Received: 3 June 2021 | Revised: 6 December 2021 | Accepted: 19 December 2021

DOI: 10.1002/jnr.25005

RESEARCH ARTICLE

JOURNAL OF Neuroscience Research

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

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Funding information
Eunice Kennedy Shriver National Institute of Child Health & Human Development, Grant/Award Number: R01HD075806; NICHD Developmental Psychology Training Grant, Grant/Award Number: 5T32HD007109-34; NIAAA, Grant/Award Number: T32 AA007477; NIDA, Grant/Award Number: K23 DA051561; Jacobs Foundation

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 functional 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 a continuous motivational state, 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 regions 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 motivational 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, functional connectivity, monetary incentive delay task, motivation, reward, sensation seeking

Edited by Cristina Antonella Ghiani and Jeremy Hogeveen. Reviewed by Jeremy Hogeveen.

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 functional networks of the socioemotional and cognitive control systems during a motivational mental state presumed to occur in 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 & Behrens, 2014; Haber & Knutson, 2010; Roy et al., 2012). 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 future and VS activation were more strongly positively related in adolescents and adults (Galvan et al., 2007).

Significance

Neuroscience research has provided critical insights into adolescent neurodevelopment. Nevertheless, there is continued debate about their empirical support, potentially owing to their focus on functional localization and *average* youth. Using a data-driven person-specific network connectivity approach on two continuous runs of the monetary incentive delay task, we uncover two distinct subgroups for each run. During the first run, subgroups were significantly related to self-reported sensation seeking; however, this effect was attenuated in the second run and opposite in direction for the combined runs. Differences may relate to habituation or reliability over time and power across methods.

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 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 reward-seeking 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; Finn et al., 2017; Gordon et al., 2017; Poldrack, 2017) and in adolescent brain development (Lydon-Staley & Bassett, 2018).

Sensation seeking is a psychological characteristic that is principal to neurodevelopmental models (Shulman et al., 2016). In part, sensation seeking is presumed to be facilitated by reward-related, and dopamine-linked neural systems that impact an adolescent's motivation to engage in risk-taking behaviors (Ernst & Spear, 2009). Sensation seeking has been reported to have a small-to-moderate associations with general health risk behaviors (Demidenko et al., 2019), substance use disorders (Khurana et al., 2018), and simultaneous alcohol and marijuana use in adolescents (Linden-Carmichael et al., 2019). 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 ($r = 0.30$) 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 motivational processes 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 motivational 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 to date 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 and motivation processing, 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 motivational processing task meaningfully relates to individual differences in self-reported sensation seeking behaviors. Given our interest in modeling the dynamic complexity of the brain and the precedent in prior studies using GIMME with task fMRI (Beltz et al., 2013; Duffy et al., 2021; Hillary et al., 2014; Weigard et al., 2018), we do not consider modulating effects of task regressors but rather focus on comprehensively evaluating connectivity during a *motivational state*, or a state of being continuously engaged in a task in which possible gains and losses are evaluated and received. In other words, we uniquely capture relations among a broad set of ROIs to understand systems-level neural integration

during continuous motivational processing, but we do not explicitly estimate contrasts (e.g., gain > loss) as in traditional analyses of the monetary incentive delay (MID) task; thus, our GIMME networks may not reflect reward processing per se (Balodis & Potenza, 2015; Dugré et al., 2018).

Specifically, we applied GIMME to two separate runs of the MID task (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). As described above and in the neurodevelopmental literature (Demidenko et al., 2020; Sherman et al., 2018; Silverman et al., 2015; Steinberg, 2010), we focus on these ROIs given evidence for the role of DLPFC and ACC in cognitive control processes (Apps et al., 2016; Szczepanski & Knight, 2014); the role of VS, OFC, and vmPFC in motivational processes and economic decision-making (Haber & Behrens, 2014; Knutson et al., 2014; Padoa-Schioppa & Conen, 2017; Roy et al., 2012); and the role of the insula and amygdala in valence and affective processing (Knutson et al., 2014; Posner et al., 2005). Although we use network labels, such as cognitive control, reward, and salience, as heuristics, brain regions are rarely localized to specific networks (Rolls, 2014) or affective processes (Berridge, 2019); instead, they play a dynamic part in a complex interacting system (Pessoa, 2021). Thus, these network labels are intended to serve as conceptual links to the neurodevelopmental models from which the hypotheses below are derived (Casey et al., 2008; Ernst, 2014; Steinberg, 2010).

We implement GIMME's subgroup community detection algorithm to uncover potential communities of adolescents who share neural features during motivational processing, 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 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 during a presume motivational state. 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 motivational 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, 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 supplementary Section 2.1. Of the 115 participants eligible for inclusion, 104 are included in this study. Seven participants were not safe to magnetic resonance imaging (MRI) scan 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 that were administered using computer-assisted self-interviewing (Wave 1, M_{Age} = 16.8 years, SD_{Age} = 1.1). As described in supplementary Section 2.1, participants characterized as high or average/low-risk takers at Phase I on a latent Behavioral Misadventure Score that comprises 15-health risk behaviors 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 version of the task. 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

2.3.1 | 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 eight 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 eight items, such that higher scores reflect higher sensation seeking (Cronbach's $\alpha = 0.78$).

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% ($N_{\text{Wave 1}} = 104$; $M = 3.29$, $SD = 0.76$), 77% ($N_{\text{Wave 2}} = 80$; $M = 3.26$, $SD = 0.72$), and 89% ($N_{\text{Wave 3}} = 93$; $M = 3.33$, $SD = 0.56$) 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, $r = 0.82$.

2.3.2 | fMRI task

The MID task (Knutson et al., 2000) was used to measure brain activity during a motivational state that comprised both monetary gains and losses. 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 2,000 ms followed by a jittered fixation cross (1,500–4,000 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 (1,450–1,763 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 S2 and Section 2.3 for more information about the design and the task schematic). The MID task is considered a *rapid* event-related design, as the interstimulus interval is *shorter* than the hemodynamic response function (Soares et al., 2016).

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 = 7,000 ms, TE = 2,900 ms, flip angle = 8°, FOV = 25.6 cm, slice thickness = 1 mm, 208 sagittal slices; matrix = 256 × 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 = 800 ms, TE = 30 ms, flip angle = 52°, FOV = 21.6 cm, 90 × 90 matrix, volumes = 407). A field map was also acquired right before the task using spin-echo EPI (TR = 7,400 ms, TE = 80 ms, FOV = 21.6 cm, 90 × 90 matrix) with opposite phase encoding polarity (A → P, P → A).

2.5 | fMRI preprocessing and 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 et al., 2002; Jenkinson & Smith, 2001); (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 5 mm; (8) grand-mean intensity normalization of the entire 4D data set by a single multiplicative factor; and (9) high-pass temporal filtering (Gaussian-weighted least-squares straight line fitting, with sigma = 50.0 s).

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. As mentioned previously, these network labels are heuristics linked to neurodevelopmental models.

For each ROI, a 10-mm 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 and 2, the entire 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 (800 ms), 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).

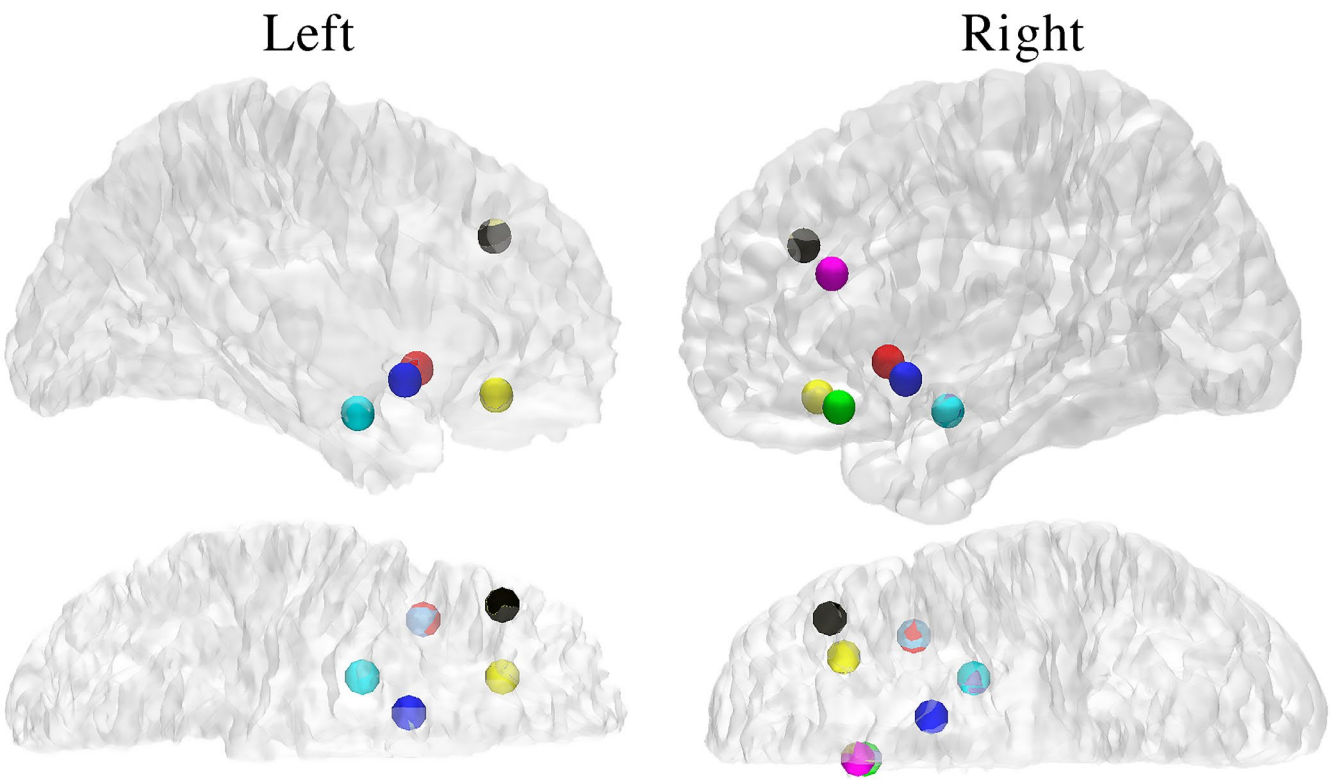

FIGURE 1 Twelve ROI coordinates projected onto an MNI glass brain. Blue, ventral striatum; green, ventromedial prefrontal cortex; pink, anterior cingulate cortex; yellow, orbitofrontal cortex; red, insula; cyan, amygdala; black, dorsolateral prefrontal cortex

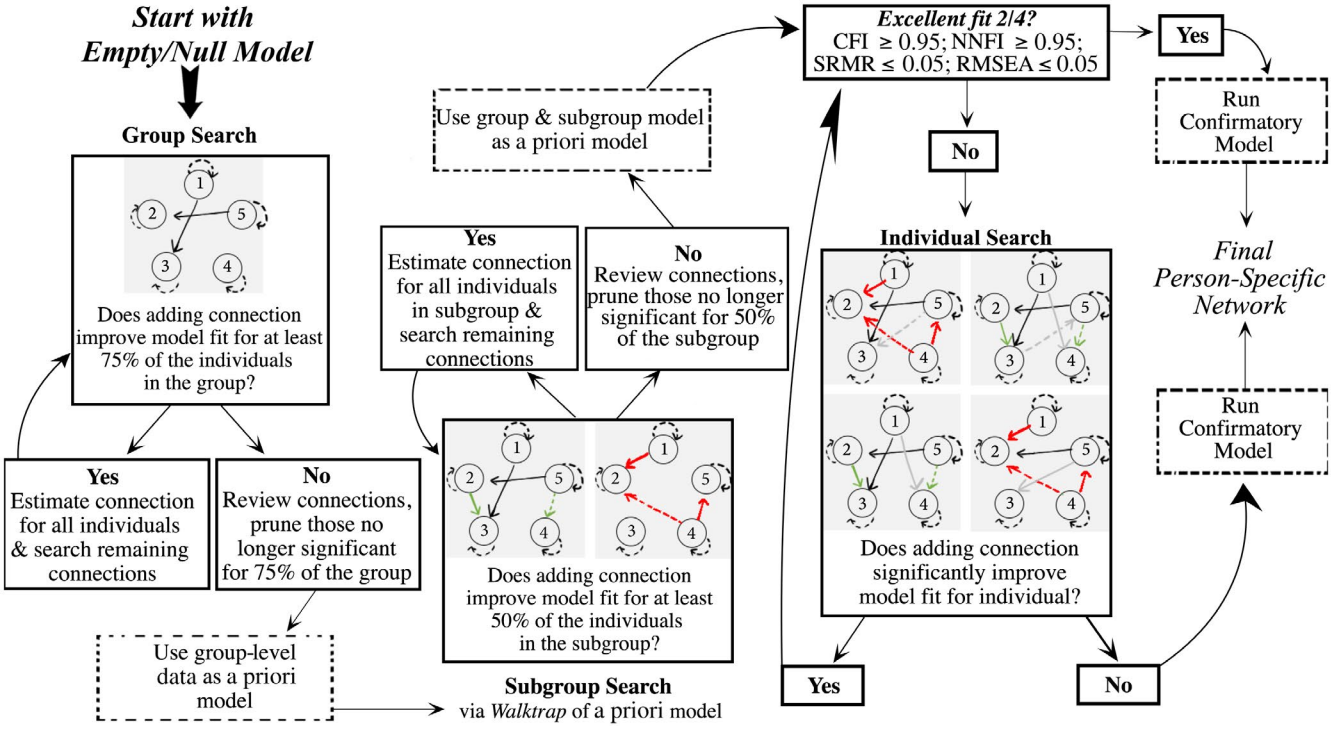

FIGURE 2 GIMME model flow chart. Lines represent: black, group connections; green, subgroup connections; gray, individual connections; solid, contemporaneous; dashed, lagged; green, Subgroup01; red, Subgroup02

2.7 | GIMME analyses

GIMME version 0.6-0 in R version 3.6.1 (R Core Team, 2020) 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: Comparative Fit Index (CFI) ≥ .95, Non-Normed Fit Index (NNFI) ≥ .95, Standardized Root Mean Square Residual (SRMR) ≤ .05, and Root Mean Square Error of Approximation (RMSEA) ≤ .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. Given that the connections are inferred through the data-driven process from the temporal information in the fMRI data, the final maps reflect estimates of directed functional connectivity (Beltz & Gates, 2017; Friston et al., 2013).

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 continuous motivational state. Each subgroup is characterized by a set of unique network connections, and each has a person-specific beta estimate that reflects its direction and magnitude. These individual subgroups and connection estimates can be examined in relation to the BSSS.

2.8 | Analysis plan

Event-related designs are often insufficiently powered to estimate the effects of specific task conditions (e.g., anticipation or feedback in the MID) on neural connectivity (see Beltz, 2018; Di & Biswal, 2017). This is especially true for *rapid* event-related designs, such as the current study's design, because the hemodynamic response function is longer than the interstimulus interval. It is also borne out by simulations using GIMME on task data (Duffy et al., 2021; Gates et al., 2011) and in empirical studies that modeled task regressors in GIMME and found little evidence for their substantial modulating effects on connectivity (Hillary et al., 2014; Price et al., 2020). Given this evidence, we focus on the connectivity among regions during a *motivational state* rather than modeling modulation by specific task phases (e.g., during individual gain or loss events).

To test Aim 1, which was to examine whether there are data-driven subgroups during motivational processing, we use GIMME to map person-specific connectivity in reward 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 (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.

We set the alpha cut-off ($p < .05$) that is conventionally used in null-hypothesis significance testing for each of the regression analyses because of the novelty of these analyses. This is consistent with recommendations for new analyses and recent perspectives on multiple comparison corrections (e.g., Rubin, 2021; Thompson et al., 2020).

3 | RESULTS

Demographic characteristics, task accuracy, and in-scanner motion during the MID task for participants are reported in Tables S2–S5.

No participants had mean head motion (Post FD) greater than 0.20, 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, $r(102) = 0.02$, or Run 02, $r(102) = -0.05$.

3.1 | Aim 1: Person-specific connectivity networks by run

For all 104 participants, GIMME networks fit the data well (see 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 (gray) 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 (Table S6), suggesting some level of stability in subgroup membership between runs. Of note, there were no significant differences in age, sex, race/ethnicity, or sensation seeking across participants who did ($N = 29$) and did not ($N = 75$) change subgroups across the two runs (see Table S7).

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, Subgroup01, 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 → vmPFC and vmPFC → ACC connections reoccurred across the two runs, but L DLPFC → L Amygdala was unique to Run 01 and ACC → 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 → L Amygdala, R DLPFC → L Amygdala, R and OFC → R VS only occurred in Run 01 and R OFC → L OFC, L DLPFC → L Amygdala only occurred in Run 02 (see Table S8).

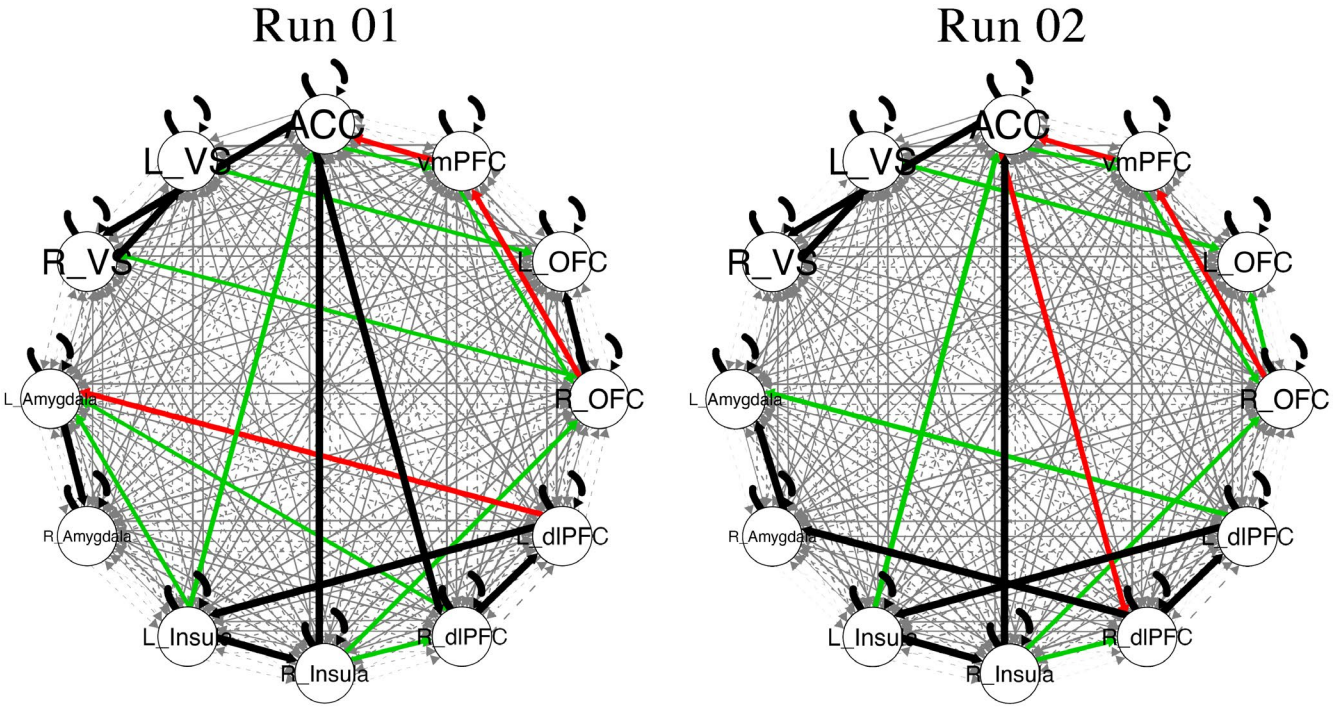

FIGURE 3 GIMME connectivity networks for each run. Black, group connection; red, Subgroup01 connections; green, Subgroup02 connections; solid, contemporaneous; dashed, lagged ($t - 1$); DLPFC, dorsolateral prefrontal cortex; OFC, orbitofrontal cortex; vmPFC, ventromedial PFC; VS, ventral striatum

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), $\Delta\chi^2(1) = 4.7$, $p = 0.03$. Subgroups did not differ in age or sex, but they did differ in Post 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 Table S9). To consider the confound of motion, we checked whether motion moderated the association between BSSS and subgroups. We found no significant ($p > 0.05$) moderation of mean Post FD (see Table S10).

There was no, however, significant association between subgroup and self-reported BSSS from Run 02 (b = 0.58), 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), $\Delta\chi^2(1) = 1.3$, $p = 0.25$. 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 Post FD.

Given the significant association between subgroup classification and 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 strength of the vmPFC → R OFC connection, $b = 0.21$, $p = 0.02$, and the R OFC → R VS connection, $b = -27$, $p = 0.01$ (see 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 motivational processing (see Table S11).

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) reoccurred across both runs. Although, as noted above, there was some stability in subgroup membership between runs, the difference in membership was statistically significant, $\chi(1) = 18.1$, $p < 0.001$, $\Phi = 0.41$; only 72% (N = 44) of the participants were consistently grouped into Subgroup01, and 72% (N = 31) of participants were consistently grouped into Subgroup02 (Table S6).

Regarding analyses of the combined runs, the GIMME networks fit the data well for all participants except one (see Table S12; Figure S4). For this participant, the model did not converge. Thus, N = 103 in the combined run analyses. Similar to the analyses conducted separately per run, two subgroups were identified for the combined run analyses. 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 no significant effect (b = −51; Table S13), 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), $\Delta\chi^2(1) = 0.9$, $p = 0.33$. 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 continuous motivational 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., MID; 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 three-wave behavioral trajectory across adolescence). To examine possible habituation effects, we considered how neural subgrouping and behavioral associations varied across runs, and 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 network connectivity mapping during a motivational state with significant links to risk-relevant behavior.

TABLE 1 Logistic regression: Sensation seeking associated with GIMME-derived subgroup from MID task data, by run, with and without Post FD ($N = 104$)

	Run 01			Run 02		
	b	*SE*	*p*	*b*	*SE*	*p*
Age	−0.18	0.17	0.28	−0.11	0.16	0.48
Sex	0.28	0.43	0.52	0.80	0.42	0.06
Post FD	48.8	18.24	0.008	29.4	15.84	0.06
BSSS	1.1	0.55	0.04	0.58	0.51	0.26

Abbreviations: BSSS, brief sensation seeking scale; Post FD, post preprocessing framewise displacement.

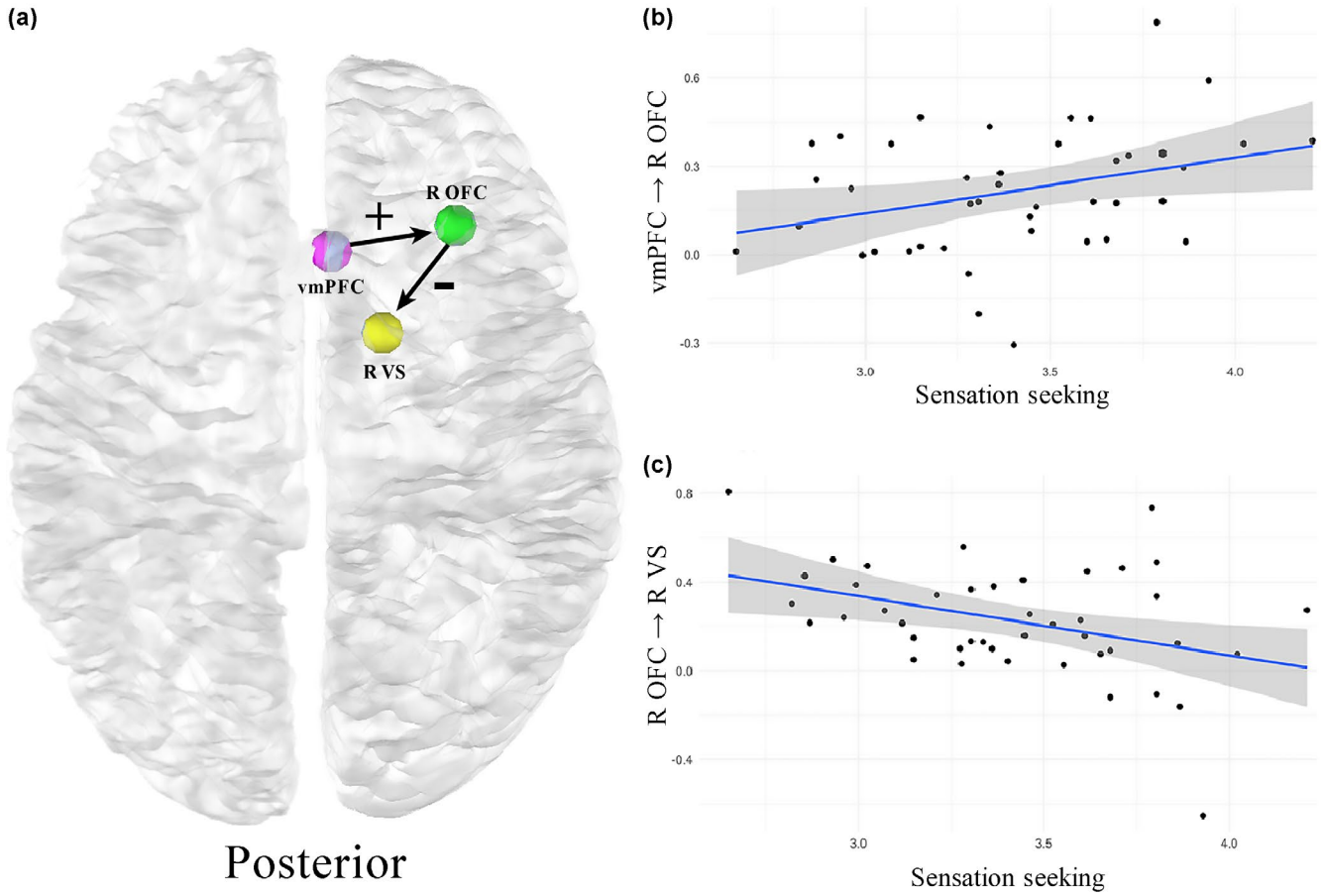

FIGURE 4 Meaningful associations between connection strength and sensation seeking in Subgroup02 during Run 01. (+), sig. positive association; (−), sig. negative association

In light of evidence for the neural habituation to reward across time (Ekhtiari et al., 2020; Plichta et al., 2012), we examined person-specific connectivity during continuous motivational processing separately for runs of the MID task in a sparse network of 12 ROIs representing cognitive control, reward, 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 motivational 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 motivational 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 during Run 02. Interestingly, activation contralateral to the latter brain regions, Left OFC and Left VS, during reward expectancy has been reported to relate to impulsive sensation seeking in a young adult sample (Chase et al., 2017). This may suggest 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 toward 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.

It is also possible that the variability across runs may be due to issues of reliability. For instance, recent work has demonstrated that both task-based fMRI (Elliott et al., 2020) and resting-state connectivity (Noble et al., 2019) suffer from poor test–retest reliability. Poor test–retest reliability may impact both subgroup partitioning (Gates et al., 2016; Pons & Latapy, 2005) and the association between network connectivity and sensation seeking. This presents a challenge when trying to determine whether differences across runs relate to habituation, motivation, reliability, or a mixture of all three. An ongoing project is evaluating the reliability of GIMME's directed connectivity estimates among different brain regions, but the test–retest reliability of GIMME's subgrouping algorithm has not been well investigated and so remains an important question for future research.

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 at the 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 ($p < 0.01$) 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.

While issues of reliability are important, differences across runs may also 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.

An important consideration in study is that participants were in a presumed general *motivational state* during the MID task, in which neural mechanisms involved in the processing of both gains and losses were consistently engaged, with potentially overlapping neural perturbations. Our reported estimates of directed functional connectivity during the MID task is therefore distinct from the field's common focus on average contrasts of anticipatory or outcome reward cues or the comparison of neural activation during gain versus loss trials (Demidenko et al., 2021; Dugré et al., 2018; Oldham et al., 2018). Thus, the ways in which our specific findings map onto established findings in the field regarding reward processing is currently unclear.

It is important, however, to highlight that there is empirical support for examining motivational processing as we did because gain and loss cues in the MID design exhibit substantial overlap in neural activation (Murray et al., 2020; Oldham et al., 2018), and brain function involves continuous time-lagged brain states (Munn et al., 2021), with "carryover" effects that are often assumed to be random (e.g., if jitter is implemented correctly)—but this is rarely examined. Nevertheless, the complex issue of reward circuitry and motivational processing during task-based fMRI requires careful theoretical and empirical future work to understand and disentangle.

In addition to generalizing the results reported here, future work should consider how variability in task length, number of runs, task type, and region selection 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. Finally, we use a priori ROIs from the adolescent literature in our analyses, and this clearly constrains our results. Specifically, recent evidence from the resting-state literature demonstrates that ROI parcellations may impact the underlying associations and interpretations (Bryce et al., 2021). Thus, future work should consider alternative ROIs and parcellations to test these and related hypotheses.

4.1 | Study considerations

The findings reported here are not without limitations. First, 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 the moderating effect of motion on the association between sensation seeking and subgroups 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; Elliott et al., 2020; Noble et al., 2019; 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. The issue of power was also critical to consider when weighing the pros and cons of modeling the coactivation of brain regions during a *motivational state* rather than the modulating effect of specific task regressors. Ultimately, choosing not to model task regressors during functional connectivity sacrifices the knowledge about the effects of different phases of reward processing. However, as in most analyses, we had to consider the conceptual and statistical trades-offs of our decision. Our goal was to assess the dynamic engagement of respective brain regions during motivational processes that are important to neurodevelopmental heuristics (Casey et al., 2019). Our related, statistical goal was to model coactivation among regions in a way that was informed by prior literature and adequately powered. Although task regressors are included in psychophysiological interaction analyses (PPI; McLaren et al., 2012), it has been reported that most modulating effects are small and statistically noisy, and therefore, require substantial power accomplished through task lengths and sample sizes in fMRI studies (Di & Biswal, 2017). Consistent with these group-level analyses in PPI, simulation studies of GIMME demonstrate that issues of power can prevent the detection of small task modulating effects, especially in rapid event-related designs like that used in the current study (Duffy et al., 2021; Gates et al., 2011). Thus, we encourage future studies to build on our empirical findings by considering the effect of task modulation in designs that are well powered to do so, such as through the creation and implementation of a slow-event-related MID task.

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 be seamlessly extrapolated to other data sets, modeling sequences, or to real-world risk-taking behavior and age-related differences without further research. This is because we used a partially

data-driven approach when fitting neural networks and did not have a second, similar data set available for cross-validation. Indeed, recent evidence in fMRI demonstrates that brain parcellations (Bryce et al., 2021), analytic pipelines (Botvinik-Nezer et al., 2020; Li et al., 2021), and other potentially subjective researcher decisions (Bloom et al., 2021; Steegen et al., 2016) impact results; hence, it is imperative that future work replicates these results in other adolescent samples, with other tasks that probe motivational processing, and using other preprocessing pipelines. Second, 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 during motivational processing and a psychological trait hypothesized to relate to real-world risk-taking behaviors. While there were no meaningful associations between age and connectivity patterns in this work, prior work has reported developmental differences in connectivity patterns (Marek et al., 2015; Oldham & Fornito, 2019) which future studies should consider. Moreover, while both habituation and reliability issues are plausible explanations for the difference in the association between subgroups and sensation seeking across runs, we cannot delineate which is more probable, given that this version of the MID task did not capture all mean response times and the reliability of fMRI connectivity (generally) and GIMME (specifically) are still being evaluated. This will be an important consideration in future work modeling functional connectivity across multiple runs of reward tasks.

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 motivational processing, 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 connectivity patterns. 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 who report greater sensation seeking may share unique patterns of functional connectivity during motivational processing and these patterns may attenuate with repeated stimulation, perhaps due to habituation to the task or reliability across runs.

DECLARATION OF TRANSPARENCY

The authors, reviewers and editors affirm that in accordance to the policies set by the *Journal of Neuroscience Research*, this manuscript presents an accurate and transparent account of the study being reported and that all critical details describing the methods and results are present.

ACKNOWLEDGMENTS

This research was supported, in part, by a grant from the *Eunice Kennedy Shriver* National Institute of Child Health & Human Development (NICHD; R01HD075806, D.P. Keating, Principal Investigator). M. Demidenko was also supported by the NICHD Developmental Psychology Training Grant (5T32HD007109-34, V.C. McLoyd & C.S. Monk). A. Weigard was supported by NIAAA T32 AA007477 (Dr. Frederic C. Blow) and NIDA K23 DA051561. A. Beltz was supported by the Jacobs Foundation. The authors thank Bennet Fauber, Krisanne Litinas, Christine Wagner, Hani Nasr, Peter Batra, Joshua Hatfield, Meredith House, Kyle Kwaiser, Kathleen LaDronka, the U-M Survey Research Operations staff, and the U-M MRI Laboratory, for their support in collecting these data. They also thank Karthik Ganesan for the Matlab script to overlay the regions of interest on a MNI glass brain.

AUTHOR CONTRIBUTIONS

M.D. and A.B. implemented the methodology, conducted formal analysis and visualization, completed necessary validation, and wrote the original draft with critical assistance from A.W. M.D. implemented the software. D.K. engaged in funding acquisition, D.K. and E.H. were involved in overall program conceptualization, project administration, acquiring resources and supervision. E.H. and M.D. curated the survey and/or imaging data. All authors participated in the review and editing of the manuscript, and read and approved the final version of the manuscript.

DATA AVAILABILITY STATEMENT

Readers seeking access to these 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.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

FIGURE S1. AHRB study Phase 1 Wave 1–Wave 3: participant's associated counties/census tracts in Southeastern Michigan during study

FIGURE S2. MID task schematic

TABLE S1. A priori MNI coordinates pulled from Neurosynth

TABLE S2. Demographics overall and by run for Aim 1/Aim 2

TABLE S3. MID accuracy

TABLE S4. Motion: Mean framewise displacement (FD) pre/post preprocessing

TABLE S5. Four fit statistics from GIMME model

TABLE S6. Crosstabs of subgrouping across runs ($N = 104$)

TABLE S7. Demographics characteristics of participant's subgroup labels that are stable or changed across Run 01 and Run 02

TABLE S8. Overlap in paths opened for Group, Subgroup02 and Subgroug02 across runs

TABLE S9. Logistic regression: Sensation seeking associated with GIMME-derived subgroup from MID task data, by run, without Post FD ($N = 104$)

TABLE S10. Logistic regression: Moderating effect of motion on association between BSSS and subgroup for Run01 and Run01

TABLE S11. Multiple regression: Individual traits of sensation seeking associated with GIMME FC path strength in Subgroup02 during MID task, by run

FIGURE S3. Connectivity strength and sensation seeking raw plots for participants in Subgroup02, by Run 01 ($N = 43$) and Run 02 ($N = 48$)

TABLE S12. Four fit statistics from GIMME model

FIGURE S4. Combined MID Run GIMME Full Model. Black, Group Paths; Red, Subgroup01 connections; Green, Subgroup02 connections; Grey, Individual Paths. Solid, Contemporaneous; Dashed, Lagged ($t - 1$). Weight is the proportion of subjects with the connection

TABLE S13. Logistic regression model predicting subgroup labels: Combined MID Runs and BSSS ($N = 103$)

Transparent Science Questionnaire for Authors

How to cite this article: Demidenko, M. I., Huntley, E. D., Weigard, A. S., Keating, D. P., & Beltz, A. M. (2022). Neural heterogeneity underlying late adolescent motivational processing is linked to individual differences in behavioral sensation seeking. *Journal of Neuroscience Research*, 100, 762–779. https://doi.org/10.1002/jnr.25005