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

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## 26 Abstract

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

48 *Keywords:* Adolescence, fMRI, Monetary Incentive Delay Task, Functional Connectivity,  
49 Reward, Sensation Seeking, Motivation

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## Significance

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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 (MID) 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.

### 61 1. Introduction

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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.

## 79 1.1 Neural Connectivity and Adolescent Reward Processing

80 Although there is considerable variability among them, most neurodevelopmental  
81 models of adolescent risk-taking behavior (Casey et al., 2008; Ernst et al., 2006; Steinberg,  
82 2008) broadly concern the interplay between brain regions implicated in: (a) cognitive control,  
83 such as the anterior cingulate cortex (ACC) and dorsolateral prefrontal cortex (DLPFC); and (b)  
84 socioemotional processing, which can be broken down into the reward and salience subsystems.  
85 The reward subsystem facilitates approach behaviors, and includes the ventral striatum (VS),  
86 orbitofrontal cortex (OFC), and ventromedial PFC (vmPFC) (Haber & Behrens, 2014; Haber &  
87 Knutson, 2010; Roy et al., 2012). The salience subsystem detects the valence of stimuli, and  
88 includes the amygdala and insula (Knutson & Greer, 2008; Posner et al., 2005). Early studies  
89 evaluated differences in mean-level activation of regions thought to contribute to sensation  
90 seeking behavior during reward processing that showed developmental differences between  
91 adults and adolescents (reviewed in Silverman et al., 2015), such that adolescents had less  
92 activation than adults in the ACC and VS when anticipating rewards (Bjork et al., 2010) but  
93 greater activation than adults in the VS and insula when receiving rewards (Galván &  
94 McGlennen, 2012). Some early studies also examined the associations between regional mean-  
95 level activations and risk-related behaviors, such that the likelihood of engaging in a risky  
96 behavior in the future and VS activation were more strongly positively related in adolescents  
97 and adults (Galvan et al., 2007).

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

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

111 Sensation seeking is a psychological characteristic that is principal to  
112 neurodevelopmental models (Shulman et al., 2016). In part, sensation seeking is presumed to be  
113 facilitated by reward-related, and dopamine-linked neural systems that impact an adolescent's  
114 motivation to engage in risk-taking behaviors (Ernst & Spear, 2009). Sensation seeking has  
115 been reported to have a small-to-moderate associations with general health risk behaviors  
116 (Demidenko et al., 2019), substance use disorders (Khurana et al., 2018) and simultaneous  
117 alcohol and marijuana use in adolescents (Linden-Carmichael et al., 2019). To date, several  
118 studies have considered the relation between mean (or group-level) connectivity and sensation-  
119 seeking. For instance, connectivity between the amygdala and the OFC during resting state  
120 using seed-based functional connectivity (i.e., detecting associations between a candidate region  
121 and all other brain regions) have been shown to be inversely related to sensation seeking (Crane  
122 et al., 2018). Also, connectivity between VS and motor areas during incentivized trials in a task  
123 using psychophysiological interaction (i.e., combining seed-based correlations and task  
124 regressors) have been shown to be positively related to sensation seeking (Crane et al., 2018;  
125 Weiland et al., 2013). Finally, mean-level connectivity patterns in the OFC and ACC estimated  
126 using Pearson's correlations from resting state data were reported to reliably predict ( $r = .30$ )  
127 sensation seeking in adults (Wan et al., 2020). Together, these studies suggest that there may be  
128 group-level links between patterns of neural connectivity and sensation seeking.

129 Nonetheless, significant questions remain about the association between connectivity  
130 and sensation seeking during adolescence, as participants in the studies reviewed above ranged  
131 in age from 18 to 85 years (Crane et al., 2018) or only included young-to-mid adults aged 21 to  
132 35 years (Wan et al., 2020). Questions about adolescent-specific motivational processes and  
133 behavior are important to answer because the developmental peak in sensation seeking seems to  
134 be between ages 14 and 20 (Harden & Tucker-Drob, 2011; Romer, 2010). Although one study  
135 examined functional connectivity patterns and sensation seeking in a late adolescent sample  
136 (18-22 years old), the study looked only at mean-level connectivity in a sample of late  
137 adolescents exposed to higher rates of adversity (Weiland et al., 2013). Thus, there is empirical  
138 evidence for meaningful associations between functional connectivity and sensation seeking at

139 the group level, but there remains a need for research on adolescents that captures individual  
140 differences.

## 141 1.2 Person Specific Connectivity

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

149 Group Iterative Multiple Model Estimation (GIMME; Gates & Molenaar, 2012) is one  
150 such modeling approach. GIMME creates sparse person-specific networks specifying data-  
151 driven connections (or edges) among brain regions of interest (ROIs) that can occur at multiple  
152 levels: group, subgroup and individual (Beltz & Gates, 2017; Gates et al., 2017). First, GIMME  
153 estimates group-level connections that are meaningful for at least 75% of individuals. Second,  
154 subgroups are identified using the Walktrap community detection algorithm (Orman & Labatut,  
155 2009), which clusters into a community individuals based on the similarity of their group-level  
156 connection magnitudes (Gates et al., 2016), and then subgroup-level connections that are  
157 meaningful for only individuals in the same subgroup are estimated. Third, individual-level  
158 connections that are unique to a person (and estimated after group- and subgroup-level  
159 connections, which improves their reliability; Gates et al., 2017) are estimated. While the final  
160 networks characterize both homogeneity (in the group-level connections – without averaging  
161 across individuals) and heterogeneity (in the individual-level connections) in a sparse network,  
162 subgroup-level connections represent both homogeneity and heterogeneity. Simulation studies  
163 have demonstrated that GIMME effectively identifies the presence of connections between  
164 ROIs and is to date an accurate method for modeling network patterns in functional time-series  
165 data, especially compared to other approaches that assume homogeneity when participants are,  
166 in fact, heterogeneous (Gates et al., 2017; Mumford & Ramsey, 2014; Smith et al., 2011).

167 GIMME has been successfully used to delineate person-specific networks in  
168 developmental and clinical research (reviewed in Beltz & Gates, 2017; Beltz & Weigard, 2019).  
169 For instance, during an alcohol-related inhibition task in young adults, the number of

170 connections within the cognitive control system changed across the transition to college in  
171 accord with alcohol use behaviors (Beltz et al. 2013). Moreover, during resting state, network  
172 connectivity patterns in subgroups effectively delineated communities of children with different  
173 clinical diagnoses (e.g., autism spectrum disorder and attention deficit hyperactivity disorder)  
174 and healthy controls (Henry et al., 2019), such that children with diagnoses were characterized  
175 by connections between the default mode, salience and ventral attention networks, whereas  
176 controls were largely characterized by within-network connections. Likewise, resting state  
177 network connectivity patterns revealed subgroups of adolescents who varied in levels of  
178 childhood violence exposure (Goetschius et al., 2020), which is particularly noteworthy because  
179 it illustrates how GIMME can differentiate - in adolescence - brain networks of children with  
180 certain experiences of adversity in a purely data-driven fashion. The ability to capture both  
181 homogeneity and heterogeneity in neural network features is critical in the study of adolescent  
182 sensation seeking and motivation processing, because risk-taking tendencies may represent only  
183 a subset of youth and not all adolescents (Bjork & Pardini, 2015).

### 184 1.3 Current Study

185 In the current study, we examine whether person-specific network connectivity during a  
186 motivational processing task meaningfully relates to individual differences in self-reported  
187 sensation seeking behaviors. Given our interest in modeling the dynamic complexity of the  
188 brain and the precedent in prior studies using GIMME with task fMRI (Beltz et al., 2013; Duffy  
189 et al., 2021; Hillary et al., 2014; Weigard et al., 2018), we do not consider modulating effects of  
190 task regressors but rather focus on comprehensively evaluating connectivity during a  
191 *motivational state*, or a state of being continuously engaged in a task in which possible gains  
192 and losses are evaluated and received. In other words, we uniquely capture relations among a  
193 broad set of ROIs to understand systems-level neural integration during continuous motivational  
194 processing, but we do not explicitly estimate contrasts (e.g., gain > loss) as in traditional  
195 analyses of the Monetary Incentive Delay (MID) task; thus, our GIMME networks may not  
196 reflect reward processing *per se* (Balodis & Potenza, 2015; Dugré et al., 2018).

197 Specifically, we applied GIMME to two separate runs of the MID task (Knutson et al.,  
198 2000) in a sample of late adolescents, focusing on 12 ROIs that reflect the cognitive control,  
199 reward and salience networks (e.g., bilateral OFC, DLPFC, Insula, Amygdala, VS, and ACC  
200 and vmPFC). As described above and in the neurodevelopmental literature (Demidenko et al.,

201 2020; Sherman et al., 2018; Silverman et al., 2015; Steinberg, 2010), we focus on these ROIs  
202 given evidence for the role of dlPFC and ACC in cognitive control processes (Apps et al., 2016;  
203 Szczepanski & Knight, 2014); the role of VS, OFC and vmPFC in motivational processes and  
204 economic decision-making (Haber & Behrens, 2014; Knutson et al., 2014; Padoa-Schioppa &  
205 Conen, 2017; Roy et al., 2012); and the role of the insula and amygdala in valence and affective  
206 processing (Knutson et al., 2014; Posner et al., 2005). Although we use network labels, such as  
207 cognitive control, reward and salience, as heuristics, brain regions are rarely localized to  
208 specific networks (Rolls, 2014) or affective processes (Berridge, 2019); instead, they play a  
209 dynamic part in a complex interacting system (Pessoa, 2021). Thus, these network labels are  
210 intended to serve as conceptual links to the neurodevelopmental models from which the  
211 hypotheses below are derived (Casey et al., 2008; Ernst, 2014; Steinberg, 2010).

212 We implement GIMME's subgroup community detection algorithm to uncover potential  
213 communities of adolescents who share neural features during motivational processing, and then  
214 we examine how these features relate to adolescent sensation seeking behavior. Given that  
215 reported poor within-participant reliability in task-based fMRI may be attributed to habituation  
216 (Elliott et al., 2020), or waning vigilance or novelty in reward systems triggered by fMRI tasks  
217 (Ekhtiari et al., 2020; Plichta et al., 2012), we also consider the network connectivity during the  
218 combined and individual MID run time-series.

219 Our study is comprised of three aims. In Aim 1, we map person-specific connectivity in  
220 reward processing regions separately for each run of the MID task, exploring whether there are  
221 data-driven subgroups during a presume motivational state. In Aim 2, we examine whether  
222 there are meaningful associations between network features (such as subgroup membership and  
223 connection strength) and sensation seeking separately by run. In Aim 3, we compare estimated  
224 connections between Run 01 and Run 02 to detect potential habituation across runs and repeat  
225 Aims 1 and 2 for the combined runs to evaluate the robustness of findings from the individual  
226 runs for the combined time-series. We expect to find substantial individual differences in  
227 motivational processing, evidenced by person-specific networks, but given the novelty of this  
228 approach, we do not have expectations about whether data-driven subgroups will exist.  
229 Nevertheless, we do hypothesize that connectivity strength between reward and cognitive  
230 control ROIs will be related to sensation seeking based on common neurodevelopmental models  
231 that implicate regions, including the VS, OFC, vmPFC and/or dlPFC, in the relationship to



232 sensation seeking (Casey et al., 2008; Casey et al., 2019; Ernst et al., 2006; Shulman et al.,  
233 2016; Steinberg, 2008).

## 234 2. Methods

### 235 2.1 Participants

236 Participants in this study are a Phase II subsample ( $N = 104$ ;  $M_{Age} = 19.3$ ;  $SD_{Age} = 1.3$ ;  
237 57% Female; 71% White, 14% Black, non-Hispanic, 6% Hispanic/Latinx) of adolescents from  
238 the Adolescent Health Risk Behavior (AHRB) study described in supplementary Section 2.1. Of  
239 the 115 participants eligible for inclusion, 104 are included in this study. Seven participants  
240 were not safe to magnetic resonance imaging (MRI) scan ( $n = 7$ ), and four completed the scan  
241 but were excluded from analyses due to non-recoverable artifacts in the images ( $n = 3$ ) or failing  
242 to respond during the MID task ( $n = 1$ ).

243 During Phase I, participants completed behavioral questionnaires, including sensation  
244 seeking, across three waves at 18-month intervals beginning in mid-to-late adolescence that  
245 were administered using computer assisted self-interviewing (Wave 1,  $M_{Age} = 16.8$  years,  $SD_{Age}$   
246  $= 1.1$ ). As described in supplementary Section 2.1, participants characterized as high or  
247 average/low risk takers at Phase I on a latent Behavioral Misadventure Score that comprises 15-  
248 health risk behaviors were recruited to participate in the neuroimaging Phase II. The behavioral  
249 data from Wave 1 to Wave 3 are used here in assessments of sensation seeking for each  
250 participant (described below). During Wave 1, participants completed surveys in school,  
251 administered using computer assisted self-interviewing, and during Wave 2 and Wave 3,  
252 participants completed surveys on their own time using web-based computer assisted  
253 interviewing.

### 254 2.2 Procedures

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

## 261 2.3 Measures

262 *Sensation Seeking*: Participants completed the Brief Sensation Seeking Scale (BSSS),  
263 which is an 8-item self-report measure of novelty-seeking behaviors (Hoyle et al., 2002).  
264 Participants responded on a 5-point Likert-scale for 8 items: (1) “strongly disagree” to (5)  
265 “strongly agree.” Example items are “*I would like to explore strange places*” or “*I would like to*  
266 *try bungee jumping*”. The BSSS is a revised version of the earlier SSS (Horvath & Zuckerman,  
267 1993; Zuckerman et al., 1978) that updates behavioral descriptions and language, and that  
268 removes similar items (e.g., related to alcohol) (Arnett, 1994; Hoyle et al., 2002). The  
269 composite variable is the average of the 8 items, such that higher scores reflect higher sensation  
270 seeking (Cronbach’s  $\alpha = .78$ ).

271 In order to utilize the longitudinal sensation seeking data from Phase I of this study,  
272 growth curves were used to estimate behavior at Wave 3 (most proximal to the scan) for all  
273 participants. Specifically, SAS 9.4 PROC NLMIXED (SAS Institute Inc., Cary, NC) was used  
274 to fit mixed-effects growth curve models to the three waves of BSSS data treating the intercept  
275 as a random effect and using an unstructured error covariance matrix; the intercept was  
276 calculated at Wave 3. Across the three waves, 100% ( $N_{Wave 1} = 104$ ;  $M = 3.29$ ,  $SD = .76$ ), 77%  
277 ( $N_{Wave 2} = 80$ ;  $M = 3.26$ ,  $SD = .72$ ) and 89% ( $N_{Wave 3} = 93$ ;  $M = 3.33$ ,  $SD = .56$ ) of participants  
278 provided BSSS data. Full information maximum likelihood estimation was used in combination  
279 with empirical Bayes estimates to provide intercepts for all 104 participants in the sample  
280 (Rubin, 1976). As expected, the individual BSSS intercept estimates were highly correlated  
281 with the observed Wave 3 self-reported BSSS,  $r = .82$ .

282 *fMRI Task*: The MID task (Knutson et al., 2000) was used to measure brain activity  
283 during a motivational state that comprised both monetary gains and losses. The MID is a well-  
284 established task for assessing reward processing, and the version used here is administered in  
285 the Adolescent Brain Cognitive Development Study (Casey et al., 2018). The task consists of  
286 three phases: anticipation, probe and feedback. Each trial starts with a cue type (i.e., Win \$0.20,  
287 Win \$5, Lose \$5, Lose \$0.20, or No Money At Stake) presented on the screen for 2000 ms  
288 followed by a jittered fixation cross (1500–4000 ms). Next, the target probe cue (187–500 ms)  
289 appears and requires participants to respond in order to win or not lose money, and it is  
290 followed by the feedback phase (1450 – 1763 ms) during which participants are informed if  
291 they receive the reward. Two MID runs were administered; each lasted 5:42 min and consistent

292 of 407 volumes (See Supplemental Figure S2 and Section 2.3 for more information about the  
293 design and the task schematic). The MID task is considered a *rapid* event-related design, as the  
294 inter-stimulus interval is *shorter* than the hemodynamic response function (Soares et al., 2016).

#### 295 2.4 fMRI Acquisition

296 Data were acquired using a GE Discovery MR750 3.0 Tesla scanner with a standard  
297 adult-sized coil (Milwaukee, WI). A full-brain high-resolution T1 SPGR PROMO scan was  
298 acquired for registration (TR = 7000ms, TE = 2900ms, flip angle = 8°, FOV = 25.6 cm, slice  
299 thickness = 1 mm, 208 sagittal slices; matrix = 256 x 256). Next, two functional T2\*-weighted  
300 BOLD MID runs were acquired in the axial plane using a multiband EPI sequence (MB  
301 factor=6) of 60 contiguous axial 2.4 mm slices (TR = 800ms, TE = 30 ms, flip angle = 52°,  
302 FOV = 21.6 cm, 90x90 matrix, volumes = 407). A fieldmap was also acquired right before the  
303 task using spin-echo EPI (TR = 7400ms, TE = 80 ms, FOV = 21.6 cm, 90x90 matrix) with  
304 opposite phase encoding polarity (A→P, P→A).

#### 305 2.5 fMRI Preprocessing & Time-series Extractions

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

#### 317 2.6 Region of Interest Identification and Time-series Extraction

318 Several steps were completed to extract the time-series data for GIMME analyses. First,  
 319 central coordinates for 12 ROIs (see Figure 1; Supplementary Section 2.6 Table S1 for specific  
 320 MNI coordinates) were selected using Neurosynth (Neurosynth.org) based on previous  
 321 literature (Galvan, 2010; Sherman et al., 2018). These regions belong to three networks: the  
 322 cognitive control network, which consists of the bilateral DLPFC, and ACC; the reward  
 323 network, which consists of the bilateral VS, vmPFC and OFC; and the salience network, which  
 324 consists of the bilateral amygdala and insula. As mentioned previously, these network labels are  
 325 heuristics linked to neurodevelopmental models.

326 For each ROI, a 10mm sphere around the central coordinate was used to extract the  
 327 mean signal intensities at each volume for each of the two runs. For Aims 1-2, the entire time-  
 328 series from each separate run was used, however, for Aim 3, the concatenated time-series across  
 329 the two runs was used. Due to the rapid volume acquisition (800ms), each run was down-  
 330 sampled (retaining every other volume) after preprocessing, as has been suggested (Beltz &  
 331 Gates, 2017) and used in other fast-acquisition methods, such as functional near-infrared  
 332 spectroscopy (Pinti et al., 2019).

333

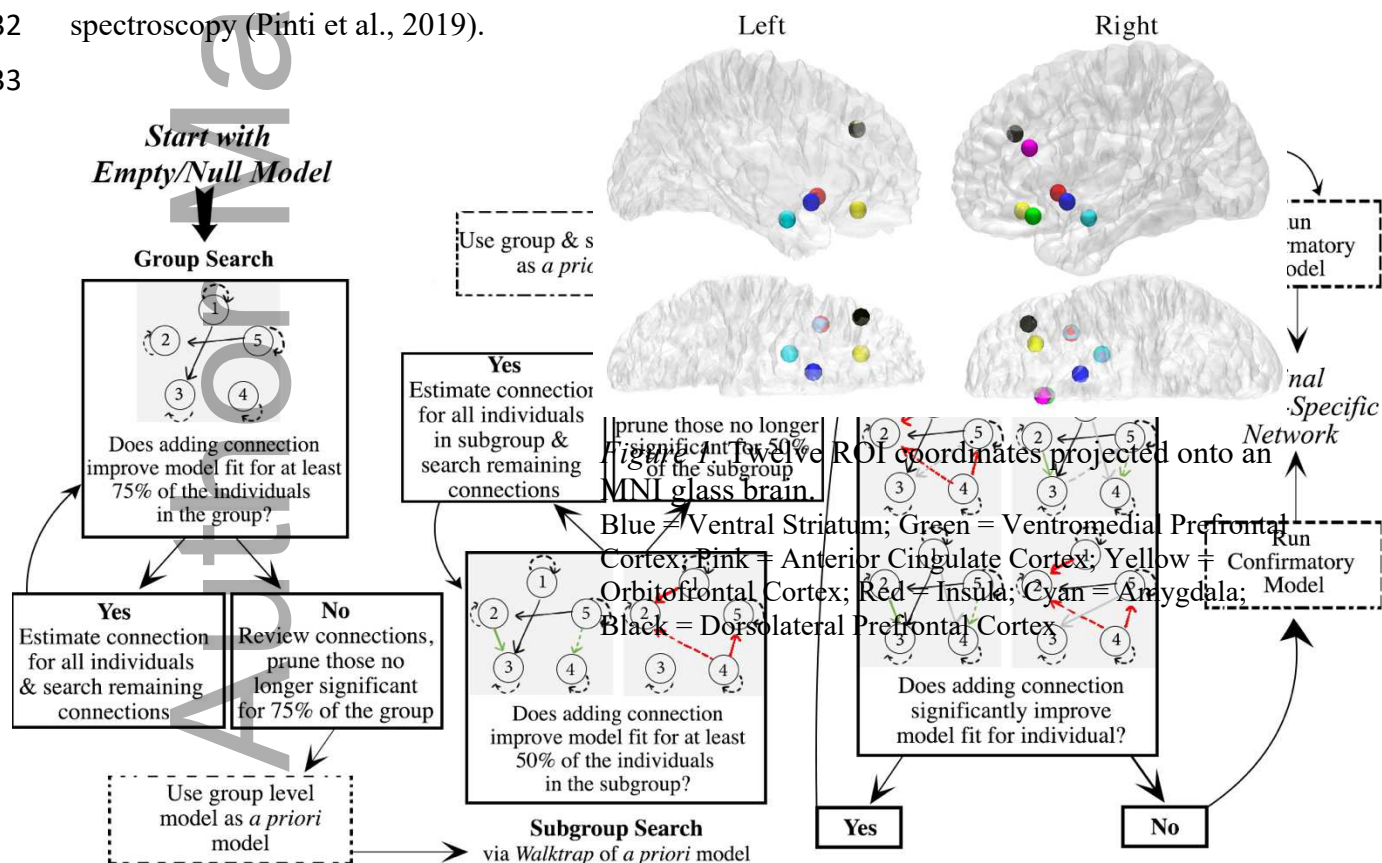


Figure 2. GIMME Model Flow Chart.

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

## 334 2.7 GIMME Analyses

335 GIMME version 0.6-0 in R version 3.6.1 (R Core Team, 2020) was used to estimate  
336 time-lagged ( $t-1$ ) and contemporaneous ( $t$ ) network connections in unified structural equation  
337 models (uSEM), which combine vector autoregressions and structural equation models,  
338 respectively, for each individual within a grouping algorithm that contains subgrouping via  
339 community detection. GIMME estimates network connections through a data-driven search  
340 process that uses Lagrange multiplier tests to select connections at the group, subgroup and  
341 individual level that most improve model fit. The sequential steps of the GIMME search process  
342 are summarized in Figure 2. At the beginning of these steps, we estimate autoregressive  
343 connections as part of a “null” model, as this search strategy has been demonstrated to improve  
344 recovery of other connections in temporally dense data (Lane et al., 2019). Then, starting with  
345 this null model, group-level connections that best improve fit for the at least 75% of the sample  
346 are iteratively estimated for all participants. After the estimation of the group-level connections,  
347 GIMME uses this *a priori* model to inform subgroup detection. Subgroups are estimated using a  
348 data-driven community detection technique to cluster individuals with common sets of  
349 interconnected ROIs via Walktrap. For each subgroup, connections that improve fit for at least  
350 50% of individuals in the subgroup are iteratively estimated for all participants in the subgroup  
351 (Gates et al., 2017). After subgroup detection and connection estimation are complete, the group  
352 and subgroup *a priori* models are used in the iterative data-driven estimation of individual-level  
353 connections that uniquely characterize participants and improve their model fit. At each of these  
354 three steps, the algorithm stops its search when: a) the model fits well according to two out of  
355 four fit statistics: Comparative Fit Index (CFI)  $\geq .95$ , Non-Normed Fit Index (NNFI)  $\geq .95$ ,  
356 Standardized Root Mean Square Residual (SRMR)  $\leq .05$  and Root Mean Square Error of  
357 Approximation (RMSEA)  $\leq .05$ ; or b) modification indices indicate no additional connections  
358 will significantly improve fit– whichever comes first. The former is a stopping rule  
359 implemented to avoid overfitting. Given that the connections are inferred through the data-  
360 driven process from the temporal information in the fMRI data, the final maps reflect estimates  
361 of directed functional connectivity (Beltz & Gates, 2017; Friston et al., 2013).

362 To characterize individual differences in GIMME-derived networks, we focus on  
363 subgroup membership and individual coefficients from the networks when examining links to  
364 sensation seeking behavior. Subgroups are identified in GIMME (if they exist) and reflect

365 neural network similarities among some sets of participants during the MID continuous  
366 motivational state. Each subgroup is characterized by a set of unique network connections, and  
367 each has a person-specific beta estimate that reflects its strength and magnitude. These  
368 individual subgroups and connection estimates can be examined in relation to the BSSS.

## 369 2.8 Analysis Plan

370 Event-related designs are often insufficiently powered to estimate the effects of specific  
371 task conditions (e.g., anticipation or feedback in the MID) on neural connectivity (see Beltz,  
372 2018; Di & Biswal, 2017). This is especially true for *rapid* event-related designs, such as the  
373 current study's design, because the HRF is longer than the inter-stimulus interval. It is also  
374 borne out by simulations using GIMME on task data (Duffy et al., 2021; Gates et al., 2011) and  
375 in empirical studies that modeled task regressors in GIMME and found little evidence for their  
376 substantial modulating effects on connectivity (Hillary et al., 2014; Price et al., 2020). Given  
377 this evidence, we focus on the connectivity among regions during a *motivational state* rather  
378 than modeling modulation by specific task phases (e.g., during individual gain or loss events).

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

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

393 Finally, to test Aim 3, we i) compare estimated connections between Run 01 and Run 02  
394 to detect potential habituation across runs and ii) repeat Aims 1 and 2 for the concatenated time-  
395 series to evaluate the robustness of neural connectivity and its BSSS associations in the full

396 time-series. Specifically, we: (a) examine whether data-driven subgroups are identified, and  
397 then if subgroups are identified, we (b) use logistic regression to evaluate whether BSSS is  
398 significantly ( $p < .05$ ) associated with the subgroups and evaluate which subgroup connections  
399 may be driving links with BSSS with follow-up multiple regression analyses, as we did in Aim  
400 2.

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

### 405 3. Results

406 Demographic characteristics, task accuracy and in-scanner motion during the MID task  
407 for participants are reported in supplementary Tables S2-S5, respectively. No participants had  
408 mean head motion (Post FD) greater than .20, and so based on prior recommendations (Park et  
409 al., 2018), no participants are excluded from analyses for this reason. Furthermore, BSSS was  
410 not significantly associated with mean post FD for Run 01,  $r(102) = .02$ , or Run 02,  $r(102) = -$   
411 .05.

#### 412 3.1 Aim 1: Person-specific Connectivity Networks by Run

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

419 There were notable similarities and differences between the GIMME group-level  
420 networks for each run. For instance, there were consistent connections among the bilateral VS,  
421 amygdala and insula regions, L VS and ACC, L insula and L DLPFC, and R insula and ACC  
422 regions, but different connections between ACC and R DLPFC regions of the cognitive control  
423 network at the group-level. The GIMME community detection algorithm also identified two  
424 subgroups in each run of the MID, but the number of participants in each subgroup and the  
425 subgroup-level connections differed. For Run 01, 61 participants were in Subgroup01 and 43



426 participants were in Subgroup02. For Run 02, 56 participants were in Subgroup01 and 48  
 427 participants were grouped into Subgroup02. Notably, the majority of individuals who were  
 428 grouped into Subgroup01 and Subgroup02 in the first run were also grouped into the same  
 429 subgroup in the second run (Supplemental Table S6), suggesting some level of stability in  
 430 subgroup membership between runs. Of note, there were no significant differences in age, sex,  
 431 race/ethnicity, or sensation seeking across participants who did ( $N = 29$ ) and did not ( $N = 75$ )  
 432 change subgroups across the two runs (see supplemental Table S7).

433 For each run, the more homogeneous subgroup, Subgroup02, was represented by dense  
 434 within-reward-network connections and a greater number of connections between cognitive  
 435 control, reward and salience networks than the heterogeneous subgroup, Subgroup 01, which  
 436 had fewer subgroup connections. With respect to subgroup connections, patterns were relatively  
 437 consistent across runs. Participants in the heterogeneous subgroup, Subgroup01, had three  
 438 subgroup-level connections during each run; two were the same and one differed, such that R  
 439 OFC  $\rightarrow$  vmPFC and vmPFC  $\rightarrow$  ACC connections reoccurred across the two runs, but L dlPFC  
 440  $\rightarrow$  L Amygdala was unique to Run 01 and ACC  $\rightarrow$  R dlPFC was unique to Run 02. Participants  
 441 in the more homogeneous subgroup, Subgroup02, had nine and eight connections per run,  
 442 respectively; they were similar except L Insula  $\rightarrow$  L Amygdala, R dlPFC  $\rightarrow$  L Amygdala, R and  
 443 OFC  $\rightarrow$  R VS only occurred in Run 01 and R OFC  $\rightarrow$  L OFC, L dlPFC  $\rightarrow$  L Amygdala only  
 444 occurred in Run 02 (see Table S8).

445

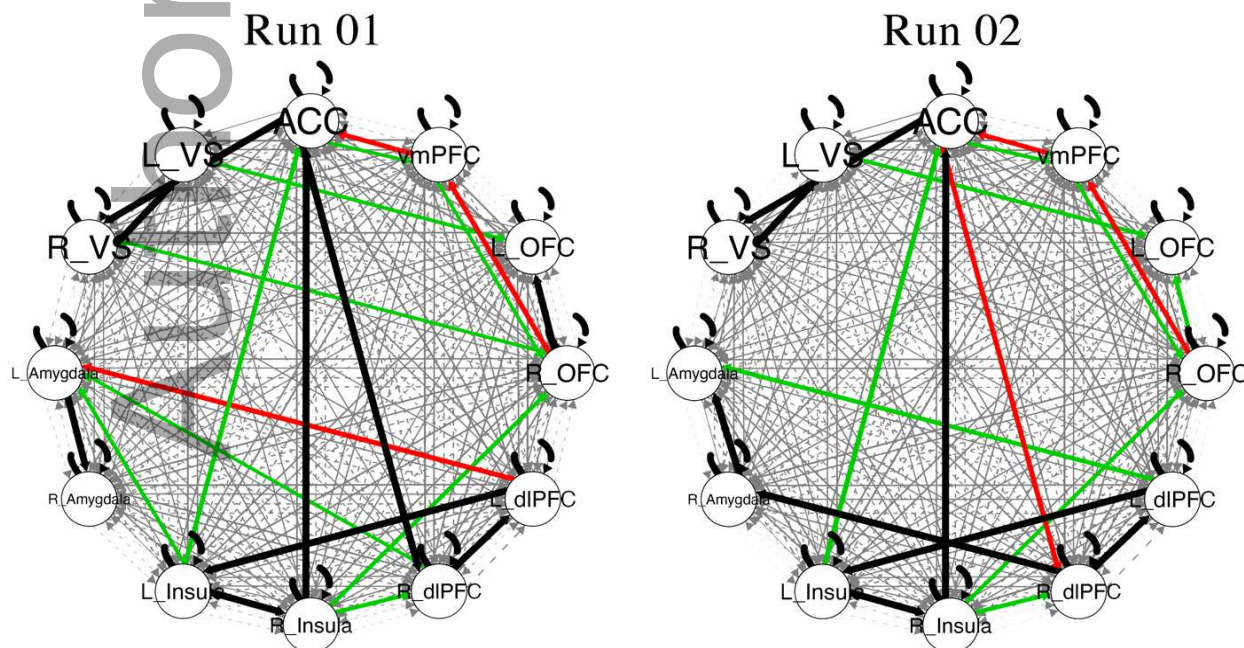


Figure 3. GIMME Connectivity Networks for Each Run.

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



### 446 3.2 Aim 2: Subgroup and Connection Strength Associations with Sensation Seeking

447 For Aim 2, we evaluated whether the subgroups identified in Aim 1 were related to  
 448 BSSS. In a logistic regression model, there was a significant association between subgroup and  
 449 self-reported BSSS for Run 01 ( $b = 1.1$ ), OR = 3.1 (see Table 1), such that a unit increase in  
 450 BSSS was associated with a 3.1:1 increase in the odds of being in Subgroup02, which is  
 451 characterized by several subgroup level connections among reward and salience regions. The  
 452 model that included BSSS (AIC = 126.9) fit the data significantly better than the model without  
 453 BSSS (AIC = 131.4),  $\Delta\chi^2(1)=4.7, p = .03$ . Subgroups did not differ in age or sex, but they did  
 454 differ in FD, such that there was greater motion observed for participants in Subgroup02. This  
 455 effect is unchanged with (Table 1) and without the covariate of motion (e.g., mean Post FD) in  
 456 the model (see supplementary Table S9). To consider the confound of motion, we checked  
 457 whether motion moderated the association between BSSS and subgroups. We found no  
 458 significant ( $p < .05$ ) moderation of mean Post FD (see Supplemental Table S10).

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

	Run 01			Run 02		
	<i>B</i>	SE	<i>p</i>	<i>b</i>	SE	<i>p</i>
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

470 PostFD = Post Preprocessing Framework Displacement;  
 471 BSSS = Brief Sensation Seeking Scale

472 Subgroups also did not differ in age, sex, or FD.

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.

473 Given the significant prediction of subgroup classification from BSSS in Run 01, with  
 474 Subgroup02 being linked to increased BSSS, we explored whether BSSS was associated with  
 475 person-specific beta weights (i.e., connection strength) of subgroup-level connections in  
 476 Subgroup02 for Run 01.

477 Exploratory multiple regression  
 478 analyses revealed that the  
 479 strengths of the vmPFC → R  
 480 OFC connection,  $b = .21$ ,  $p =$   
 481  $.02$ , and the R OFC → R VS  
 482 connection,  $b = -.27$ ,  $p = .01$  (see  
 483 Figure 4) were significantly  
 484 associated with BSSS. Hence,  
 485 increased self-reported sensation  
 486 seeking was positively

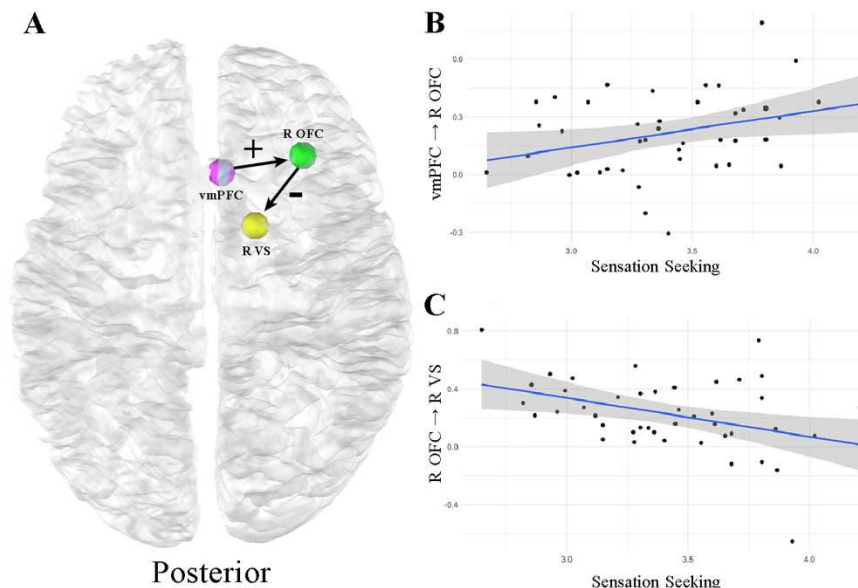
487 associated with connectivity  
 488 strength between the vmPFC and  
 489 R OFC (Figure 4B), and sensation

490 seeking was negatively associated with connectivity strength between R OFC and R VS (Figure  
 491 4C) – which are all regions that are associated with motivational processing (see Table S11).

### 492 3.3 Aim 3: Subgroup Associations with Sensation Seeking in Combined MID Runs

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

502 Regarding analyses of the combined runs, the GIMME networks fit the data well for all  
 503 participants except one (see Table S12; Figure S4), thus  $N = 103$  in these analyses. For this



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

504 participant, the model did not converge. As for the analyses conducted separately per run, two  
505 subgroups were identified. The number of participants differed across each subgroup, with 34 in  
506 Subgroup01 and 69 in Subgroup02. Subgroups were comparable in the number of subgroup-  
507 level connections estimated for Subgroup01 and Subgroup02, with 19 and 16 connections,  
508 respectively. Both Subgroup01 and Subgroup02 had connections within the reward and salience  
509 networks as well as dense network connections between reward, salience, and cognitive control.  
510 When examining whether self-reported BSSS predicted subgroup membership, there was not a  
511 significant effect ( $b = -.51$ ; supplemental Table S13), such that the model that included BSSS  
512 (AIC = 129.6) did not fit the data significantly better than the model without BSSS (AIC 130.5),  
513  $\Delta\chi^2(1)=0.9, p = .33$ . This suggests that the positive association between sensation seeking and  
514 subgroups that was present for Run 01 was not reflected when the runs were combined.

#### 515 4. Discussion

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

531 In light of evidence for the neural habituation to reward across time (Plichta et al., 2012;  
532 Ekhtiari et al., 2020), we examined person-specific connectivity during continuous motivational  
533 processing separately for runs of the MID task in a sparse network of 12 ROIs representing

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

545         With respect to sensation seeking, when modeling each run separately, we found a  
546 significant association between community-based subgroups and self-reported sensation  
547 seeking. Specifically, our analyses revealed that the more homogenous subgroup, Subgroup02,  
548 had significantly higher sensation seeking than Subgroup01. This effect, however, was only  
549 significant when subgroups were defined in the first run, suggesting that changes in subgroup  
550 membership across the runs may have impacted associations with sensation seeking. Similar to  
551 prior work that found associations between OFC connectivity and motivational traits (Crane et  
552 al., 2018; Wan et al., 2020), we found a significant positive association in connectivity strength  
553 between vmPFC—Right OFC and sensation seeking, and a negative association in connectivity  
554 strength between Right OFC—Right VS and sensation seeking for Subgroup02 during Run 01,  
555 but not Run 02. Interestingly, activation contralateral to the latter brain regions, Left OFC and  
556 Left VS, during reward expectancy has been reported to relate to impulsive sensation seeking in  
557 a young adult sample (Chase et al., 2017). This may suggest that the OFC, which is important  
558 for stimulus-value representations, tracking internal values, and goal-directed and affective  
559 behavior (Haber & Behrens, 2014; Padoa-Schioppa & Conen, 2017; Szczepanski & Knight,  
560 2014), may be relevant for individual differences in reward seeking, but only for a specific  
561 subset of adolescents. Given the exploratory nature of this finding, it requires further  
562 investigation and replication in future work.

563         There were other important differences across runs. Although 72% of participants  
564 maintained their subgroup assignments across runs (i.e., were in the homogeneous subgroup in

565 both runs or the heterogeneous subgroup in both runs), the differences in grouping between runs  
566 appear to be meaningful because the association with sensation seeking decreased from the first  
567 to the second. This is consistent with recent findings, indicating that some of this decrease may  
568 be attributable to habituation (Elliott et al., 2020; Plichta et al., 2012), which is especially  
569 relevant to reward regions modeled here (Ekhtiari et al., 2020). Specifically, motivation towards  
570 approaching and receiving rewards may be attenuated with repeated runs due to strategic  
571 changes in attentional processes (Failing & Theeuwes, 2018) and/or become habitual over time  
572 (Michaelsen & Esch, 2021). This might be reflected in the dynamics of reward, salience and  
573 cognitive control networks that consequently decrease the association of neural features with  
574 reward relevant behaviors.

575         It is also possible that the variability across runs may be due to issues of reliability. For  
576 instance, recent work has demonstrated that both task-based fMRI (Elliott et al., 2020) and  
577 resting state connectivity (Noble et al., 2019) suffer from poor test-retest reliability. Poor test-  
578 retest reliability may impact both subgroup partitioning (Gates et al., 2016; Pons & Latapy,  
579 2005) and the association between network connectivity and sensation seeking. This presents a  
580 challenge when trying to determine whether differences across runs relate to habituation,  
581 motivation, reliability, or a mixture of all three. An ongoing project is evaluating the reliability  
582 of GIMME's directed connectivity estimates amongst different brain regions, but the test-retest  
583 reliability of GIMME's subgrouping algorithm has not been well investigated and so remains an  
584 important question for future research.

585         When we repeated our analyses using the combined MID runs, we found further changes  
586 in subgroup memberships as well as with subgroup associations with sensation seeking. While  
587 two subgroups were, again, detected in combined runs, these two subgroups were both more  
588 homogeneous and represented by more connections between reward, salience, and cognitive  
589 control networks than when the runs were analyzed separately. Moreover, the subgroup  
590 association with sensation seeking was not significant and negative; this is a striking deviation  
591 from the significant and positive association in Run 01 and even the positive (but non-  
592 significant) association in Run 02. This stark difference might reflect methodological artifacts,  
593 such as greater signal quality and stability with a longer duration scan (Gordon et al., 2017), or  
594 greater statistical power, which would be expected to cause more connections to be estimated at  
595 the subgroup level, rather than individual level, because the 50% threshold for subgroup

596 connections becomes easier to meet. GIMME adds connections interactively at the group and  
597 subgroup level that are significant ( $p < .01$ ) for a large proportion of individuals (75% and 50%  
598 for the group and subgroup levels, respectively). Likewise, the model at the individual level  
599 retains/adds connections that meet the significance threshold and then the model fit criterion  
600 threshold (Gates & Molenaar, 2012). By doubling our time-series data (concatenating runs), this  
601 increases the likelihood that a connection would have been incorporated into the group and  
602 subgroup level models, especially in scenarios where connections were near the significance  
603 threshold in the shorter time series. Future connectivity work should consider issues of power  
604 and simultaneous changes stemming from individual differences across the time-series.

605 While issues of reliability are important, differences across runs may also reflect  
606 meaningful individual differences in how network dynamics change across time. For example,  
607 connectivity patterns have been shown to reflect some variability in individuals across runs in  
608 both static and dynamic networks (Fong et al., 2019). Moreover, it appears likely that the  
609 variability across runs may have both influenced subgroup partitioning (Gates et al., 2016; Pons  
610 & Latapy, 2005) and the association between network connectivity and sensation seeking.  
611 Future work should reconsider these associations in the context of test-retest of network  
612 connectivity metrics (Beck & Jackson, 2020), the specific assumptions of GIMME, and the  
613 effect of different fMRI protocols, such as non-multiband data, different head motion  
614 corrections, and alternative reward, salience and cognitive control ROI coordinates.

615 An important consideration in study is that participants were in a presumed general  
616 *motivational state* during the MID task, in which neural mechanisms involved in the processing  
617 of both gains and losses were consistently engaged, with potentially overlapping neural  
618 perturbations. Our reported estimates of directed functional connectivity during the MID task is  
619 therefore distinct from the field's common focus on average contrasts of anticipatory or  
620 outcome reward cues or the comparison of neural activation during gain versus loss trials  
621 (Demidenko et al., 2021; Dugré et al., 2018; Oldham et al., 2018). Thus, the ways in which our  
622 specific findings map onto established findings in the field regarding reward processing is  
623 currently unclear. It is important, however, to highlight that there is empirical support for  
624 examining motivational processing as we did because gain and loss cues in the MID design  
625 exhibit substantial overlap in neural activation (Murray et al., 2020; Oldham et al., 2018), and  
626 brain function involves continuous time-lagged brain states (Munn et al., 2021), with

627 “carryover” effects that are often assumed to be random (e.g., if jitter is implemented correctly)  
628 – but this is rarely examined. Nevertheless, the complex issue of reward circuitry and  
629 motivational processing during task-based fMRI requires careful theoretical and empirical  
630 future work to understand and disentangle.

631 In addition to generalizing the results reported here, future work should consider how  
632 variability in task length, number of runs, task type and region selection impact findings. Some  
633 researchers have proposed that increasing the amount of data, or task length (Gordon et al.,  
634 2017), and aggregating across modalities (Elliott et al., 2019) may improve reliability and  
635 generalizability. Although these suggestions certainly have merit, there may be an inherent  
636 trade-off between the measurement improvements that result from increasing the length of a  
637 task, and measurement decrements that occur due to habituation or other state-related changes  
638 linked to longer tasks. Furthermore, cognitive states induced by different tasks have been shown  
639 to be characterized by different connectivity patterns explaining different amounts of variance  
640 in behavior (Greene et al., 2018). Hence, considering how group-, subgroup- and individual-  
641 level network patterns may vary across the course of reward tasks and the impact of this  
642 variability on sensation seeking may facilitate the field’s understanding of adolescent risk  
643 taking. Finally, we use *a priori* ROIs from the adolescent literature in our analyses, and this  
644 clearly constrains our results. Specifically, recent evidence from the resting state literature  
645 demonstrates that ROI parcellations may impact the underlying associations and interpretations  
646 (Bryce et al., 2021). Thus, future work should consider alternative ROIs and parcellations to test  
647 these and related hypotheses.

#### 648 4.1 Study Considerations

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

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

659         Second, although the main sample used here is two times greater than the median  
660 sample used in neuroimaging studies (Szucs & Ioannidis, 2020), the analyses focused on the  
661 brain-behavior associations for Subgroup02 were smaller, and therefore, may be less robust than  
662 results involving the full sample. Given the issues of reliability and power in fMRI analyses  
663 (Button et al., 2013; Elliott et al., 2020; Noble et al., 2019; Szucs & Ioannidis, 2017), we cannot  
664 extrapolate our exploratory analyses examining the association between specific connection  
665 strengths and BSSS. As such, these results warrant replication in an independent sample. The  
666 issue of power was also critical to consider when weighing the pros and cons of modeling the  
667 coactivation of brain regions during a *motivational state* rather than the modulating effect of  
668 specific task regressors. Ultimately, choosing not to model task regressors during functional  
669 connectivity sacrifices the knowledge about the effects of different phases of reward processing.  
670 However, as in most analyses, we had to consider the conceptual and statistical trades-offs of  
671 our decision. Our goal was to assess the dynamic engagement of respective brain regions during  
672 motivational processes that are important to neurodevelopmental heuristics (Casey et al., 2019).  
673 Our related, statistical goal was to model coactivation among regions in a way that was  
674 informed by prior literature and adequately powered. Although task regressors are included in  
675 psychophysiological interaction analyses (PPI; McLaren et al., 2012), it has been reported that  
676 most modulating effects are small and statistically noisy, and therefore, require substantial  
677 power accomplished through task lengths and sample sizes in fMRI studies (Di & Biswal,  
678 2017). Consistent with these group-level analyses in PPI, simulation studies of GIMME  
679 demonstrate that issues of power can prevent the detection of small task modulating effects,  
680 especially in rapid event-related designs like that used in the current study (Duffy et al., 2021;  
681 Gates et al., 2011). Thus, we encourage future studies to build on our empirical findings by  
682 considering the effect of task modulation in designs that are well powered to do so, such as  
683 through the creation and implementation of a slow-event-related MID task.

684         Third, the networks are based on several key *a priori* ROIs. Although GIMME  
685 simulations have demonstrated that omission of variables (i.e., the third variable problem) does  
686 not greatly impact recovery of connections (Gates et al., 2017), future work should consider



687 how subgrouping and connection strength are altered when using different combinations of  
688 regions.

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

696 Although our study is based on a tenet of the imbalance hypothesis and we found a  
697 significant brain-behavior relation, findings cannot be seamlessly extrapolated to other datasets,  
698 modeling sequences, or to real-world risk-taking behavior and age-related differences without  
699 further research. This is because we used a partially data-driven approach when fitting neural  
700 networks and did not have a second, similar dataset available for cross-validation. Indeed,  
701 recent evidence in fMRI demonstrates that brain parcellations (Bryce et al., 2021), analytic  
702 pipelines (Botvinik-Nezer et al., 2019; Li et al., 2021) and other potentially subjective  
703 researcher decisions (Bloom et al., 2021; Steegen et al., 2016) impact results; hence, it is  
704 imperative that future work replicates these results in other adolescent samples, with other tasks  
705 that probe motivational processing, and using other preprocessing pipelines. Second,  
706 associations between self-reported sensation seeking and real-world risk-taking are often small-  
707 to-medium in adolescent samples (Demidenko et al., 2019). Instead, our findings represent the  
708 link between brain function during motivational processing and a psychological trait  
709 hypothesized to relate to real-world risk-taking behaviors. While there were not meaningful  
710 associations between age and connectivity patterns in this work, prior work has reported  
711 developmental differences in connectivity patterns (Marek et al., 2015; Oldham & Fornito,  
712 2019) which future studies should consider. Moreover, while both habituation and reliability  
713 issues are plausible explanations for the difference in the association between subgroups and  
714 sensation seeking across runs, we cannot delineate which is more probable, given that this  
715 version of the MID task did not capture all mean response times and the reliability of fMRI  
716 connectivity (generally) and GIMME (specifically) are still being evaluated. This will be an

717 important consideration in future work modeling functional connectivity across multiple runs of  
718 reward tasks.

## 719 4.2 Conclusions

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

737

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 750 designed and executed the study and data collection and provided critical feedback on the  
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752 **Data Sharing:** Readers seeking access to this data should contact Dr. Daniel Keating  
 753 ([keatingd@umich.edu](mailto:keatingd@umich.edu)) or Michael Demidenko ([demidenm@umich.edu](mailto:demidenm@umich.edu)). Access will be granted  
 754 to named individuals in accordance with ethical procedures governing the reuse of sensitive  
 755 data. Infrastructure is currently being developed in collaboration with the Inter-university  
 756 Consortium for Political and Social Research (ICPSR) at the University of Michigan  
 757 (<https://www.icpsr.umich.edu>) to archive and share data in an ethically approved manner and  
 758 will be shared at a later TBD date.

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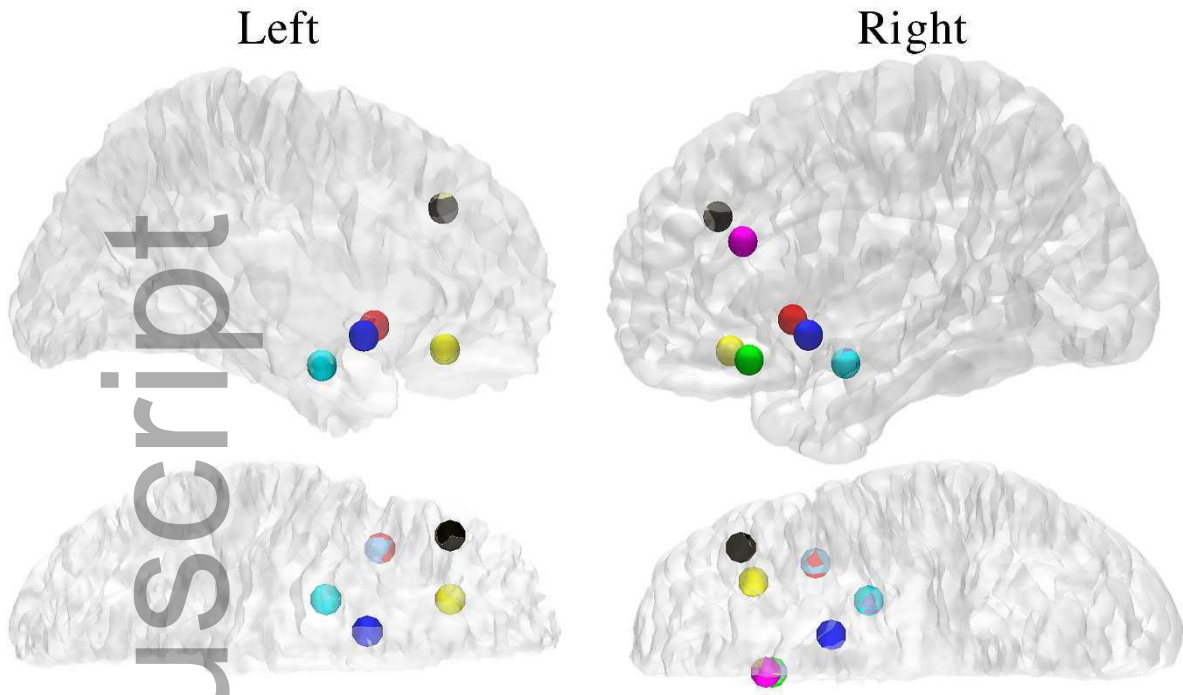


Figure 1

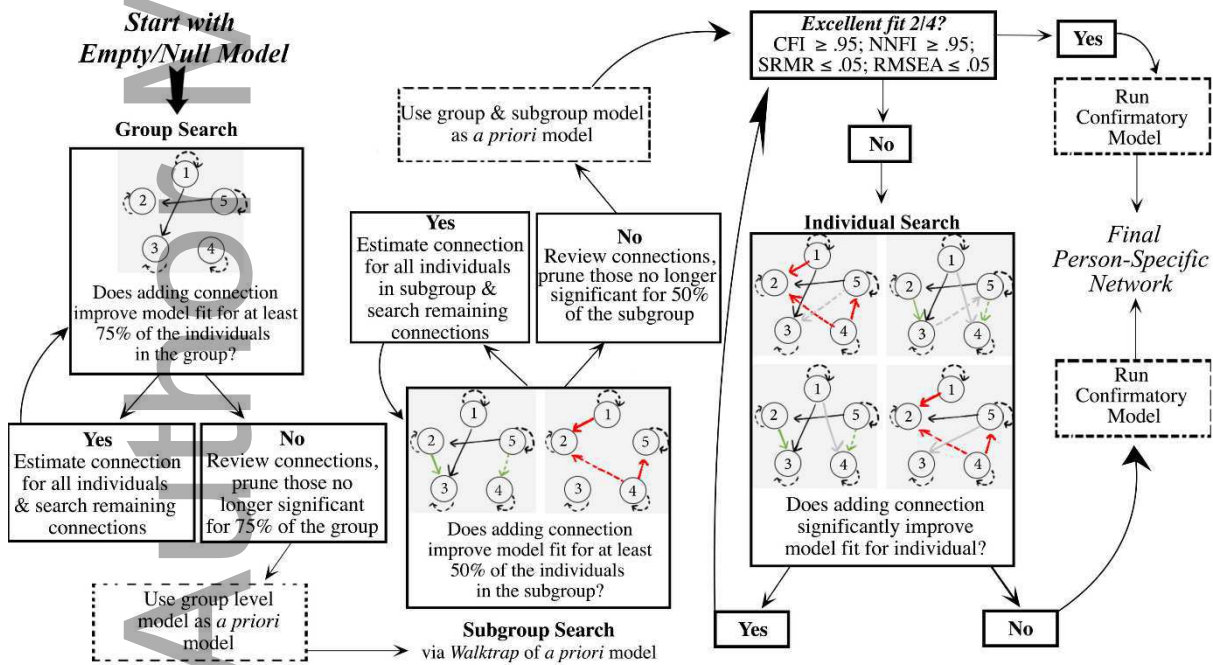


Figure 2

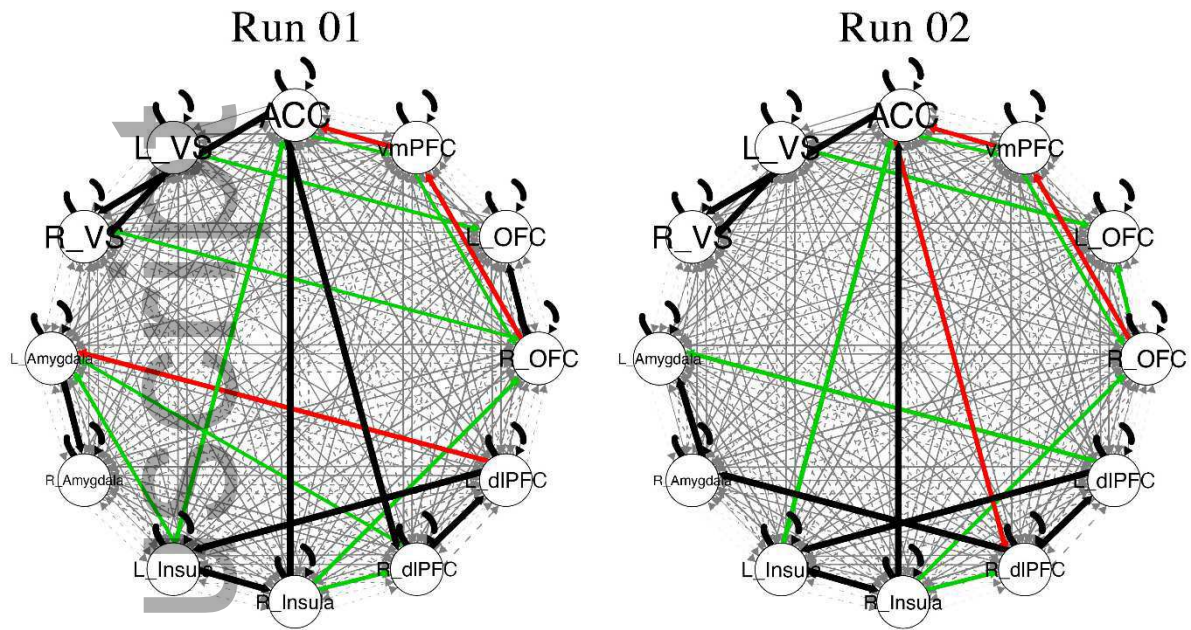


Figure 3

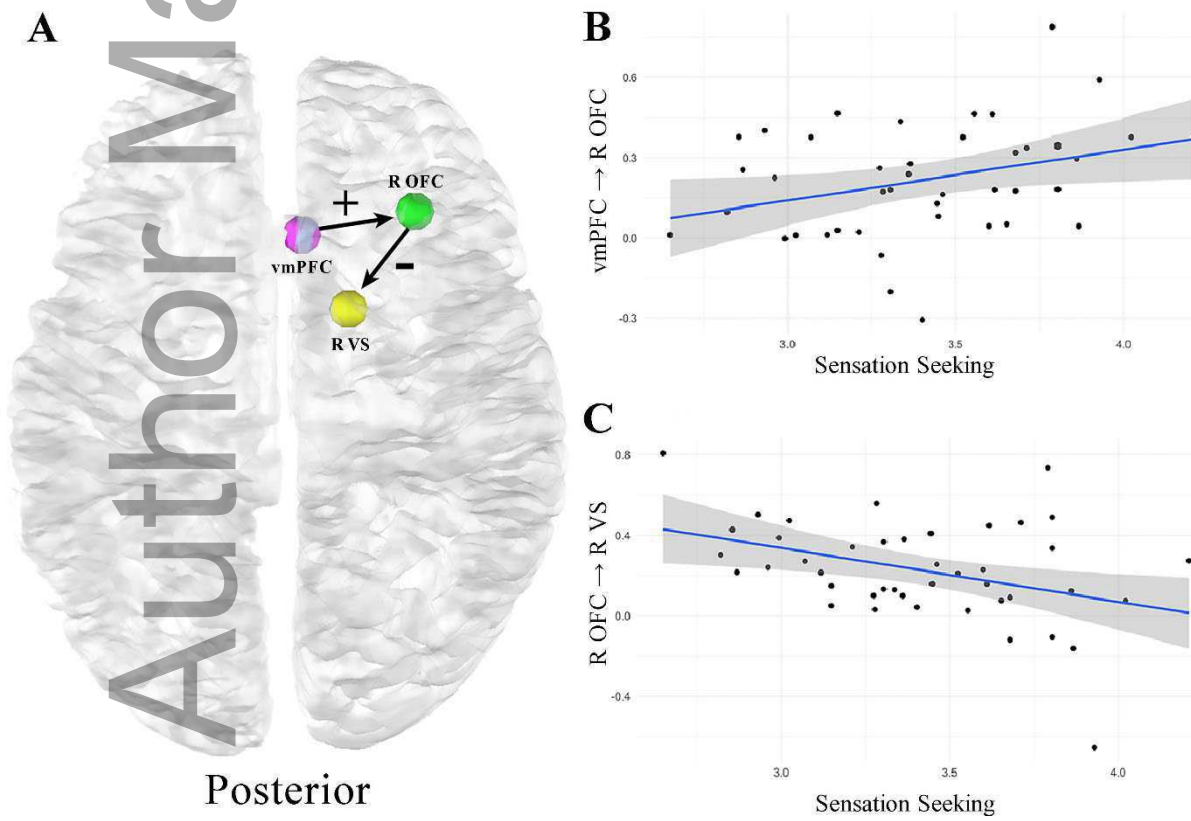
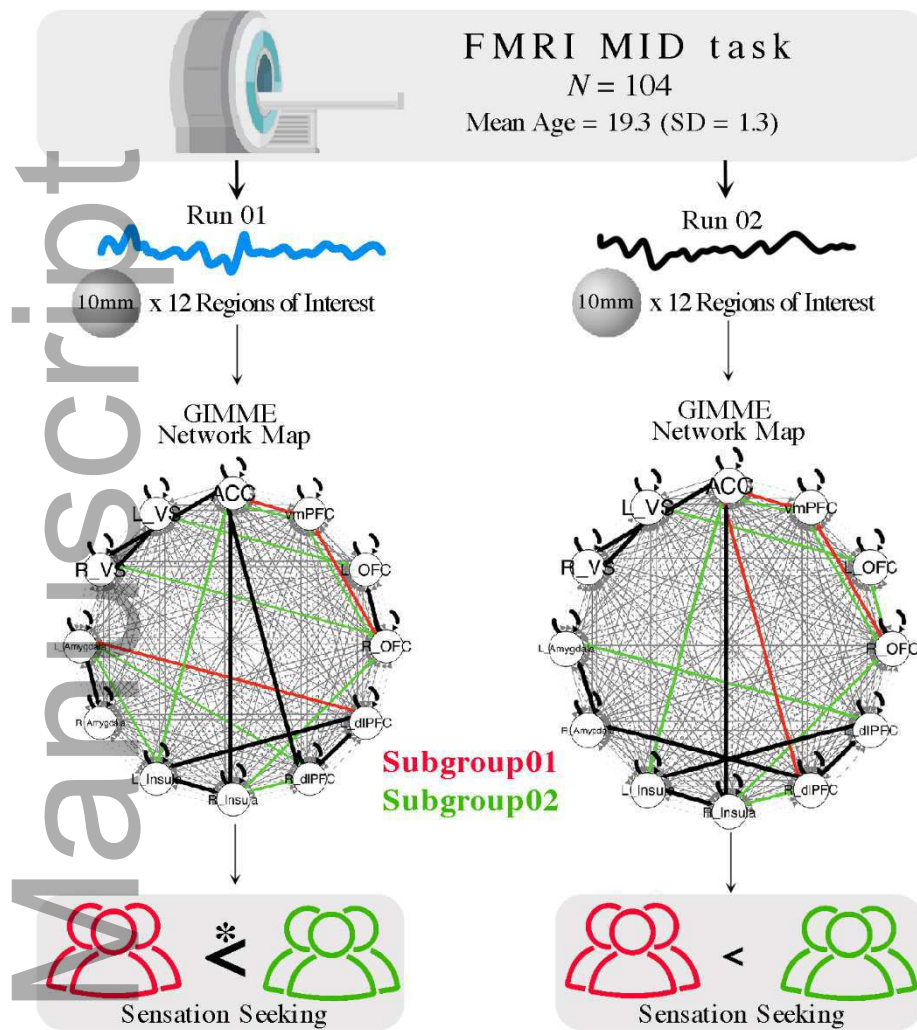
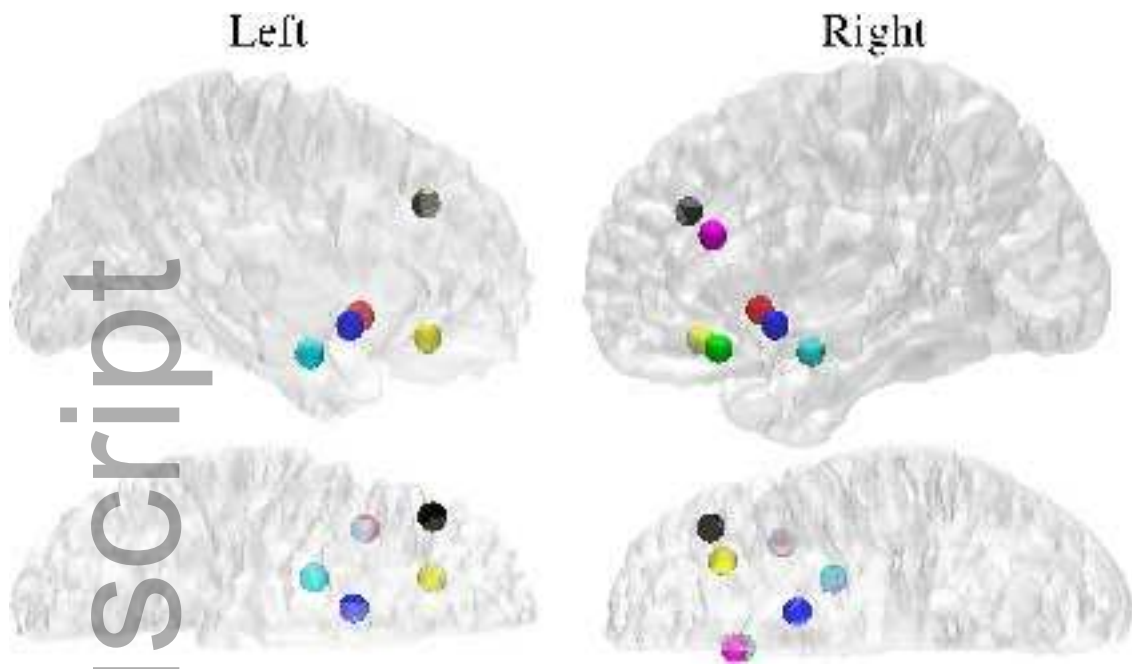


Figure 4



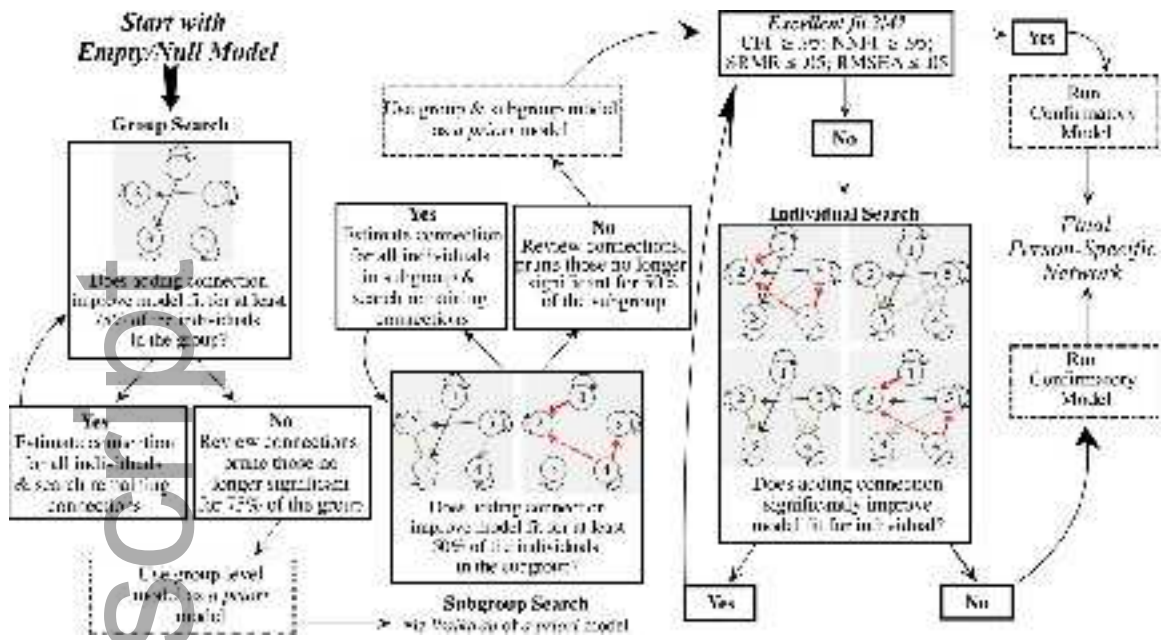
Graphical abstract



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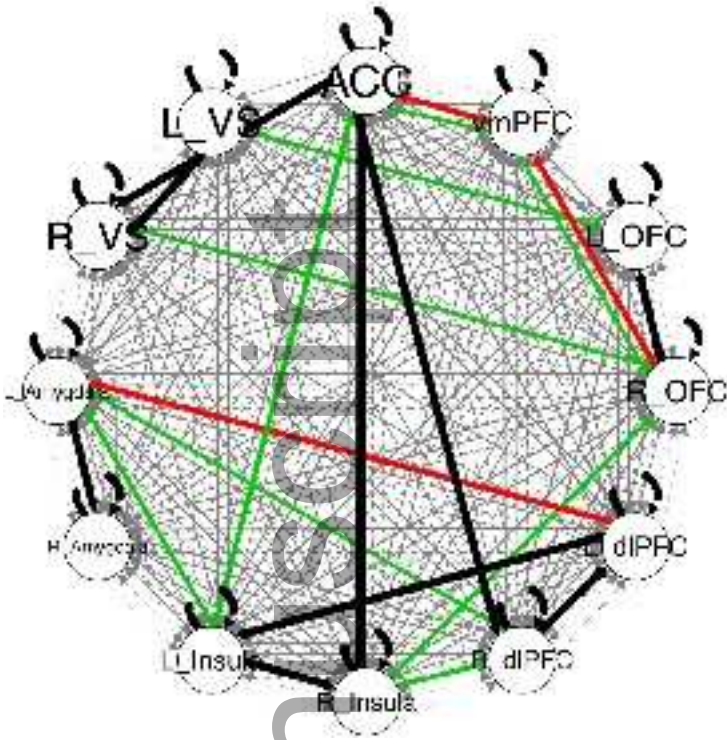
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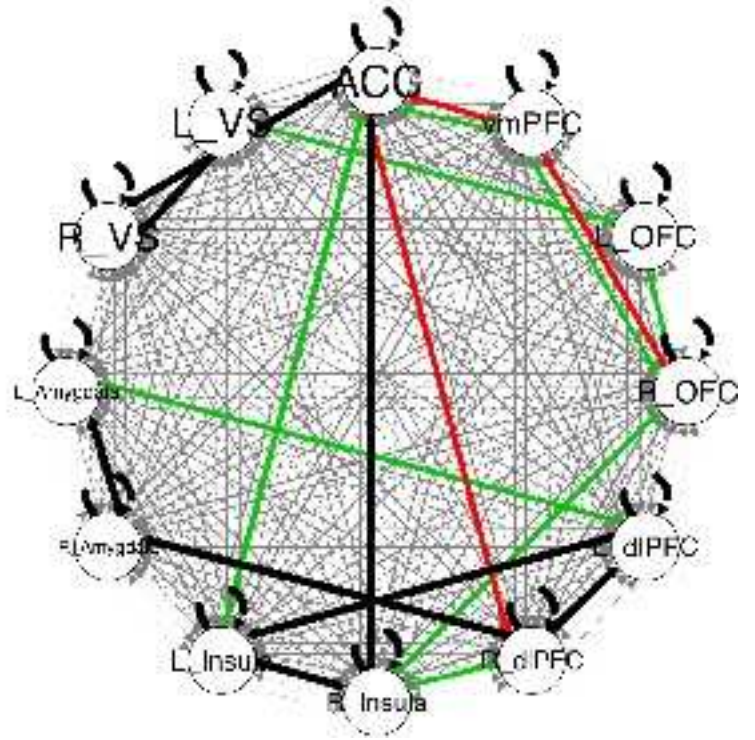


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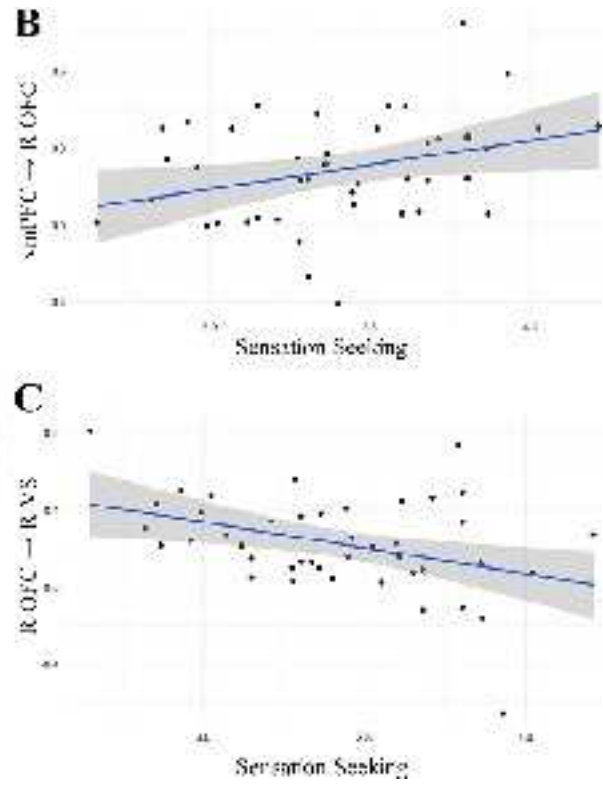
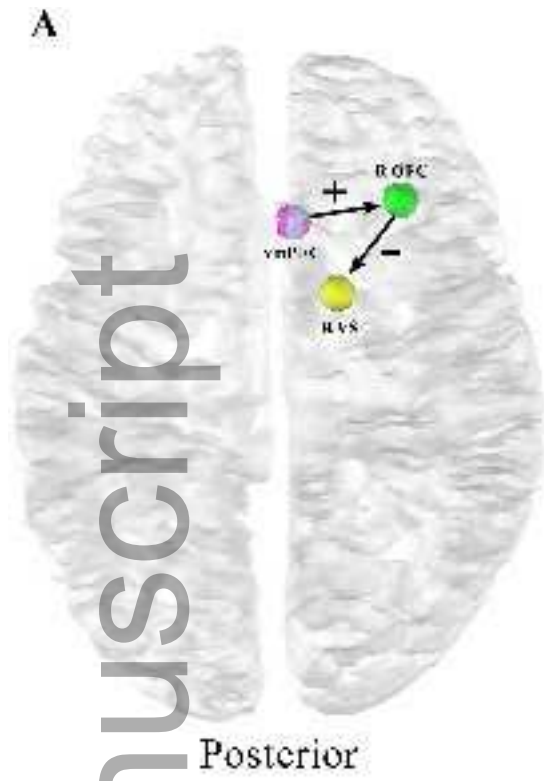


Run 02



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