Neural heterogeneity underlying late adolescent reward processing is linked to individual differences in behavioral sensation seeking

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Data Sharing: Readers seeking access to this data should contact Dr. Daniel Keating (keatingd@umich.edu) or Michael Demidenko (demidenm@umich.edu). Access will be granted to named individuals in accordance with ethical procedures governing the reuse of sensitive data. Infrastructure is currently being developed in collaboration with the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan (<https://www.icpsr.umich.edu>) to archive and share data in an ethically approved manner and will be shared at a later TBD date.

Conflict of Interest. The authors declare that they have no conflicts of interest.

Abstract

Adolescent risk-taking, including sensation seeking (SS), is often attributed to developmental changes in connectivity among brain regions implicated in cognitive control and reward processing. Despite considerable scientific and popular interest in this neurodevelopmental framework, there are few empirical investigations of adolescent network connectivity—let alone examinations of its links to SS behavior. The studies that have been done focus on mean-based approaches and leave unanswered questions about individual differences in neurodevelopment and behavior. The goal of this paper is to take a person-specific approach to the study of adolescent functional connectivity during reward processing, and to examine links between connectivity and self-reported SS behavior in 104 adolescents ($M_{Age}=19.3$; $SD_{Age}=1.3$). Using group iterative multiple model estimation (GIMME), person-specific connectivity during two neuroimaging runs of a monetary incentive delay task was estimated among 12 *a priori* brain regions of interest representing reward, cognitive, and salience networks. Two data-driven subgroups were detected, a finding that was consistent between both neuroimaging runs, but associations with SS were only found in the first run, potentially reflecting neural habituation in the second run. Specifically, the subgroup that had unique connections between reward-related regions had greater SS and showed a distinctive relation between connectivity strength in the reward network and SS. These findings provide novel evidence for heterogeneity in adolescent brain-behavior relations by showing that subsets of adolescents have unique associations between neural reward processing and SS. Findings have broader implications for future work on reward processing, as they demonstrate that brain-behavior relations may attenuate across runs.

Keywords: Adolescence, fMRI, Monetary Incentive Delay Task, Network Connectivity, Reward, Sensation Seeking

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1. Introduction

Adolescent risk-taking behavior, including sensation seeking, has been a central focus for developmental research, interventions, and policy largely because it is a leading cause of death and disease during an otherwise healthy period of life (Kann et al., 2018). Neuroscience research has provided critical insights into the neurodevelopment during adolescence (Casey, 2015). For instance, there are varying degrees of support for a set of related models contending that normative changes in the cognitive control system (e.g., dorsolateral prefrontal cortex) and socioemotional system (e.g., ventral striatum and amygdala) during adolescence predispose youth to the sensation seeking characteristic of this developmental period. (Casey et al., 2008; Ernst et al., 2006; Shulman et al., 2016; Steinberg, 2008). Although the implications of these models have been far-reaching, there is continued debate about their empirical support and applicability to all youth, potentially owing to their focus on functional localization and quantitative methods that average across youth who may vary widely on relevant dimensions (Beltz, 2018; Bjork & Pardini, 2015; Willoughby et al., 2013). The goal of this study is to begin to fill that knowledge gap by characterizing adolescent-specific networks of the socioemotional and cognitive control systems during a reward processing task and examining their associations with self-reported sensation seeking behavior.

1.1 Neural Connectivity and Adolescent Reward Processing

Although there is considerable variability among them, most neurodevelopmental models of adolescent risk-taking behavior (Casey et al., 2008; Ernst et al., 2006; Steinberg, 2008) broadly concern the interplay between brain regions implicated in: (a) cognitive control, such as the anterior cingulate cortex (ACC) and dorsolateral prefrontal cortex (DLPFC); and (b) socioemotional processing, which can be broken down into the reward and salience subsystems.

The reward subsystem facilitates approach behaviors, and includes the ventral striatum (VS), orbitofrontal cortex (OFC), and ventromedial PFC (vmPFC) (Haber & Knutson, 2010; Haber & Behrens, 2014). The salience subsystem detects the valence of stimuli, and includes the amygdala and insula (Knutson & Greer, 2008; Posner et al., 2005). Early studies evaluated differences in mean-level activation of regions thought to contribute to sensation seeking behavior during reward processing that showed developmental differences between adults and adolescents (reviewed in Silverman et al., 2015), such that adolescents had less activation than adults in the ACC and VS when anticipating rewards (Bjork et al., 2010) but greater activation than adults in the VS and insula when receiving rewards (Galván & McGlennen, 2012). Some early studies also examined the associations between regional mean-level activations and risk-related behaviors, such that the likelihood of engaging in a risky behavior in the future and VS activation were more strongly positively related in adolescents and adults (Galvan et al., 2007).

Although informative, these early studies generally did not consider functional integration among the multiple regions that constitute each system or network (Pessoa, 2017). Connectivity studies, however, have the potential to map patterns among integrated neural networks (Beltz, 2018; Lydon-Staley & Bassett, 2018). Specifically, connectivity overcomes limitations of functional localization by evaluating the covariation, or functional dynamics, among regional activations, which is emphasized in most theories of the neural underpinnings of adolescent risk-taking behavior (Beltz, 2018; Meisel et al., 2019). Furthermore, although prior studies have used connectivity analyses, methods have often averaged across adolescents in an attempt to describe normative development. In contrast, person-specific connectivity takes an individual differences approach by modeling at the subgroup, or even at the individual, level. This is important because there is growing evidence of extreme individual differences in both

neural function (Becht & Mills, 2020; Gordon et al., 2017; Finn et al., 2017; Poldrack, 2017) and in adolescent brain development (Lydon-Staley & Bassett, 2018).

To date, several studies have considered the relation between mean (or group-level) connectivity and sensation-seeking. For instance, connectivity between the amygdala and the OFC during resting state using seed-based functional connectivity (i.e., detecting associations between a candidate region and all other brain regions) have been shown to be inversely related to sensation seeking (Crane et al., 2018). Also, connectivity between VS and motor areas during incentivized trials in a task using psychophysiological interaction (i.e., combining seed-based correlations and task regressors) have been shown to be positively related to sensation seeking (Crane et al., 2018; Weiland et al., 2013). Finally, mean-level connectivity patterns in the OFC and ACC estimated using Pearson's correlations from resting state data were reported to reliably predict ($r = .30$) sensation seeking in adults (Wan et al., 2020). Together, these studies suggest that there may be group-level links between patterns of neural connectivity and sensation seeking.

Nonetheless, significant questions remain about the association between connectivity and sensation seeking during adolescence, as participants in the studies reviewed above ranged in age from 18 to 85 years (Crane et al., 2018) or only included young-to-mid adults aged 21 to 35 years (Wan et al., 2020). Questions about adolescent-specific reward connectivity and behavior are important to answer because the developmental peak in sensation seeking seems to be between ages 14 and 20 (Harden & Tucker-Drob, 2011; Romer, 2010). Although one study examined functional connectivity patterns and sensation seeking in a late adolescent sample (18-22 years old), the study looked only at mean-level connectivity in a sample of late adolescents exposed to higher rates of adversity (Weiland et al., 2013). Thus, there is empirical

evidence for meaningful associations between functional connectivity and sensation seeking at the group level, but there remains a need for research on adolescents that captures individual differences.

1.2 Person Specific Connectivity

One promising way to accurately capture individual differences in the neural networks underlying adolescent reward processing is to use a person-specific connectivity approach that avoids assumptions about uniformity (Beltz, 2018; Lydon-Staley & Bassett, 2018). Given the heterogeneity of functional networks (Finn et al., 2017) and adolescent behaviors (Bjork & Pardini, 2015), modeling person-specific covariation among regional activations may capture effects that are only present, or only particularly strong, in a subset of individuals or even that are unique to a single individual (see Beltz & Gates, 2017).

Group Iterative Multiple Model Estimation (GIMME; Gates & Molenaar, 2012) is one such modeling approach. GIMME creates sparse person-specific networks specifying data-driven connections (or edges) among brain regions of interest (ROIs) that can occur at multiple levels: group, subgroup and individual (Beltz & Gates, 2017; Gates et al., 2017). First, GIMME estimates group-level connections that are meaningful for at least 75% of individuals. Second, subgroups are identified using the Walktrap community detection algorithm (Orman & Labatut, 2009), which clusters into a community individuals based on the similarity of their group-level connection magnitudes (Gates et al., 2016), and then subgroup-level connections that are meaningful for only individuals in the same subgroup are estimated. Third, individual-level connections that are unique to a person (and estimated after group- and subgroup-level connections, which improves their reliability; Gates et al., 2017) are estimated. While the final networks characterize both homogeneity (in the group-level connections – without averaging

across individuals) and heterogeneity (in the individual-level connections) in a sparse network, subgroup-level connections represent both homogeneity and heterogeneity. Simulation studies have demonstrated that GIMME effectively identifies the presence of connections between ROIs and is an accurate method for modeling network patterns in functional time-series data, especially compared to other approaches that assume homogeneity when participants are, in fact, heterogeneous (Gates et al., 2017; Mumford & Ramsey, 2014; Smith et al., 2011).

GIMME has been successfully used to delineate person-specific networks in developmental and clinical research (reviewed in Beltz & Gates, 2017; Beltz & Weigard, 2019). For instance, during an alcohol-related inhibition task in young adults, the number of connections within the cognitive control system changed across the transition to college in accord with alcohol use behaviors (Beltz et al. 2013). Moreover, during resting state, network connectivity patterns in subgroups effectively delineated communities of children with different clinical diagnoses (e.g., autism spectrum disorder and attention deficit hyperactivity disorder) and healthy controls (Henry et al., 2019), such that children with diagnoses were characterized by connections between the default mode, salience and ventral attention networks, whereas controls were largely characterized by within-network connections. Likewise, resting state network connectivity patterns revealed subgroups of adolescents who varied in levels of childhood violence exposure (Goetschius et al., 2020), which is particularly noteworthy because it illustrates how GIMME can differentiate - in adolescence - brain networks of children with certain experiences of adversity in a purely data-driven fashion. The ability to capture both homogeneity and heterogeneity in neural network features is critical in the study of adolescent sensation seeking, because risk-taking tendencies may represent only a subset of youth and not all adolescents (Bjork & Pardini, 2015).

1.3 Current Study

In the current study, we examine whether person-specific network connectivity during a reward processing task meaningfully relates to individual differences in self-reported sensation seeking behaviors. We accomplish this by applying GIMME to two separate runs of the Monetary Incentive Delay task (MID; Knutson et al., 2000) in a sample of late adolescents, focusing on 12 ROIs that reflect the cognitive control, reward and salience networks (e.g., bilateral OFC, DLPFC, Insula, Amygdala, VS, and ACC and vmPFC), and that have been central to the neurodevelopmental literature (Demidenko et al., 2020; Sherman et al., 2018). Specifically, we implement GIMME's subgroup community detection algorithm to uncover potential communities of adolescents who share neural features, and then we examine how these features relate to adolescent sensation seeking behavior. Given that reported poor within-participant reliability in task-based fMRI may be attributed to habituation (Elliott et al., 2020), or waning vigilance or novelty of in reward systems triggered by fMRI tasks (Ekhtiari et al., 2020; Plichta et al., 2012), we also consider the network connectivity during the combined and individual MID run time-series.

Our study is comprised of three aims. In Aim 1, we map person-specific connectivity in reward processing regions separately for each run of the MID task, exploring whether there are data-driven subgroups. In Aim 2, we examine whether there are meaningful associations between network features (such as subgroup membership and connection strength) and sensation seeking separately by run. In Aim 3, we compare estimated connections between Run 01 and Run 02 to detect potential habituation across runs and repeat Aims 1 and 2 for the combined runs to evaluate the robustness of findings from the individual runs for the combined time-series. We expect to find substantial individual differences in reward processing,

evidenced by person-specific networks, but given the novelty of this approach, we do not have expectations about whether data-driven subgroups will exist. Nevertheless, we do hypothesize that connectivity strength between reward and cognitive control ROIs will be related to sensation seeking based on common neurodevelopmental models that implicate regions, including the VS, OFC, vmPFC and/or dlPFC, in the relationship to sensation seeking (Casey et al., 2008; Casey et al., 2019; Ernst et al., 2006; Shulman et al., 2016; Steinberg, 2008).

2. Methods

2.1 Participants

Participants in this study are a Phase II subsample ($N = 104$; $M_{Age} = 19.3$; $SD_{Age} = 1.3$; 57% Female; 71% White, 14% Black, non-Hispanic, 6% Hispanic/Latinx) of adolescents from the Adolescent Health Risk Behavior (AHRB) study described in Demidenko et al. (2019). Of the 115 participants eligible for inclusion, 104 are included in this study. Seven participants were not safe to magnetic resonance imaging (MRI) scan ($n = 7$), and four completed the scan but were excluded from analyses due to non-recoverable artifacts in the images ($n = 3$) or failing to respond during the MID task ($n = 1$).

During Phase I, participants completed behavioral questionnaires, including sensation seeking, across three waves at 18-month intervals beginning in mid-to-late adolescence (Wave 1, $M_{Age} = 16.8$ years, $SD_{Age} = 1.1$). Participants characterized as high or average/low risk takers at Phase I (described in Demidenko et al., 2020) were recruited to participate in the neuroimaging Phase II. The behavioral data from Wave 1 to Wave 3 are used here in assessments of sensation seeking for each participant (described below). During Wave 1, participants completed surveys in school, administered using computer assisted self-

interviewing, and during Wave 2 and Wave 3, participants completed surveys on their own time using web-based computer assisted interviewing.

2.2 Procedures

All study procedures were approved by the University of Michigan Institutional Review Board. Upon arrival for Phase II neuroimaging, research staff reviewed instructions of the MID task. Participants were informed of the cue-related outcomes and completed a practice trial. Participants were explicitly informed that their performance, or cumulative earnings during the MID (maximum of \$30), would be associated with the compensation they received at the end of the visit.

2.3 Measures

Sensation Seeking: Participants completed the Brief Sensation Seeking Scale (BSSS), which is an 8-item self-report measure of novelty-seeking behaviors (Hoyle et al., 2002). Participants responded on a 5-point Likert-scale for 8 items: (1) “strongly disagree” to (5) “strongly agree.” Example items are “*I would like to explore strange places*” or “*I would like to try bungee jumping*”. The BSSS is a revised version of the earlier SSS (Horvath & Zuckerman, 1993; Zuckerman et al., 1978) that updates behavioral descriptions and language, and that removes similar items (e.g., related to alcohol) (Arnett, 1994; Hoyle et al., 2002). The composite variable is the average of the 8 items, such that higher scores reflect higher sensation seeking (Cronbach’s $\alpha = .78$).

In order to utilize the longitudinal sensation seeking data from Phase I of this study, growth curves were used to estimate behavior at Wave 3 (most proximal to the scan) for all participants. Specifically, SAS 9.4 PROC NLMIXED (SAS Institute Inc., Cary, NC) was used to fit mixed-effects growth curve models to the three waves of BSSS data treating the intercept

as a random effect and using an unstructured error covariance matrix; the intercept was calculated at Wave 3. Across the three waves, 100% ($N_{Wave\ 1} = 104$; $M = 3.29$, $SD = .76$), 77% ($N_{Wave\ 2} = 80$; $M = 3.26$, $SD = .72$) and 89% ($N_{Wave\ 3} = 93$; $M = 3.33$, $SD = .56$) of participants provided BSSS data. Full information maximum likelihood estimation was used in combination with empirical Bayes estimates to provide intercepts for all 104 participants in the sample (Rubin, 1976). As expected, the individual BSSS intercept estimates were highly correlated with the observed Wave 3 self-reported BSSS, $r = .82$.

fMRI Task: The MID task (Knutson et al., 2000) was used to measure brain activity during monetary reward and punishment. The MID is a well-established task for assessing reward processing, and the version used here is administered in the Adolescent Brain Cognitive Development Study (Casey et al., 2018). The task consists of three phases: anticipation, probe and feedback. Each trial starts with a cue type (i.e., Win \$0.20, Win \$5, Lose \$5, Lose \$0.20, or No Money At Stake) presented on the screen for 2000 ms followed by a jittered fixation cross (1500–4000 ms). Next, the target probe cue (187–500 ms) appears and requires participants to respond in order to win or not lose money, and it is followed by the feedback phase (1450 – 1763 ms) during which participants are informed if they receive the reward. Two MID runs were administered; each lasted 5:42 min and consistent of 407 volumes (See Supplemental Figure S1 and Section 2.3 for more information about the design and the task schematic).

2.4 fMRI Acquisition

Data were acquired using a GE Discovery MR750 3.0 Tesla scanner with a standard adult-sized coil (Milwaukee, WI). A full-brain high-resolution T1 SPGR PROMO scan was acquired for registration (TR = 7000ms, TE = 2900ms, flip angle = 8° , FOV = 25.6 cm, slice thickness = 1 mm, 208 sagittal slices; matrix = 256 x 256). Next, two functional T2*-weighted

BOLD MID runs were acquired in the axial plane using a multiband EPI sequence (MB factor=6) of 60 contiguous axial 2.4 mm slices (TR = 800ms, TE = 30 ms, flip angle = 52°, FOV = 21.6 cm, 90x90 matrix, volumes = 407). A fieldmap was also acquired right before the task using spin-echo EPI (TR = 7400ms, TE = 80 ms, FOV = 21.6 cm, 90x90 matrix) with opposite phase encoding polarity (A→P, P→A).

2.5 fMRI Preprocessing & Time-series Extractions

FMRI data: (1) were reconstructed; (2) had realignment and field map correction applied in SPM12; and (3) had physiological noise removed using RETROICOR (Glover et al., 2000). Preprocessing was then completed using FSL (FMRIB's Software Library, www.fmrib.ox.ac.uk/fsl) FEAT (FMRI Expert Analysis Tool) Version 6.00. This included: (4) registration to high resolution structural and standard space MNI 152 image using FLIRT using a Full search 12 DOF (Jenkinson & Smith, 2001; Jenkinson, Bannister, Brady, & Smith, 2002); (5) motion correction using MCFLIRT (Jenkinson et al., 2002); (6) non-brain removal using BET (Smith, 2002); (7) spatial smoothing using a Gaussian kernel of FWHM 5mm; (8) grand-mean intensity normalisation of the entire 4D dataset by a single multiplicative factor; and (9) highpass temporal filtering (Gaussian-weighted least-squares straight line fitting, with sigma=50.0s).

2.6 Region of Interest Identification and Time-series Extraction

Several steps were completed to extract the time-series data for GIMME analyses. First, central coordinates for 12 ROIs (See Figure 1; Supplementary Section 2.6 Table S1 for specific MNI coordinates) were selected using Neurosynth (Neurosynth.org) based on previous literature (Galvan, 2010; Sherman et al., 2018). These regions belong to three networks: the cognitive control network, which consists of the bilateral DLPFC, and ACC; the reward network, which consists of the bilateral VS, vmPFC and OFC; and the salience network, which consists of the bilateral amygdala and insula. For each ROI, a 10mm sphere around the central coordinate was used to extract the mean signal intensities at each volume for each of the two runs. For Aims 1-2, the time-series from each separate run was used, however, for Aim 3, the concatenated time-series across the two runs was used. Due to the rapid volume acquisition (800ms), each run was down-sampled (retaining every other volume) after preprocessing, as has been suggested (Beltz & Gates, 2017) and used in other fast-acquisition methods, such as functional near-infrared spectroscopy (Pinti et al., 2019).

Figure 1. Twelve ROI coordinates projected onto an MNI glass brain.
 Blue = Ventral Striatum; Green = Ventromedial Prefrontal Cortex; Pink = Anterior Cingulate Cortex; Yellow = Orbitofrontal Cortex; Red = Insula; Cyan = Amygdala; Black = Dorsolateral Prefrontal Cortex

Figure 2. GIMME Model Flow Chart.

Lines represent: Group connections= Black; Subgroup connections = Green; Individual connections = Grey; Solid = Contemporaneous; Dashed = Lagged; Green = Subgroup 1; Red = Subgroup 2

2.7 GIMME Analyses

GIMME version 0.6-0 in R version 3.6.1 (R Core Team, 2019) was used to estimate time-lagged ($t-1$) and contemporaneous (t) network connections in unified structural equation models (uSEM), which combine vector autoregressions and structural equation models, respectively, for each individual within a grouping algorithm that contains subgrouping via community detection. GIMME estimates network connections through a data-driven search process that uses Lagrange multiplier tests to select connections at the group, subgroup and individual level that most improve model fit. The sequential steps of the GIMME search process are summarized in Figure 2. At the beginning of these steps, we estimate autoregressive connections as part of a “null” model, as this search strategy has been demonstrated to improve

recovery of other connections in temporally dense data (Lane et al., 2019). Then, starting with this null model, group-level connections that best improve fit for the at least 75% of the sample are iteratively estimated for all participants. After the estimation of the group-level connections, GIMME uses this *a priori* model to inform subgroup detection. Subgroups are estimated using a data-driven community detection technique to cluster individuals with common sets of interconnected ROIs via Walktrap. For each subgroup, connections that improve fit for at least 50% of individuals in the subgroup are iteratively estimated for all participants in the subgroup (Gates et al., 2017). After subgroup detection and connection estimation are complete, the group and subgroup *a priori* models are used in the iterative data-driven estimation of individual-level connections that uniquely characterize participants and improve their model fit. At each of these three steps, the algorithm stops its search when: a) the model fits well according to two out of four fit statistics: $CFI \geq .95$, $NNFI \geq .95$, $SRMR \leq .05$ and $RMSEA \leq .05$; or b) modification indices indicate no additional connections will significantly improve fit– whichever comes first. The former is a stopping rule implemented to avoid overfitting.

To characterize individual differences in GIMME-derived networks, we focus on subgroup membership and individual coefficients from the networks when examining links to sensation seeking behavior. Subgroups are identified in GIMME (if they exist) and reflect neural network similarities among some sets of participants during the MID. Each subgroup is characterized by a set of unique network connections, and each has a person-specific beta estimate that reflects its strength and magnitude. These individual subgroups and connection estimates can be examined in relation to the BSSS.

2.8 Analysis Plan

To test Aim 1, which was to examine whether there are data-driven subgroups during the MID task, we use GIMME to map person-specific connectivity in reward processing ROIs separately for each run of the MID task, and then examine whether data-driven subgroups are identified. If subgroups are found, we will proceed to Aim 2.

To test Aim 2, which was to examine whether there are meaningful associations between network features (e.g., subgroup membership and connection strength) and sensation seeking, we use logistic regression to evaluate whether BSSS (i.e., Wave 3 empirical Bayes intercepts from the growth curve models) is significantly ($p < .05$) associated with the subgroups detected from the first and second runs, separately. Specifically, we predict subgroup membership from BSSS, controlling for age, sex, and head motion (mean framewise displacement, or FD). To determine which subgroup connections may be driving links with sensation seeking, significant associations are followed-up with exploratory multiple regression analyses – conducted within each subgroup separately – to examine associations between specific connection strengths that are meaningful to the subgroup and BSSS.

Finally, to test Aim 3, we i) compare estimated connections between Run 01 and Run 02 to detect potential habituation across runs and ii) repeat Aims 1 and 2 for the concatenated time-series to evaluate the robustness of neural connectivity and its BSSS associations in the full time-series. Specifically, we: (a) examine whether data-driven subgroups are identified, and then if subgroups are identified, we (b) use logistic regression to evaluate whether BSSS is significantly ($p < .05$) associated with the subgroups and evaluate which subgroup connections may be driving links with BSSS with follow-up multiple regression analyses, as we did in Aim 2.

3. Results

Demographic characteristics, task accuracy and in-scanner motion during the MID task for participants are reported in supplementary Tables S2-S5, respectively. No participants had mean head motion (Post FD) greater than .20, and so based on prior recommendations (Park et al., 2018), no participants are excluded from analyses for this reason. Furthermore, BSSS was not significantly associated with mean post FD for Run 01, $r(102) = .02$, or Run 02, $r(102) = -.05$.

3.1 Aim 1: Person-specific Connectivity Networks by Run

For all 104 participants, GIMME networks fit the data well (see Supplemental Table S5). A summary of the final networks is shown in Figure 3; network connections for the group (black), subgroup (Subgroup01 = red; Subgroup02 = green), and individual (grey) connections are presented for each run of the MID. Solid lines represent contemporaneous connections, dashed lines represent lagged connections, and the weight of each line reflects the proportion of participants with that connection.

There were notable similarities and differences between the GIMME group-level networks for each run. For instance, there were consistent connections among the bilateral VS, amygdala and insula regions, L VS and ACC, L insula and L DLPFC, and R insula and ACC regions, but different connections between ACC and R DLPFC regions of the cognitive control network at the group-level. The GIMME community detection algorithm also identified two subgroups in each run of the MID, but the number of participants in each subgroup and the subgroup-level connections differed. For Run 01, 61 participants were in Subgroup01 and 43 participants were in Subgroup02. For Run 02, 56 participants were in Subgroup01 and 48 participants were grouped into Subgroup02. Notably, the majority of individuals who were

grouped into Subgroup01 and Subgroup02 in the first run were also grouped into the same subgroup in the second run (Supplemental Table S6), suggesting some level of stability in subgroup membership between runs.

For each run, the more homogeneous subgroup, Subgroup02, was represented by dense within-reward-network connections and a greater number of connections between cognitive control, reward and salience networks than the heterogeneous subgroup, Subgroup 01, which had fewer subgroup connections. With respect to subgroup connections, patterns were relatively consistent across runs. Participants in the heterogeneous subgroup, Subgroup01, had three subgroup-level connections during each run; two were the same and one differed, such that R OFC $\rightarrow$ vmPFC and vmPFC $\rightarrow$ ACC connections reoccurred across the two runs, but L dlPFC $\rightarrow$ L Amygdala was unique to Run 01 and ACC $\rightarrow$ R dlPFC was unique to Run 02. Participants in the more homogeneous subgroup, Subgroup02, had nine and eight connections per run, respectively; they were similar except L Insula $\rightarrow$ L Amygdala, R dlPFC $\rightarrow$ L Amygdala, R and OFC $\rightarrow$ R VS only occurred in Run 01 and R OFC $\rightarrow$ L OFC, L dlPFC $\rightarrow$ L Amygdala only occurred in Run 02 (see Table S9).

Figure 3. GIMME Connectivity Networks for Each Run.

Black = Group connection; Red = Subgroup01 connections; Green = Subgroup02 connections; Solid = Contemporaneous; Dashed = Lagged ($t - 1$); dlPFC = dorsolateral prefrontal cortex; OFC = orbitofrontal cortex; vmPFC = ventromedial PFC; VS = ventral striatum

3.2 Aim 2: Subgroup and Connection Strength Associations with Sensation Seeking

For Aim 2, we evaluated whether the subgroups identified in Aim 1 were related to BSSS. In a logistic regression model, there was a significant association between subgroup and self-reported BSSS for Run 01 ($b = 1.1$), OR = 3.1 (see Table 1), such that a unit increase in BSSS was associated with a 3.1:1 increase in the odds of being in Subgroup02, which is characterized by several subgroup level connections among reward and salience regions. The model that included BSSS (AIC = 126.9) fit the data significantly better than the model without BSSS (AIC = 131.4), $\Delta\chi^2(1)=4.7$, $p = .03$. Subgroups did not differ in age or sex, but they did differ in FD, such that there was greater motion observed for participants in Subgroup02. This effect is unchanged with (Table 1) and without the covariate of motion (e.g., mean Post FD) in the model (see supplementary Table S8).

Table 1: *Logistic Regression: Sensation seeking associated with GIMME-derived subgroup from MID task data, by run, with and without PostFD (N = 104)*

	Run 01			Run 02		
	B	SE	p	b	SE	p
Age	-.18	.17	.28	-.11	.16	.48
Sex	.28	.43	.52	.80	.42	.06
PostFD	48.8	18.24	.008	29.4	15.84	.06
BSSS	1.1	.55	.04	.58	.51	.26

PostFD = Post Preprocessing Framewise Displacement;
BSSS = Brief Sensation Seeking Scale
in Run 01, such that sensation seeking was greater in Subgroup02, the size of the effect

There was not, however, a significant association between subgroup and self-reported BSSS from Run 02 ($b = .58$), OR = 1.8 (see Table 1), such that the model that included BSSS (AIC = 135.1) did not fit the data significantly better than the model without BSSS (AIC 136.4), $\Delta\chi^2(1)=1.3$, $p = .25$. Even though the direction of the effect was the same as in Run 01, such that sensation seeking was greater in Subgroup02, the size of the effect appeared to be attenuated in Run 02. Subgroups also did not differ in age, sex, or FD.

Given the significant prediction of subgroup classification from BSSS in Run 01, with Subgroup02 being linked to increased BSSS, we explored whether BSSS was associated with person-specific beta weights (i.e., connection strength) of subgroup-level connections in Subgroup02 for Run 01. Exploratory multiple regression analyses revealed that the strengths of the vmPFC → R OFC connection, $b = .21$, $p = .02$, and the R OFC → R VS connection, $b = -.27$, $p = .01$ (see

Figure 4. Meaningful associations between connection strength and sensation seeking in Subgroup02 during Run 01. (+) = sig. positive association; (-) = sig. negative association.

Figure 4) were significantly associated with BSSS. Hence, increased self-reported sensation seeking was positively associated with connectivity strength between the vmPFC and R OFC (Figure 4B), and sensation seeking was negatively associated with connectivity strength between R OFC and R VS (Figure 4C) – which are all regions that are associated with reward processing.

3.3 Aim 3: Subgroup Associations with Sensation Seeking in Combined MID Runs

We compared and contrasted GIMME results between the runs with GIMME results from the combined MID runs. Regarding comparisons between Run 01 and Run 02, there were notable differences (Figure 3). Although the group-level connections do not appear completely disparate between the two runs, only 55% of the group-level contemporaneous connections (solid black lines) re-occurred across both runs. Although, as noted above, there was some stability in subgroup membership between runs, the difference in membership was statistically significant, $\chi(1) = 18.1, p < .001, \Phi = .41$; only 72% ($N = 44$) of the participants were consistently grouped into Subgroup01, and 72% ($N = 31$) of participants were consistently grouped into Subgroup02 (Supplemental Table S6).

Regarding analyses of the combined runs, the GIMME networks fit the data well for all participants except one (see Table S10; Figure S4). For this participant, the model did not converge. As for the analyses conducted separately per run, two subgroups were identified. The number of participants differed across each subgroup, with 34 in Subgroup01 and 69 in Subgroup02. Subgroups were comparable in the number of subgroup-level connections estimated for Subgroup01 and Subgroup02, with 19 and 16 connections, respectively. Both Subgroup01 and Subgroup02 had connections within the reward and salience networks as well as dense network connections between reward, salience, and cognitive control. When examining

whether self-reported BSSS predicted subgroup membership, there was not a significant effect ($b = -51$; supplemental Table S11), such that the model that included BSSS (AIC = 129.6) did not fit the data significantly better than the model without BSSS (AIC 130.5), $\Delta\chi^2(1)=0.9$, $p = .33$. This suggests that the positive association between sensation seeking and subgroups that was present for Run 01 was not reflected when the runs were combined.

4. Discussion

We used a person-specific network connectivity analysis approach, GIMME (Gates & Molenaar, 2012), to evaluate a central question in the study of adolescent risk taking: Do individual differences in neural network connectivity during a reward processing task meaningfully relate to self-reported sensation seeking behavior? Specifically, we examined whether and how connectivity during two runs of a commonly used reward task (i.e., Monetary Incentive Delay; Knutson et al., 2000) differed between data-derived subgroups of youth in late adolescence in ways related to sensation seeking (calculated as the endpoint intercept of a 3-wave behavioral trajectory across adolescence). To examine possible habituation effects, we considered how neural subgrouping and behavioral associations varied across runs, and also compared this approach with analyses that combined the runs. We found that there were two data-derived subgroups in each run and that subgroup-level network connections were meaningfully associated with sensation seeking in the first run only. These associations were not detected when the runs were combined for analysis. To our knowledge, this is the first investigation of adolescent-specific reward network connectivity mapping with significant links to risk-relevant behavior.

In light of evidence for the neural habituation to reward across time (Plichta et al., 2012; Ekhtiari et al., 2020), we examined person-specific connectivity in reward processing regions

separately for runs of the MID task in a sparse network of 12 ROIs representing cognitive control, reward processing, and salience networks. We found that the majority of group-level connections reoccurred across runs reflecting some level of stability across connections meaningful to all individuals. Then, for each MID run the GIMME algorithm identified two subgroups. Although subgroup membership significantly differed across the runs, the majority of individuals grouped in each of the subgroups in Run 01 (72%) were also grouped in the corresponding subgroup in Run 02, suggesting some degree of stability in subgroup-specific neural connectivity features over the course of the task. Subgroup01 had greater heterogeneity (only three subgroup connections during each run) than Subgroup02, which had nine and eight subgroup connections across Run 01 and Run 02, respectively. This suggests that while there is heterogeneity in adolescent brain activity during reward processing, there are also some meaningful commonalities across subgroups of adolescents.

With respect to sensation seeking, when modeling each run separately, we found a significant association between community-based subgroups and self-reported sensation seeking. Specifically, our analyses revealed that the more homogenous subgroup, Subgroup02, had significantly higher sensation seeking than Subgroup01. This effect, however, was only significant when subgroups were defined in the first run, suggesting that changes in subgroup membership across the runs may have impacted associations with sensation seeking. Similar to prior work that found associations between OFC connectivity and reward traits (Crane et al., 2018; Wan et al., 2020), we found a significant positive association in connectivity strength between vmPFC—Right OFC and sensation seeking, and a negative association in connectivity strength between Right OFC—Right VS and sensation seeking for Subgroup02 during Run 01, but not Run 02. This suggests that the OFC, which is important for stimulus-value

representations, tracking internal values, and goal-directed and affective behavior (Haber & Behrens, 2014; Padoa-Schioppa & Conen, 2017; Szczepanski & Knight, 2014), may be relevant for individual differences in reward seeking, but only for a specific subset of adolescents. Given the exploratory nature of this finding, it requires further investigation and replication in future work.

There were other important differences across runs. Although 72% of participants maintained their subgroup assignments across runs (i.e., were in the homogeneous subgroup in both runs or the heterogeneous subgroup in both runs), the differences in grouping between runs appear to be meaningful because the association with sensation seeking decreased from the first to the second. This is consistent with recent findings, indicating that some of this decrease may be attributable to habituation (Elliott et al., 2020; Plichta et al., 2012), which is especially relevant to reward regions modeled here (Ekhtiari et al., 2020). Specifically, motivation towards approaching and receiving rewards may be attenuated with repeated runs due to strategic changes in attentional processes (Failing & Theeuwes, 2018) and/or become habitual over time (Michaelsen & Esch, 2021). This might be reflected in the dynamics of reward, salience and cognitive control networks that consequently decrease the association of neural features with reward relevant behaviors.

When we repeated our analyses using the combined MID runs, we found further changes in subgroup memberships as well as with subgroup associations with sensation seeking. While two subgroups were, again, detected in combined runs, these two subgroups were both more homogeneous and represented by more connections between reward, salience, and cognitive control networks than when the runs were analyzed separately. Moreover, the subgroup association with sensation seeking was not significant and negative; this is a striking deviation

from the significant and positive association in Run 01 and even the positive (but non-significant) association in Run 02. This stark difference might reflect methodological artifacts, such as greater signal quality and stability with a longer duration scan (Gordon et al., 2017), or greater statistical power, which would be expected to cause more connections to be estimated at the subgroup level, rather than individual level, because the 50% threshold for subgroup connections becomes easier to meet. GIMME adds connections interactively at the group and subgroup level that are significant ($p < .01$) for a large proportion of individuals (75% and 50% for the group and subgroup levels, respectively). Likewise, the model at the individual level retains/adds connections that meet the significance threshold and then the model fit criterion threshold (Gates & Molenaar, 2012). By doubling our time-series data (concatenating runs), this increases the likelihood that a connection would have been incorporated into the group and subgroup level models, especially in scenarios where connections were near the significance threshold in the shorter time series. Future connectivity work should consider issues of power and simultaneous changes stemming from individual differences across the time-series.

Differences across runs could also potentially reflect meaningful individual differences in how network dynamics change across time. For example, connectivity patterns have been shown to reflect some variability in individuals across runs in both static and dynamic networks (Fong et al., 2019). Moreover, it appears likely that the variability across runs may have both influenced subgroup partitioning (Gates et al., 2016; Pons & Latapy, 2005) and the association between network connectivity and sensation seeking. Future work should reconsider these associations in the context of test-retest of network connectivity metrics (Beck & Jackson, 2020), the specific assumptions of GIMME, and the effect of different fMRI protocols, such as

non-multiband data, different head motion corrections, and alternative reward, salience and cognitive control ROI coordinates.

In addition to generalizing the results reported here, future work should consider how variability in task length, number of runs and task type impact findings. Some researchers have proposed that increasing the amount of data, or task length (Gordon et al., 2017), and aggregating across modalities (Elliott et al., 2019) may improve reliability and generalizability. Although these suggestions certainly have merit, there may be an inherent trade-off between the measurement improvements that result from increasing the length of a task, and measurement decrements that occur due to habituation or other state-related changes linked to longer tasks. Furthermore, cognitive states induced by different tasks have been shown to be characterized by different connectivity patterns explaining different amounts of variance in behavior (Greene et al., 2018). Hence, considering how group-, subgroup- and individual-level network patterns may vary across the course of reward tasks and the impact of this variability on sensation seeking may facilitate the field's understanding of adolescent risk taking.

4.1 Study Considerations

The findings reported here are not without limitations. First, a major issue in fMRI is the effect of head motion on the quality of the underlying neural signal (Parkes et al., 2018; Power et al., 2014; Siegel et al., 2014). Although we used standard task-based fMRI motion correction (Park et al., 2018), motion may still have impacted the underlying signal. This is especially of concern given that head motion was significantly related to the Subgroups identified. However, we compared our models with and without the covariate of head motion and found our interpretations did not meaningfully change. Nonetheless, future work should consider how

different head motion correction strategies may influence the estimation of person-specific networks.

Second, although the main sample used here is two times greater than the median sample used in neuroimaging studies (Szucs & Ioannidis, 2020), the analyses focused on the brain-behavior associations for Subgroup02 were smaller, and therefore, may be less robust than results involving the full sample. Given the issues of reliability and power in fMRI analyses. (Button et al., 2013; Szucs & Ioannidis, 2017), we cannot extrapolate our exploratory analyses examining the association between specific connection strengths and BSSS. As such, these results warrant replication in an independent sample.

Third, the networks are based on several key *a priori* ROIs. Although GIMME simulations have demonstrated that omission of variables (i.e., the third variable problem) does not greatly impact recovery of connections (Gates et al., 2017), future work should consider how subgrouping and connection strength are altered when using different combinations of regions.

Fourth, due to some missing sensation seeking data, we used full information maximum likelihood to estimate a sensation seeking score at Wave 3 (closest to when neuroimaging was conducted) for all individuals. This strategy may have introduced additional noise into our models, especially if missingness was related to an unaccounted variable. However, the strategy also allowed us to maximize our sample size (i.e., by not excluding participants with missing Wave 3 data), and our estimated intercept was significantly related to the observed data increasing our confidence in the observed associations.

Although our study is based on a tenet of the imbalance hypothesis and we found a significant brain-behavior relation, findings cannot easily be extrapolated to real-world risk-

taking behavior without further research. Associations between self-reported sensation seeking and real-world risk-taking are often small-to-medium in adolescent samples (Demidenko et al., 2019). Instead, our findings represent the link between brain function and a psychological trait hypothesized to relate to real-world risk-taking behaviors.

4.2 Conclusions

This study is among the first to evaluate a central tenet of the developmental imbalance hypothesis using a data-driven person-specific network connectivity approach that characterizes group-, subgroup- and individual-level connections. When mapping sparse networks of connections among cognitive control and socioemotional ROIs during a reward paradigm, we found two subgroups – one “homogenous” with a greater number of shared connections, and one “heterogeneous” with fewer shared connections – with the homogeneous group having higher self-reported sensation seeking than the heterogeneous group. Further, the strengths of select homogeneous subgroup connections, such as the Right OFC—Right VS and vmPFC—Right OFC, were negatively and positively associated with self-reported sensation seeking, respectively. This implies that reward related behaviors are meaningfully related to connectivity patterns derived from person-specific networks. Note, however, brain-behavior relations varied by run, such that connectivity between reward regions was significantly related to sensation seeking only during the first run, but not the second run or when the runs were combined. These findings suggest young adults that report greater sensation seeking may share unique patterns of network connectivity during reward processing and these patterns may attenuate with repeated stimulation, perhaps due to habituation to the task.

References

- Arnett, J. (1994). Sensation seeking: A new conceptualization and a new scale. *Personality and Individual Differences*, 16(2), 289–296. [https://doi.org/10.1016/0191-8869\(94\)90165-1](https://doi.org/10.1016/0191-8869(94)90165-1)
- Becht, A. I., & Mills, K. L. (2020). Modeling Individual Differences in Brain Development. *Biological Psychiatry*. <https://doi.org/10.1016/j.biopsych.2020.01.027>
- Beck, E. D., & Jackson, J. J. (2020). Consistency and change in idiographic personality: A longitudinal ESM network study. *Journal of Personality and Social Psychology*, 118(5), 1080–1100. <https://doi.org/10.1037/pspp0000249>
- Beltz, A. M. (2018). Connecting Theory and Methods in Adolescent Brain Research. *Journal of Research on Adolescence*, 28(1), 10–25. <https://doi.org/10.1111/jora.12366>
- Beltz, A. M., & Gates, K. M. (2017). Network Mapping with GIMME. *Multivariate Behavioral Research*, 52(6), 789–804. <https://doi.org/10.1080/00273171.2017.1373014>
- Beltz, A. M., Gates, K. M., Engels, A. S., Molenaar, P. C. M., Pulido, C., Turrisi, R., Berenbaum, S. A., Gilmore, R. O., & Wilson, S. J. (2013). Changes in Alcohol-Related Brain Networks Across the First Year of College: A Prospective Pilot Study Using fMRI Effective Connectivity Mapping. *Addictive Behaviors*, 38(4), 2052–2059. <https://doi.org/10.1016/j.addbeh.2012.12.023>
- Beltz, A. M., & Weigard, A. (2019). Methodological Advances in Leveraging Neuroimaging Datasets in Adolescent Substance Use Research. *Current Addiction Reports*, 6(4), 495–503. <https://doi.org/10.1007/s40429-019-00275-x>
- Bjork, J. M., & Pardini, D. A. (2015). Who are those “risk-taking adolescents”? Individual differences in developmental neuroimaging research. *Developmental Cognitive Neuroscience*, 11, 56–64. <https://doi.org/10.1016/j.dcn.2014.07.008>

- Bjork, J. M., Smith, A. R., Chen, G., & Hommer, D. W. (2010). Adolescents, Adults and Rewards: Comparing Motivational Neurocircuitry Recruitment Using fMRI. *PLOS ONE*, 5(7), e11440. <https://doi.org/10.1371/journal.pone.0011440>
- Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, 14(5), 365–376. <https://doi.org/10.1038/nrn3475>
- Casey, B. J. (2015). Beyond simple models of self-control to circuit-based accounts of adolescent behavior. *Annual Review of Psychology*, 66, 295–319. <https://doi.org/10.1146/annurev-psych-010814-015156>
- Casey, B. J., Cannonier, T., Conley, M. I., Cohen, A. O., Barch, D. M., Heitzeg, M. M., Soules, M. E., Teslovich, T., Dellarco, D. V., Garavan, H., Orr, C. A., Wager, T. D., Banich, M. T., Speer, N. K., Sutherland, M. T., Riedel, M. C., Dick, A. S., Bjork, J. M., Thomas, K. M., ... ABCD Imaging Acquisition Workgroup. (2018). The Adolescent Brain Cognitive Development (ABCD) study: Imaging acquisition across 21 sites. *Developmental Cognitive Neuroscience*, 32, 43–54. <https://doi.org/10.1016/j.dcn.2018.03.001>
- Casey, B. J., Getz, S., & Galvan, A. (2008). The adolescent brain. *Developmental Review : DR*, 28(1), 62–77. <https://doi.org/10.1016/j.dr.2007.08.003>
- Casey, B. J., Heller, A. S., Gee, D. G., & Cohen, A. O. (2019). Development of the emotional brain. *Neuroscience Letters*, 693, 29–34. <https://doi.org/10.1016/j.neulet.2017.11.055>
- Crane, N. A., Gorka, S. M., Phan, K. L., & Childs, E. (2018). Amygdala-orbitofrontal functional connectivity mediates the relationship between sensation seeking and alcohol

use among binge-drinking adults. *Drug and Alcohol Dependence*, 192, 208–214.

<https://doi.org/10.1016/j.drugalcdep.2018.07.044>

Demidenko, M. I., Huntley, E. D., Jahn, A., Thomason, M. E., Monk, C. S., & Keating, D. P.

(2020). Cortical and subcortical response to the anticipation of reward in high and average/low risk-taking adolescents. *Developmental Cognitive Neuroscience*, 44, 100798. <https://doi.org/10.1016/j.dcn.2020.100798>

Demidenko, M. I., Huntley, E. D., Martz, M. E., & Keating, D. P. (2019). Adolescent Health

Risk Behaviors: Convergent, Discriminant and Predictive Validity of Self-Report and Cognitive Measures. *Journal of Youth and Adolescence*, 48(9), 1765–1783.

<https://doi.org/10.1007/s10964-019-01057-4>

Ekhtiari, H., Kuplicki, R., Aupperle, R. P., & Paulus, M. P. (2020). It is Never as Good the Second Time Around: Brain Areas Involved in Salience Processing Habituate During Repeated Drug Cue Exposure in Methamphetamine and Opioid Users. *BioRxiv*, 2020.04.18.036368. <https://doi.org/10.1101/2020.04.18.036368>

Elliott, M. L., Knodt, A. R., Ireland, D., Morris, M. L., Poulton, R., Ramrakha, S., Sison, M. L., Moffitt, T. E., Caspi, A., & Hariri, A. R. (2020). What Is the Test-Retest Reliability of Common Task-Functional MRI Measures? New Empirical Evidence and a Meta-Analysis: *Psychological Science*. <https://doi.org/10.1177/0956797620916786>

Ernst, M., Pine, D. S., & Hardin, M. (2006). Triadic model of the neurobiology of motivated behavior in adolescence. *Psychological Medicine*, 36(3), 299–312. <https://doi.org/10.1017/S0033291705005891>

- Failing, M., & Theeuwes, J. (2018). Selection history: How reward modulates selectivity of visual attention. *Psychonomic Bulletin & Review*, 25(2), 514–538.
<https://doi.org/10.3758/s13423-017-1380-y>
- Finn, E. S., Scheinost, D., Finn, D. M., Shen, X., Papademetris, X., & Constable, R. T. (2017). Can brain state be manipulated to emphasize individual differences in functional connectivity? *NeuroImage*, 160, 140–151.
<https://doi.org/10.1016/j.neuroimage.2017.03.064>
- Fong, A. H. C., Yoo, K., Rosenberg, M. D., Zhang, S., Li, C.-S. R., Scheinost, D., Constable, R. T., & Chun, M. M. (2019). Dynamic functional connectivity during task performance and rest predicts individual differences in attention across studies. *NeuroImage*, 188, 14–25. <https://doi.org/10.1016/j.neuroimage.2018.11.057>
- Galvan, A. (2010). Adolescent development of the reward system. *Frontiers in Human Neuroscience*, 4, 6. <https://doi.org/10.3389/neuro.09.006.2010>
- Galvan, A., Hare, T., Voss, H., Glover, G., & Casey, B. J. (2007). Risk-taking and the adolescent brain: Who is at risk? *Developmental Science*, 10(2), F8–F14.
<https://doi.org/10.1111/j.1467-7687.2006.00579.x>
- Galván, A., & McGlennen, K. M. (2012). Enhanced Striatal Sensitivity to Aversive Reinforcement in Adolescents versus Adults. *Journal of Cognitive Neuroscience*, 25(2), 284–296. https://doi.org/10.1162/jocn_a_00326
- Gates, K. M., Henry, T., Steinley, D., & Fair, D. A. (2016). A Monte Carlo Evaluation of Weighted Community Detection Algorithms. *Frontiers in Neuroinformatics*, 10, 45.
<https://doi.org/10.3389/fninf.2016.00045>

- Gates, K. M., Lane, S. T., Varangis, E., Giovanello, K., & Guiskewicz, K. (2017). Unsupervised Classification During Time-Series Model Building. *Multivariate Behavioral Research*, 52(2), 129–148. <https://doi.org/10.1080/00273171.2016.1256187>
- Gates, K. M., & Molenaar, P. C. M. (2012). Group search algorithm recovers effective connectivity maps for individuals in homogeneous and heterogeneous samples. *NeuroImage*, 63(1), 310–319. <https://doi.org/10.1016/j.neuroimage.2012.06.026>
- Glover, G. H., Li, T. Q., & Ress, D. (2000). Image-based method for retrospective correction of physiological motion effects in fMRI: RETROICOR. *Magnetic Resonance in Medicine*, 44(1), 162–167. [https://doi.org/10.1002/1522-2594\(200007\)44:1<162::aid-mrm23>3.0.co;2-e](https://doi.org/10.1002/1522-2594(200007)44:1<162::aid-mrm23>3.0.co;2-e)
- Goetschius, L. G., Hein, T. C., McLanahan, S. S., Brooks-Gunn, J., McLoyd, V. C., Dotterer, H. L., Lopez-Duran, N., Mitchell, C., Hyde, L. W., Monk, C. S., & Beltz, A. M. (2020). Association of Childhood Violence Exposure With Adolescent Neural Network Density. *JAMA Network Open*, 3(9). <https://doi.org/10.1001/jamanetworkopen.2020.17850>
- Gordon, E. M., Laumann, T. O., Gilmore, A. W., Newbold, D. J., Greene, D. J., Berg, J. J., Ortega, M., Hoyt-Drazen, C., Gratton, C., Sun, H., Hampton, J. M., Coalson, R. S., Nguyen, A. L., McDermott, K. B., Shimony, J. S., Snyder, A. Z., Schlaggar, B. L., Petersen, S. E., Nelson, S. M., & Dosenbach, N. U. F. (2017). Precision Functional Mapping of Individual Human Brains. *Neuron*, 95(4), 791-807.e7. <https://doi.org/10.1016/j.neuron.2017.07.011>
- Greene, A. S., Gao, S., Scheinost, D., & Constable, R. T. (2018). Task-induced brain state manipulation improves prediction of individual traits. *Nature Communications*, 9(1), 1–13. <https://doi.org/10.1038/s41467-018-04920-3>

- Haber, S. N., & Knutson, B. (2010). The Reward Circuit: Linking Primate Anatomy and Human Imaging. *Neuropsychopharmacology*, 35(1), 4–26. <https://doi.org/10.1038/npp.2009.129>
- Haber, S. N., & Behrens, T. E. J. (2014). The Neural Network Underlying Incentive-Based Learning: Implications for Interpreting Circuit Disruptions in Psychiatric Disorders. *Neuron*, 83(5), 1019–1039. <https://doi.org/10.1016/j.neuron.2014.08.031>
- Harden, K. P., & Tucker-Drob, E. M. (2011). Individual differences in the development of sensation seeking and impulsivity during adolescence: Further evidence for a dual systems model. *Developmental Psychology*, 47(3), 739–746. <https://doi.org/10.1037/a0023279>
- Henry, T. R., Feczko, E., Cordova, M., Earl, E., Williams, S., Nigg, J. T., Fair, D. A., & Gates, K. M. (2019). Comparing directed functional connectivity between groups with confirmatory subgrouping GIMME. *NeuroImage*, 188, 642–653. <https://doi.org/10.1016/j.neuroimage.2018.12.040>
- Horvath, P., & Zuckerman, M. (1993). Sensation seeking, risk appraisal, and risky behavior. *Personality and Individual Differences*, 14(1), 41–52. [https://doi.org/10.1016/0191-8869\(93\)90173-Z](https://doi.org/10.1016/0191-8869(93)90173-Z)
- Hoyle, R. H., Stephenson, M. T., Palmgreen, P., Lorch, E. P., & Donohew, R. L. (2002). Reliability and validity of a brief measure of sensation seeking. *Personality and Individual Differences*, 32(3), 401–414. [https://doi.org/10.1016/S0191-8869\(01\)00032-0](https://doi.org/10.1016/S0191-8869(01)00032-0)
- Jenkinson, M., Bannister, P., Brady, M., & Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. *NeuroImage*, 17(2), 825–841.

- Jenkinson, M., & Smith, S. (2001). A global optimisation method for robust affine registration of brain images. *Medical Image Analysis*, 5(2), 143–156.
- Kann, L., McManus, T., Harris, W. A., Shanklin, S. L., Flint, K. H., Queen, B., Lowry, R., Chyen, D., Whittle, L., Thornton, J., Lim, C., Bradford, D., Yamakawa, Y., Leon, M., Brener, N., & Ethier, K. A. (2018). Youth Risk Behavior Surveillance—United States, 2017. *Morbidity and Mortality Weekly Report. Surveillance Summaries (Washington, D.C.: 2002)*, 67(8), 1–114. <https://doi.org/10.15585/mmwr.ss6708a1>
- Knutson, B., & Greer, S. (2008). Anticipatory affect: Neural correlates and consequences for choice. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 363(1511), 3771–3786. <https://doi.org/10.1098/rstb.2008.0155>
- Knutson, B., Westdorp, A., Kaiser, E., & Hommer, D. (2000). FMRI visualization of brain activity during a monetary incentive delay task. *NeuroImage*, 12(1), 20–27. <https://doi.org/10.1006/nimg.2000.0593>
- Lane, S. T., Gates, K. M., Pike, H. K., Beltz, A. M., & Wright, A. G. C. (2019). Uncovering general, shared, and unique temporal patterns in ambulatory assessment data. *Psychological Methods*, 24(1), 54–69. <https://doi.org/10.1037/met0000192>
- Lydon-Staley, D. M., & Bassett, D. S. (2018). The Promise and Challenges of Intensive Longitudinal Designs for Imbalance Models of Adolescent Substance Use. *Frontiers in Psychology*, 9. <https://doi.org/10.3389/fpsyg.2018.01576>
- Meisel, S. N., Fosco, W. D., Hawk, L. W., & Colder, C. R. (2019). Mind the gap: A review and recommendations for statistically evaluating Dual Systems models of adolescent risk behavior. *Developmental Cognitive Neuroscience*, 39, 100681. <https://doi.org/10.1016/j.dcn.2019.100681>

- Michaelsen, M. M., & Esch, T. (2021). Motivation and reward mechanisms in health behavior change processes. *Brain Research*, 1757, 147309.
<https://doi.org/10.1016/j.brainres.2021.147309>
- Mumford, J. A., & Ramsey, J. D. (2014). Bayesian networks for fMRI: A primer. *NeuroImage*, 86, 573–582. <https://doi.org/10.1016/j.neuroimage.2013.10.020>
- Orman, G. K., & Labatut, V. (2009). A Comparison of Community Detection Algorithms on Artificial Networks. In J. Gama, V. S. Costa, A. M. Jorge, & P. B. Brazdil (Eds.), *Discovery Science* (pp. 242–256). Springer. https://doi.org/10.1007/978-3-642-04747-3_20
- Padoa-Schioppa, C., & Conen, K. E. (2017). Orbitofrontal Cortex: A Neural Circuit for Economic Decisions. *Neuron*, 96(4), 736–754.
<https://doi.org/10.1016/j.neuron.2017.09.031>
- Park, H. R. P., Kostandyan, M., Boehler, C. N., & Krebs, R. M. (2018). Smiling faces and cash bonuses: Exploring common affective coding across positive and negative emotional and motivational stimuli using fMRI. *Cognitive, Affective, & Behavioral Neuroscience*, 18(3), 550–563. <https://doi.org/10.3758/s13415-018-0587-3>
- Parkes, L., Fulcher, B., Yücel, M., & Fornito, A. (2018). An evaluation of the efficacy, reliability, and sensitivity of motion correction strategies for resting-state functional MRI. *NeuroImage*, 171, 415–436. <https://doi.org/10.1016/j.neuroimage.2017.12.073>
- Pessoa, L. (2017). A Network Model of the Emotional Brain. *Trends in Cognitive Sciences*, 21(5), 357–371. <https://doi.org/10.1016/j.tics.2017.03.002>
- Pinti, P., Scholkmann, F., Hamilton, A., Burgess, P., & Tachtsidis, I. (2019). Current Status and Issues Regarding Pre-processing of fNIRS Neuroimaging Data: An Investigation of

- Diverse Signal Filtering Methods Within a General Linear Model Framework. *Frontiers in Human Neuroscience*, 12. <https://doi.org/10.3389/fnhum.2018.00505>
- Plichta, M. M., Schwarz, A. J., Grimm, O., Morgen, K., Mier, D., Haddad, L., Gerdes, A. B. M., Sauer, C., Tost, H., Esslinger, C., Colman, P., Wilson, F., Kirsch, P., & Meyer-Lindenberg, A. (2012). Test–retest reliability of evoked BOLD signals from a cognitive–emotive fMRI test battery. *NeuroImage*, 60(3), 1746–1758. <https://doi.org/10.1016/j.neuroimage.2012.01.129>
- Pons, P., & Latapy, M. (2005). Computing Communities in Large Networks Using Random Walks. In pInar Yolum, T. Güngör, F. Gürgen, & C. Özturan (Eds.), *Computer and Information Sciences—ISCIS 2005* (pp. 284–293). Springer. https://doi.org/10.1007/11569596_31
- Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, 17(3), 715–734. <https://doi.org/10.1017/S0954579405050340>
- Power, J. D., Mitra, A., Laumann, T. O., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2014). Methods to detect, characterize, and remove motion artifact in resting state fMRI. *NeuroImage*, 84, 320–341. <https://doi.org/10.1016/j.neuroimage.2013.08.048>
- R Core Team. (2019). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Ram, N., & Grimm, K. J. (2009). Growth Mixture Modeling: A Method for Identifying Differences in Longitudinal Change Among Unobserved Groups. *International Journal of Behavioral Development*, 33(6), 565–576. <https://doi.org/10.1177/0165025409343765>

- Romer, D. (2010). Adolescent Risk Taking, Impulsivity, and Brain Development: Implications for Prevention. *Developmental Psychobiology*, 52(3), 263–276.
<https://doi.org/10.1002/dev.20442>
- Rubin, D. B. (1976). Inference and missing data. *Biometrika*, 63(3), 581–592.
<https://doi.org/10.1093/biomet/63.3.581>
- Sherman, L., Steinberg, L., & Chein, J. (2018). Connecting brain responsivity and real-world risk taking: Strengths and limitations of current methodological approaches. *Developmental Cognitive Neuroscience*, 33, 27–41.
<https://doi.org/10.1016/j.dcn.2017.05.007>
- Shulman, E. P., Smith, A. R., Silva, K., Icenogle, G., Duell, N., Chein, J., & Steinberg, L. (2016). The dual systems model: Review, reappraisal, and reaffirmation. *Developmental Cognitive Neuroscience*, 17, 103–117. <https://doi.org/10.1016/j.dcn.2015.12.010>
- Siegel, J. S., Power, J. D., Dubis, J. W., Vogel, A. C., Church, J. A., Schlaggar, B. L., & Petersen, S. E. (2014). Statistical improvements in functional magnetic resonance imaging analyses produced by censoring high-motion data points. *Human Brain Mapping*, 35(5), 1981–1996. <https://doi.org/10.1002/hbm.22307>
- Silverman, M. H., Jedd, K., & Luciana, M. (2015). Neural networks involved in adolescent reward processing: An activation likelihood estimation meta-analysis of functional neuroimaging studies. *NeuroImage*, 122, 427–439.
<https://doi.org/10.1016/j.neuroimage.2015.07.083>
- Smith, S. M. (2002). Fast robust automated brain extraction. *Human Brain Mapping*, 17(3), 143–155. <https://doi.org/10.1002/hbm.10062>

- Smith, S. M., Miller, K. L., Salimi-Khorshidi, G., Webster, M., Beckmann, C. F., Nichols, T. E., Ramsey, J. D., & Woolrich, M. W. (2011). Network modelling methods for FMRI. *NeuroImage*, 54(2), 875–891. <https://doi.org/10.1016/j.neuroimage.2010.08.063>
- Steinberg, L. (2008). A Social Neuroscience Perspective on Adolescent Risk-Taking. *Developmental Review: DR*, 28(1), 78–106. <https://doi.org/10.1016/j.dr.2007.08.002>
- Szczepanski, S. M., & Knight, R. T. (2014). Insights into human behavior from lesions to the prefrontal cortex. *Neuron*, 83(5), 1002–1018. <https://doi.org/10.1016/j.neuron.2014.08.011>
- Szucs, D., & Ioannidis, J. P. A. (2017). Empirical assessment of published effect sizes and power in the recent cognitive neuroscience and psychology literature. *PLOS Biology*, 15(3), e2000797. <https://doi.org/10.1371/journal.pbio.2000797>
- Szucs, D., & Ioannidis, J. PA. (2020). Sample size evolution in neuroimaging research: An evaluation of highly-cited studies (1990–2012) and of latest practices (2017–2018) in high-impact journals. *NeuroImage*, 221, 117164. <https://doi.org/10.1016/j.neuroimage.2020.117164>
- Wan, Z., Rolls, E. T., Cheng, W., & Feng, J. (2020). Sensation-seeking is related to functional connectivities of the medial orbitofrontal cortex with the anterior cingulate cortex. *NeuroImage*, 116845. <https://doi.org/10.1016/j.neuroimage.2020.116845>
- Weiland, B. J., Welsh, R. C., Yau, W.-Y. W., Zucker, R. A., Zubieta, J.-K., & Heitzeg, M. M. (2013). Accumbens functional connectivity during reward mediates sensation-seeking and alcohol use in high-risk youth. *Drug and Alcohol Dependence*, 128(1), 130–139. <https://doi.org/10.1016/j.drugalcdep.2012.08.019>

Willoughby, T., Good, M., Adachi, P. J. C., Hamza, C., & Tavernier, R. (2013). Examining the link between adolescent brain development and risk taking from a social-developmental perspective. *Brain and Cognition*, 83(3), 315–323.

<https://doi.org/10.1016/j.bandc.2013.09.008>

Zuckerman, M. S., Eysenck, S. B. G., & Eysenck, H. J. (1978). Sensation seeking in England and America: Cross-cultural, age, and sex comparisons. *Journal of Consulting and Clinical Psychology*, 46(1), 139–149. <https://doi.org/10.1037/0022-006x.46.1.139>