow. Similarly, nodes in the FPCN and FPRN have the lowest levels of synchrony when compared to frustration. Our results suggest that synchronization theory needs yet another update. Specifically, one that accounts for evidence showing that the FPCN is flexible during cognitive control—including flow—tasks, even when reward subnetwork nodes remain inflexible (see Cole *et al.*, 2013).

Like nearly all theories in communication, synchronization theory is rooted in a verbal model. One limitation of verbal models is uncertainty about when a hypothesis has adequately been derived, tested, supported, or falsified (Guest & Martin, 2021). As such, we join recent calls for developing formal theory (Fisher & Hamilton, 2021; Huskey *et al.*, 2020; van Rooij & Baggio, 2021) and argue that formal theoretical models are a vital next step. Control theoretic models (for a review, see Lydon-Staley, Cornblath, Blevins, & Bassett, 2021) offer a promising opportunity for formalizing synchronization theory.

Conclusion

In this study, we investigated the relationship between media content, flow, and brain network dynamics. Our results speak broadly to the field. Flow experiences during media use have been implicated in well-being. Our results show that flow corresponds with increased synchrony among structures in reward networks and increased flexibility among structures in the FPCN. Moreover, our project clarifies the neural systems, and their responses, that researchers should examine in subsequent research linking measures of well-being with neural responses.

Citation Diversity Statement

Citation disparities exist in communication research (Chakravartty, Kuo, Grubbs, & McIlwain, 2018; Trepte & Loths, 2020; Wang *et al.*, 2021). We quantify our citation practices by including a citation diversity statement (Supplemental Section 12, Figure S18; Zurn, Bassett, & Rust, 2020).

Acknowledgments

This work was supported by The Ohio State University School of Communication Miller Research Award.

Supporting Information

Additional Supporting Information may be found in the online version of this article.

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