Predictors of Attrition in Longitudinal Neuroimaging Research: Inhibitory Control, Head Movement, and Resting-State Functional Connectivity

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Abstract

Attrition is a major problem in longitudinal neuroimaging studies, as it may lead to unreliable estimates of the stability of trait-like processes over time, of the identification of risk factors for clinical outcomes, and of the effects of treatment. Identification of characteristics associated with attrition has implications for participant recruitment and participant retention to achieve representative longitudinal samples. We investigated inhibitory control deficits, head motion, and resting-state functional connectivity within the cognitive control network (CCN) as predictors of attrition. Ninety-seven individuals with remitted major depressive disorder or healthy controls completed a functional magnetic resonance imaging scan, which included a go/no-go task and resting-state functional connectivity. Approximately 2 months later, participants were contacted and invited to return for a second scan. Seventeen individuals were lost to follow-up or declined to participate in the follow-up scan. Worse inhibitory control was correlated with greater movement within the scanner, and each predicted a greater likelihood of attrition, with movement mediating the effects of inhibitory control on attrition. Individuals who dropped out of the study exhibited greater movement than nondropouts across 9 of the 14 runs of the scan, with medium-to-large effect sizes. Finally, exploratory analyses suggested that attenuated resting-state connectivity with the CCN (particularly in bilateral dorsolateral prefrontal cortex) was associated with greater likelihood of attrition after accounting for head motion at several levels of analysis. Inhibitory control and movement within the scanner are associated with attrition, and should be considered for strategic oversampling and participant retention strategies to ensure generalizability of results in longitudinal studies.

Keywords: attrition; connectivity; dropout; fMRI; head motion; inhibition

Introduction

LONGITUDINAL RESEARCH IS an important method for examining changes in cognitive and psychiatric processes over time (Riskind and Alloy, 2006). A common challenge in conducting longitudinal studies, including those involving neuroimaging methods, is attrition, or the loss of study participants over time (Carter et al., 2008; Swift et al., 2017; Young et al., 2006). Although investigators may choose to ignore the effects of attrition, it is an important issue to consider for several reasons. In addition to undermining power for longitudinal analyses as a result of decreased sample size, failing to properly consider attrition can be problematic

if attrition is systematic—that is, if it is associated with participant characteristics (i.e., not missing at random). The generalizability of results of longitudinal studies may be undermined when attrition is related to participant characteristics (Gustavson et al., 2012). Attrition in longitudinal studies may lead to biased or unreliable estimates of the stability of trait-like processes over time, the identification of risk factors for clinical outcomes, and the effects of treatment (Dawson et al., 2017; Swift et al., 2017; Twisk and de Vente, 2002). Identification of characteristics associated with attrition has implications for study recruitment and participant retention strategies if studies are to achieve longitudinal samples that are representative of target populations.

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Furthermore, prior longitudinal studies have identified a variety of demographic and clinical characteristics associated with attrition, including younger age (de Graaf et al., 2000; Lamers et al., 2012; Powell et al., 2013), lower socioeconomic status (Lewis et al., 2016; Stange et al., 2016), and less education (Bellón et al., 2010; de Graaf et al., 2000; Gustavson et al., 2012; Huurre et al., 2007; Lamers et al., 2012). In terms of psychiatric factors, individuals who have symptoms or diagnoses of internalizing disorders such as depression and anxiety (Andreescu et al., 2008; Chang et al., 2009; de Graaf et al., 2000; Heron et al., 2004; Issakidis and Andrews, 2004; Katona and Shankar, 2004; Lamers et al., 2012; Lewis et al., 2016; Matthews et al., 2004), and externalizing disorders including attention-deficit hyperactivity disorder (ADHD) (Johnson et al., 2008), substance abuse (de Graaf et al., 2000; Gage et al., 2015; Matthews et al., 2004), and disruptive behavior disorders (Johnson et al., 2008; Wolke et al., 2009) also have a greater likelihood of attrition in longitudinal studies. Although the precise mechanisms by which these characteristics confer risk for attrition often are not apparent, several cognitive and behavioral features of participants that commonly are associated with psychopathology could predispose participants to fail to return for follow-up appointments. On neuropsychological tasks, individuals who ultimately drop out of longitudinal studies have been found to perform more poorly on indices of cognitive functioning, including having slower processing speed, worse delayed verbal recall (Dawson et al., 2017; Levin et al., 2000; Matthews et al., 2004, 2006; van Beijsterveldt et al., 2002), and less attentional flexibility (Stange et al., 2016).

One component of cognitive functioning that could be particularly important for understanding possible mechanisms of attrition in neuroimaging research is inhibitory control. Inhibitory control refers to the capacity to voluntarily inhibit prepotent attentional or behavioral responses (Langenecker et al., 2007a; Miyake et al., 2000), deficits of which are implicated in a variety of forms of psychopathology, such as mood disorders, anxiety disorders, psychotic disorders, and substance use disorders (e.g., Joormann and Vanderlind, 2014; McTeague et al., 2016, 2017). Furthermore, inhibitory control may be especially useful for complying with the demands of a variety of tasks in daily life, including focusing attention on goal-relevant stimuli and regulating emotions (e.g., Joormann and Vanderlind, 2014; Langenecker et al., 2014).

Participating in functional magnetic resonance imaging (fMRI) scans as part of a research study likely requires inhibitory control. These studies require participants to lie very still during long scan sessions, while inhibiting the desire to move to improve physical comfort (e.g., to adjust one's body or scratch an itch). Participants also may need to exert inhibitory control to regulate emotional discomfort that arises from making mistakes on tasks while in the scanner, emotional responses to probes, or to inhibit the urge to fall asleep. Thus, to the extent that inhibitory control improves the subjective experience of being in the scanner and control over behavior while in the scanner, it is plausible that it also would predict the degree to which participants are willing to return to the study for another scan session as part of a longitudinal fMRI study. Although no studies to our knowledge have investigated this question, studies have found that poor cognitive ability, impulsivity, symptoms in-

cluding inattention and hyperactivity-impulsivity, and body mass index (BMI) were associated with greater head movement (Couvry-Duchesne et al., 2016; Kong et al., 2014; Siegel et al., 2017).

Inhibitory control is commonly measured using behavioral tasks such as the parametric go/no-go (PGNG) test, which require individuals to inhibit behavioral responses to certain stimuli (Langenecker et al., 2007a). However, other behaviors also may provide information about inhibitory control. For example, within the context of fMRI, head movement can be measured within the scanner. Given that during scans participants are frequently reminded to stay very still, movement could represent difficulty inhibiting the prepotent desire to move. Head movement within the scanner is a significant problem for neuroimaging researchers, as imperfect correction strategies must be used to account for excessive head motion artifacts before extracting fMRI signal from scan images (Johnstone et al., 2006; Power et al., 2012, 2014, 2017; Zeng et al., 2014).

In addition, to better understand biological mechanisms of inhibitory control, investigators can study neural correlates such as intrinsic connectivity networks. The brain is organized into coherent large-scale functional networks in which patterns of activity are correlated over time (Menon, 2011; Seeley et al., 2007; Yeo et al., 2011), and individual differences in connectivity may illustrate the strength, coherence, or integrity of the network (Seeley et al., 2007). For example, impairments in inhibitory control may be related to attenuated resting-state connectivity within the cognitive control network (CCN) (Stange et al., 2017a), a frontoparietal system critical for problem solving and executive functioning (Menon, 2011). Additional networks commonly studied in relation to cognition and emotion include the default mode network (DMN; active during rest) (Buckner et al., 2008) and the salience and emotion network (SEN; active in response to stimuli relevant to current goals) (Seeley et al., 2007). However, no studies to our knowledge have linked connectivity within and between intrinsic networks to attrition in the context of longitudinal studies.

Based on this rationale and the limited existing literature examining predictors of attrition, we examined several variables as predictors of attrition in the context of a longitudinal fMRI study of cognition in individuals with remitted major depressive disorder (MDD) and healthy controls (HCs). In terms of clinical variables, we hypothesized that worse inhibitory control and greater movement within the scanner (particularly toward the end of the scan session and toward the end of each task) would predict attrition. We also explored whether individuals who have residual symptoms of depression, who have a history of MDD, or who have ADHD would be less likely to return for a second visit. We explored the relationship between attrition and connectivity within and between intrinsic connectivity networks during resting-state fMRI after adjusting for head movement. We hypothesized that attenuated connectivity within the CCN would be associated with greater likelihood of attrition. Acknowledging that movement may confound the accurate assessment of connectivity metrics, this hypothesis was exploratory. Finally, we examined at what stage of the scan session motion might be most associated with attrition, which could have implications for improving comfort or engagement with the tasks during the scan.

Materials and Methods

Participants

This study was approved by the University of Michigan (UM) and the University of Illinois at Chicago (UIC) Institutional Review Boards. All participants provided written informed consent. Participants were recruited using flyers and multiple postings on the Internet and public transportation. All participants completed an assessment battery of cognitive and diagnostic measures, followed by an MRI. Participants were remitted from MDD if they previously met DSM-IV-TR criteria for at least one major depressive episode, but currently met criteria for remission, as assessed by the Diagnostic Interview for Genetic Studies (DIGS) (Nurnberger et al., 1994). HCs did not meet current or past criteria for MDD or any other Axis I or II psychiatric disorder. Participants were required to be medication free for 30 days before the scan. Those with substance abuse or dependence within the past 6 months were excluded. Diagnosis of past MDD or HC status as determined using the DIGS (Nurnberger et al., 1994) was confirmed using a modified Family Interview for Genetic Studies (FIGS) (Maxwell, 1992) completed with a parent, guardian, or close sibling. Both the DIGS and the FIGS have demonstrated good reliability and validity (Bucholz et al., 1994; Maxwell, 1992). The final sample included 52 individuals with remitted MDD (20 UM, 32 UIC) and 45 HCs (20 UM, 25 UIC) between 18 and 23 years of age (67% female) who completed an fMRI scan. Sixteen individuals ($n = 14$, all in the remitted MDD group) had reported diagnoses of ADHD (no convergent childhood information was obtained from school records).

All participants were invited to return for a second fMRI scan ~ 2 months later ($M = 57.66$ days, $SD = 39.73$). Participant retention was managed in several well-known ways, including regular e-mail communications from the study coordinator (who was the coordinator for the entire study period), bimonthly mailings (self-report questionnaires on symptoms), obtaining a collateral contact, and specific communications from the principal investigator if no replies were obtained. All participants received these procedures before being considered to be lost to attrition.

Measures

Inhibitory control. Inhibitory control was assessed using behavioral indices from the PGNG test. The PGNG test (described in detail elsewhere) (Langenecker et al., 2007a; Votruba and Langenecker, 2013) was administered to all participants early in the scan session to assess sustained context-based inhibitory control and inhibitory processing speed, aspects of cognitive control. The task involves responding as quickly and as accurately as possible to certain target types (letters of the alphabet rapidly presented on a computer screen), while inhibiting prepotent responses to targets that repeat, and static nontargets. The task yields two variables that were used for analysis: parametric go/no-go percent correct inhibition (PGNG-PCI; task-related fMRI results to be reported elsewhere), the primary index of inhibitory control, and processing speed on correct go trials (parametric go/no-go reaction time; PGNG-RT). The PGNG has demonstrated good construct validity and retest reliability in healthy

and depressed samples (Langenecker et al., 2007a,b; Peters et al., 2015; Votruba and Langenecker, 2013).

Intelligence. We administered a computerized adaptation of the Shipley verbal IQ test (Shipley, 1940), a brief yet robust measure of crystallized and fluid verbal intelligence (Langenecker et al., 2007a,b).

Depression symptoms. Symptoms of depression were measured with the Hamilton Depression Rating Scale (Hamilton, 1960), which was administered by trained interviewers at baseline.

fMRI acquisition

At UM, an eyes-open resting-state scan was acquired over 8 min on a 3.0 T GE Signa scanner (Milwaukee, WI) using T2*-weighted single shot reverse spiral sequence with the following parameters: 90° flip, field-of-view 20, matrix size = 64 × 64, slice thickness = 4 mm, 30 ms echo time, 29 slices. Eyes-open, resting-state scans at UIC were collected for 8 min on a 3.0 T GE Discovery scanner (Milwaukee, WI) using parallel imaging with Array coil Spatial Sensitivity Encoding (ASSET) = 1 and T2* gradient-echo axial echo planar imaging with the following parameters: 90° flip, field-of-view 22, matrix size = 64 × 64, slice thickness = 3 mm, 22.2 ms echo time, 44 slices. Both sites used repetition time (TRs) of 2000 ms and a total of 240 TRs for the resting scans. Also at both sites, high-resolution anatomic T1 scans were obtained for spatial normalization; motion was minimized with foam pads, a visual tracking line (UIC only) and/or cross on the display (UIC and UM), and by conveying the importance of staying still to participants.

Although the primary focus of the present article was on inhibitory control performance and resting-state connectivity, we evaluated movement across other tasks that were completed in the scanner. The scan session consisted of a total of 14 runs. Runs 1 to 4 were blocks of the PGNG test; runs 5–8 were part of a Semantic List-Learning Task (Schallmo et al., 2015; results to be reported elsewhere); runs 9–13 were part of the facial emotion perception test (Langenecker et al., 2005; Rapport et al., 2002; results reported elsewhere: Jenkins et al., 2016); and run 14 was the resting-state scan (Jacobs et al., 2014, 2016; Stange et al., 2017a). Movement was calculated between each TR for each participant. Within each run, the average standard deviation of movement realignment for all x , y , and z translations from MCFLIRT was used as an estimate of head motion for that run. The average of these 14 movement values was computed for each person as the primary index of movement, with *post hoc* analyses investigating differential associations between movement and attrition by run.

In addition, behavioral observations during scanning were coded (1 when present, 0 when absent), including failure to respond to tasks consistently, reports of feeling anxious, behavior that was noticeably restless, and drowsiness that was either verbally or behaviorally indicated (through eye camera).

Functional connectivity MRI preprocessing

Several steps were taken to reduce the potential impact of sources of noise and artifact. Slice timing was completed with SPM8 (www.fil.ion.ucl.ac.uk/spm/doc/) and motion

correction algorithms (and other preprocessing steps) were applied using FSL (<http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/>). Coregistration of structural images to functional images was followed with spatial normalization of the coregistered T1-sprgr to the Montreal Neurological Institute (MNI) 152 brain template. The resulting normalization matrix then was applied to the slice-time-corrected time series data. These normalized T2* time series data were spatially smoothed with a 5 mm Gaussian kernel resulting in T2* images with isotropic voxels, 2 mm on each side.

Time series data were detrended and mean centered. Motion parameters were regressed out (Jo et al., 2013). Based upon recent literature (Jo et al., 2013; Power et al., 2012, 2014), motion volumes were identified based on any TR to TR movement exceeding 0.5 mm and did not differ between remitted MDD and HC groups. Preprocessing did not involve “scrubbing” of motion volumes (e.g., with aCompCor; Behzadi et al., 2007); although this procedure attenuates motion-related artifacts when mean signals are used, it provides no additional benefit in terms of motion artifact reduction or connectivity specificity (Muschelli et al., 2014) and may even introduce distortions between seeds and nodes in a nonlinear way (Jo et al., 2013). Movement also was addressed in connectivity analyses using regression of individuals’ own white matter and cerebrospinal fluid signals (top five principal components) as recommended in the recent literature (Behzadi et al., 2007; Jo et al., 2013; Power et al., 2012, 2017). Global signal was not regressed due to collinearity violations with gray matter signal, problematic misestimates of anticorrelations (Fox et al., 2009), and because it does not diminish distortion in distance–micromovement relationships (Jo et al., 2013). For example, although motion can be the source of artifact in connectivity correlations, global signal regression may exacerbate distance-dependent bias, making residual signal more susceptible to the presence of motion, and by extension, to the levels of censoring (Murphy et al., 2009; Saad et al., 2012). Finally time series were band-pass filtered over 0.01–0.10 Hz. Correlation coefficients were calculated between mean time course for seed regions and all other voxels of the brain, resulting in a three-dimensional correlation coefficient image (r image). These r images were transformed to z scores using a Fisher transformation.

Defining the CCN, SEN, and DMN

According to the triple-network model of Menon (2011), we created models of connectivity masks for three large networks: DMN, SEN, and CCN. The DMN is the same mask as from Yeo and colleagues (2011). The CCN was created by the combination of the dorsal attention and frontoparietal network masks, and the SEN was created by combination of ventral attention and limbic networks, all from the initial seven networks reported in Yeo and colleagues (2011). The triple-network model is presented here for simplicity.

Three separate factorial (group $\times$ side $\times$ seed) network models were created from seeds within each of these networks. Each of these network models contained three bilateral seeds within a given network. The CCN model contained dorsolateral prefrontal cortex (dlPFC), inferior parietal lobule (IPL), and dorsal anterior cingulate (dACC) seeds; the SEN model contained amygdala, subgenual anterior cingulate (sgACC), and inferior ventral striatum (VSi) seeds; and the

DMN model contained posterior cingulate (PCC), dorsomedial prefrontal cortex (dmPFC), and hippocampus (HPF) seeds, based on Yeo and colleagues (2011). Seeds were spherical: in the CCN, dlPFC (PFCI; coordinates: $-45, 29, 32; 45, 29, 32$), IPL (PGA; coordinates: $-52, -50, 49; 52, -50, 49$), dACC (PFCmp; coordinates: $-5, 22, 47; 5, 22, 47$); in the SEN, amygdala ($-23, -5, -19; 23, -5, -19$); sgACC ($-4, 21, -8; 4, 21, -8$), VSi ($-9, 9, -8; 9, 9, -8$); in the DMN, PCC ($-5, -49, -25; 5, -49, -25$), dmPFC ($-7, 46, -2; 7, 46, -2$), HPF ($-30, -12, -18; 30, -12, -18$); each seed contained 19 voxels. Each of the three network masks was used to examine connectivity within and between each of these three models, yielding variables extracted from SPM8 for each person, representing connectivity between each seed (six seeds in each model) and each of the three network masks, which were investigated on an exploratory basis (Supplementary Data; Supplementary Data are available online at www.liebertpub.com/brain). Covariates in the SPM models included site, gender, and head motion (SD of x, y , and z movement coordinates across TRs for each subject).

Statistical analyses

Logistic regressions were used to examine the degree to which each predictor (in separate models for each predictor) was associated with likelihood of attrition. Primary predictors of attrition were inhibitory control (PGNG-PCI), movement, and resting-state functional connectivity. Exploratory analyses examined demographics and clinical variables as predictors of attrition. For ease of interpretation of odds ratios, continuous variables that served as predictors of attrition were Z -standardized. In the event that average movement predicted attrition, we planned to conduct a follow-up mixed-effects analysis of variance (ANOVA) to determine whether the relationship between movement and attrition was specific to certain portions of the scan. Finally, on an exploratory basis, we examined partial correlations between attrition and connectivity within and between intrinsic connectivity networks after controlling for head movement (Supplementary Table S1).

Results

Preliminary correlational analyses with movement

As expected, PGNG-PCI was negatively correlated with movement within the scanner ($r = -0.24, p = 0.02$). PGNG-PCI was positively correlated with PGNG-RT ($r = 0.22, p = 0.03$). Behaviorally coded observations during the scan indicated that participants who had more movement during the scan demonstrated problems with responding consistently ($r = 0.27, p = 0.01$) and reported feeling anxious or restless ($r = 0.24, p = 0.03; r = 0.30, p < 0.01$). Sleepiness during the scan was not associated with movement ($r = 0.13, p = 0.23$); however, sleepiness and feeling restless were negatively associated with PGNG-PCI ($r = -0.24, p = 0.03; r = -0.25, p = 0.02$). BMI was not associated with movement or with PGNG-PCI ($r = -0.05, p = 0.64; r = 0.11, p = 0.27$) (Siegel et al., 2017).

Hypothesized predictors of attrition

Of the 97 individuals who began the study, 17 did not return for scan 2 as they were either lost to follow-up

FIG. 1. Indirect relationship between inhibitory control deficits and likelihood of study attrition/dropout, mediated by average movement across the fMRI scan. fMRI, functional magnetic resonance imaging.

($n = 14$) or did not complete scan 2 for reasons of comfort ($n = 3$).^{*} This rate of attrition is well within the acceptable range for longitudinal studies (Prenoveau et al., 2011; Stange et al., 2016, 2017b; Young et al., 2006), yet provided sufficient variability to investigate individual differences that might distinguish between these groups. Attrition did not differ by site (UM: 5/27; UIC: 12/53; $\chi^2 = 0.12$, $p = 0.73$).

As hypothesized, worse inhibitory control predicted a greater likelihood of attrition (logistic regression Wald $\chi^2 = 4.38$, $p = 0.04$, OR = 0.56, 95% CI = 0.32–0.96, $R^2 = 0.08$; Mean PGNG-PCI score for dropouts: 44.17%; for nondropouts: 55.28%). In addition, greater overall movement within the scanner also predicted greater likelihood of attrition (Wald $\chi^2 = 5.39$, $p = 0.02$, OR = 1.74, 95% CI = 1.09–2.77, $R^2 = 0.09$).[†] Given that inhibitory control and movement were significantly associated with one another as well as with attrition, we conducted a mediation path analysis to evaluate the plausibility of inhibitory control deficits as a mechanism underlying the relationship between movement and attrition. In other words, we examined whether movement in the scanner could serve as a behavioral indicator of inhibitory deficits that confer risk for attrition. Mediation analyses employed a bootstrapping approach with $N = 5000$ bootstrap resamples and a 95% confidence interval to assess indirect effects (Preacher and Hayes, 2008). Supporting this hypothesis, there was a significant indirect relationship between inhibitory control deficits and attrition through movement within the scanner (Fig. 1). Inhibitory control and head motion predicted a combined 16% of the variance in dropout (Nagelkerke $R^2 = 0.16$).

Exploratory predictors of attrition

Although not the primary focus of the article, for the interest of the reader and to rule out alternative explanations for the effects of inhibitory control and movement on attrition, we conducted supplemental exploratory analyses of demographic, behavioral, and clinical variables plausibly related to attrition based on the extant literature. Attrition was not associated with gender, age, education level, IQ, race or ethnicity, or study site (p 's > 0.09). Based on behaviorally coded observations, responding inconsistently, being tired,

and feeling anxious or restless were not associated with attrition (p 's > 0.10). Diagnostic group (remitted MDD vs. HC) was not significantly associated with attrition: of the 17 individuals who dropped out, 11 were HCs and 6 were remitted MDD (Wald $\chi^2 = 2.67$, $p = 0.10$, OR = 0.40, 95% CI = 0.14–1.20, Nagelkerke $R^2 = 0.05$). Attrition also was not associated with residual symptoms of depression (Wald $\chi^2 = 0.09$, $p = 0.76$, OR = 0.79, 95% CI = 0.18–3.54, $R^2 = 0.002$) or with diagnosis of ADHD as suggested by prior reports (Johnson et al., 2008) (Wald $\chi^2 = 0.16$, $p = 0.53$, OR = 0.72, 95% CI = 0.15–3.57, $R^2 = 0.003$).

Exploration of attrition by scan run

Although we used average movement within the scanner as the main indicator of movement, as a *post hoc* strategy we also explored whether the relationship between movement and attrition was specific to certain portions of the scan or runs within given tasks. To examine this question, we conducted a 2×14 mixed-effects repeated-measures ANOVA with attrition as a dichotomous between-subjects factor, scan run as a within-subjects factor, and movement during each run as the dependent variable. Results are displayed in Figure 2. Consistent with the results of the logistic regression already reported, there was a significant main effect of group ($F(1,95) = 6.87$, $p = 0.003$, $\eta_p^2 = 0.09$), such that individuals who dropped out had significantly greater movement than individuals who did not drop out. In addition, there was a significant main effect of run ($F(4.93,95) = 9.50$, $p < 0.001$, $\eta_p^2 = 0.07$), suggesting that there was significant variability in movement over time. These main effects were qualified by a significant two-way interaction between attrition and run ($F(13,95) = 1.94$, $p < 0.001$, $\eta_p^2 = 0.02$). *Post hoc* tests revealed that individuals who dropped out had greater movement on runs 1, 2, 4, 5, 6, 7, 8, 13, and 14, but not on runs 3, 9, 10, 11, or 12 (Table 1). In addition, the simple effect of run was significant for individuals who dropped out ($F(4.55,95) = 5.55$, $p < 0.001$, $\eta_p^2 = 0.15$), and was weaker but still significant for individuals who did not drop out ($F(3.47,95) = 2.77$, $p = 0.04$, $\eta_p^2 = 0.07$).

Exploratory intrinsic connectivity network correlates of attrition

In addition to examining clinical and behavioral predictors, we also explored whether resting-state connectivity within and between the CCN, SEN, and DMN would be associated with attrition after controlling for head movement. Although it is

^{*}Attrition rates did not differ by technicians who ran the fMRI visits ($\chi^2 = 2.93$, $p = 0.40$).

[†]The relationship between head motion and attrition was maintained when controlling for study site ($p = 0.02$).

FIG. 2. Mixed-effects ANOVA with dropout condition as a dichotomous between-groups factor (non-dropouts displayed separately by HC and rMDD status for illustrative purposes), scan run as a within-subjects factor, and movement during each run as the dependent variable. Error bars represent standard errors. ANOVA, analysis of variance; HC, healthy control; rMDD, remitted major depressive disorder.

possible that associations between connectivity and attrition are confounded to some degree by relationships with head motion (Behzadi et al., 2007; Jo et al., 2013; Power et al., 2012, 2017), we provide these results for interested readers in the Supplementary Data (inhibitory control, motion, and connectivity influenced by motion may share variance in predicting dropout). Six of the connectivity variables were significantly correlated with attrition; four of these involved CCN seeds or the CCN mask: right dIPFC to CCN mask, left dIPFC to SEN and DMN masks, right PCC to DMN mask, right dmPFC to DMN mask, and left HPF to CCN mask (Supplementary Table S1; Supplementary Fig. S1). All correlations were negative, such that lower connectivity within or between networks was associated with greater likelihood of attrition. Right dIPFC to CCN mask connectivity also was positively correlated with inhibitory control performance ($r=0.23$, $p=0.02$), consistent with the hypothesis that connectivity within the CCN may

facilitate cognitive control and related outcomes (e.g., staying still in the scanner and enhancing study compliance).[‡]

Discussion

The aim of this study was to evaluate variables associated with attrition from a longitudinal neuroimaging study of young adults. We found that worse inhibitory control and greater head motion within the scanner (throughout most of the scan session) were associated with a greater likelihood of attrition across follow-up. Mediation analyses suggested that movement served as a behavioral indicator of inhibitory deficits, which conferred risk for attrition. In addition, lower resting-state functional connectivity within and across networks (particularly with the CCN) was associated with attrition. Importantly, these results appeared to be specific to inhibitory control and connectivity and did not appear to be due to the influence of diagnostic group, current depressive symptoms, lower IQ, site, or other behavioral indices of performance and discomfort within the scanner. These findings provide initial evidence of the importance of evaluating inhibitory control and head movement as indicators of possible risk for nonrandom attrition from longitudinal neuroimaging studies.

Although prior studies have identified several characteristics that often are associated with risk for attrition, to our knowledge, our case study is the first study to explicitly evaluate inhibitory control and head movement as predictors of attrition. These results have important implications for future neuroimaging studies. Given that deficits in inhibitory control were associated with greater movement and more discomfort within the scanner, it seems plausible that one reason these individuals were less likely to return for a follow-up scan is that the experience of the initial scan was less pleasant or more challenging as a result of deficits in

TABLE 1. DIFFERENCES BETWEEN INDIVIDUALS WHO DID AND DID NOT DROP OUT BASED ON STANDARD DEVIATIONS IN TRANSLATION OF HEAD MOVEMENT BY SCAN RUN

Run	Dropout mean (SD)	Nondropout mean (SD)	t	d
1	0.13 (0.12)	0.06 (0.05)	4.22***	0.80
2	0.14 (0.13)	0.08 (0.07)	2.72**	0.57
3	0.13 (0.11)	0.09 (0.09)	1.87	0.46
4	0.14 (0.13)	0.08 (0.07)	2.37*	0.52
5	0.09 (0.08)	0.05 (0.04)	2.91**	0.61
6	0.11 (0.09)	0.06 (0.05)	2.37*	0.53
7	0.13 (0.10)	0.08 (0.08)	2.27*	0.56
8	0.14 (0.11)	0.09 (0.09)	2.01*	0.50
9	0.12 (0.09)	0.09 (0.10)	1.16	0.32
10	0.08 (0.05)	0.06 (0.05)	0.85	0.23
11	0.07 (0.05)	0.06 (0.05)	0.98	0.25
12	0.07 (0.05)	0.06 (0.04)	0.81	0.22
13	0.12 (0.13)	0.06 (0.04)	3.42***	0.61
14	0.15 (0.12)	0.09 (0.08)	2.66**	0.60

Standard deviations are based upon calculation of standard deviation for each x , y , and z translation for each run, respectively, and then creating an average of these for each group by run.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

[‡]Per the suggestion of a reviewer, we also tested a mediational model whereby right dIPFC-to-CCN connectivity leads to poorer inhibitory control that leads to higher risk for attrition; the bootstrapped confidence interval for the indirect effect contained 0 and thus was not significant ($B = -0.56$, $SE = 0.79$, 95% CI -2.89 to 0.27).

cognitive control (although it should be noted that behaviorally coded restless in the scanner was not associated with attrition). To the extent that inhibitory control is associated with other variables that may be of interest in longitudinal studies (e.g., clinical group differences), attrition of these individuals could result in the apparent mitigation of group differences over time, leading to problematic conclusions about the stability and reliability of neuroimaging results. Thus, future work might consider strategically oversampling individuals who may be at higher risk for dropout based on factors such as poor inhibitory control.

Although resting-state connectivity analyses were exploratory, it is interesting that attenuated connectivity within the CCN, and between the CCN and the DMN, was associated with attrition. Prior work has suggested that attenuated connectivity within the CCN could represent a less coherent network, which could undermine cognitive control and contribute to cognitive biases (Stange et al., 2017a). In addition, the dlPFC is thought to be a key region for inhibitory control, suggesting that weaker connectivity with this seed could reflect a biological marker of worse inhibitory control (Stange et al., 2017a) and hence risk for attrition, among other outcomes. Relatedly, attenuated connectivity between the CCN and DMN might represent difficulty with recruiting CCN regions to switch from self-reflective to task-relevant thinking (Marchetti et al., 2016). To the extent that this is maladaptive, this could interfere with a variety of functions in a way that might interfere with study compliance. Despite the associations identified between several components of network connectivity and attrition, several other seed-to-network connectivity variables were not associated with attrition. We expected that the connectivity with the CCN would be related to inhibitory control and head motion; however, given that the connectivity analyses were relatively exploratory, we included all seed-to-network connectivity variables within the context of the triple network model. Future longitudinal studies with larger sample sizes should replicate these analyses before further speculating about why only certain components of connectivity might be associated with attrition.

Our exploratory analysis of demographic and clinical variables did not replicate results from prior studies that have shown that younger age, less education, more symptoms of depression, and ADHD were associated with attrition (Andreescu et al., 2008; Bellón et al., 2010; Chang et al., 2009; de Graaf et al., 2000; Gustavson et al., 2012; Heron et al., 2004; Huurre et al., 2007; Issakidis and Andrews, 2004; Johnson et al., 2008; Katona and Shankar, 2004; Lamers et al., 2012; Lewis et al., 2016; Matthews et al., 2004; Powell et al., 2013). We suspect this may be due to specific characteristics of the present sample, which was recruited for an fMRI study as young adults (age 18–23 years) who were remitted from depression (and thus had low levels of symptoms), and most of whom had 12–16 years of education. Thus, a restricted range of variability on these measures (age, education, and symptoms) might be the most parsimonious explanation for why these factors were not associated with attrition in the present sample. Rates of attrition in our study (at 18%) were lower than those of most prior studies already reviewed, in which attrition ranged from 13% to 87% across a variety of age ranges. However, attrition rates likely vary considerably based on sample population and study procedures such as length and burden of

follow-up (about 2 months in our study, but longer in many other studies); thus, it cannot be assumed that our results necessarily generalize to all populations and to different types of studies. Future studies with larger samples and broader inclusion criteria will be needed to more comprehensively test these other factors as potential indicators of risk for attrition, and to replicate the results of this study to determine generalizability.

Our study is the first to our knowledge to explore how head motion is associated with attrition differentially across the course of a scan session. These data potentially have implications for understanding more about when to help participants feel more comfortable or more engaged with the scan tasks. In our data, smaller group differences were observed during runs 9–12 during a facial emotion processing task. One speculative explanation is that this task might have been more interesting or engaging than other tasks participants completed, thus perhaps requiring less inhibitory control to remain still, leading to less ability to distinguish individuals who are at risk for dropout. In contrast, other portions of the study (e.g., the last run, which was a resting-state scan that may have been less engaging, and the go/no-go task that is designed to be cognitively challenging) showed more apparent differences between dropouts and nondropouts, perhaps because these tasks required more inhibitory control to remain focused or prevent oneself from moving. Future studies should consider reporting data on attrition rates in relation to head motion across scan runs to either corroborate or note the limitations to the generalizability of these results.

Several strategies may be considered to reduce problems associated with attrition. To achieve a representative longitudinal sample, investigators may need to strategically oversample individuals who are at risk for attrition (Anderson et al., 2017), perhaps based on individual differences in inhibitory control or behavior (e.g., movement) during the first scan. It also may be beneficial to engage strategies to facilitate the retention of participants who are at risk for attrition. For example, using a mock scanner, providing breaks between scan sequences, or ensuring sufficient time for participants to physically adjust in the scanner environment before the scan might improve comfort. In addition, administering a brief postscan satisfaction interview or survey to assess comfort during the scan could lead to the enhancement of scanning procedures and help to identify individuals whose scanning experiences could be improved in the future. Other strategies such as contacting these individuals more frequently across follow-up or enhanced incentives to stay active in the study for individuals at risk for attrition potentially also could be useful. It might also be useful to plan extra time to check on individuals' comfort before starting the scanning session, particularly for individuals who are known to have worse inhibitory control. Although sometimes infeasible, if head motion is detected during the scan itself, it is possible that offering participants a chance to readjust would improve their subjective experience and make them more likely to return for future study visits that include scanning. Of course, future studies will need to investigate effects of such interventions before strong claims can be made about the effectiveness of these strategies.

In addition to oversampling participants who may be at risk for attrition to minimize attrition bias, several procedural strategies may be implemented to enhance participant retention.

These include asking participants for current contact information at each study visit for themselves and for two individuals who are likely to know their whereabouts; maintaining participant tracking databases (Cotter et al., 2002); maintaining consistency in study staff or interviewers over time; regular telephone reminders; mailing thank-you cards as well as birthday and holiday cards; sending a study newsletter or updates on the project's status; facilitating timely incentive payments; and facilitating travel to appointments (e.g., paying for convenient transportation), particularly when study locations are relatively inaccessible (e.g., are far away from participants' homes) (Arean et al., 2003; Ashing-Giwa and Ganz, 2000; Gauthier and Clark, 1999; Hessol et al., 2001; Leonard et al., 2003; Parra-Medina et al., 2004; Russell et al., 2001; Scott, 2004; Yancey et al., 2006).

Despite the novel contribution of this study and the strengths of using an unmedicated remitted depressed sample, a number of limitations must be noted. First, the sample of individuals who dropped out was relatively small, as was the proportion of variance in dropout that was predicted, so results must be replicated before firmer conclusions can be drawn. Second, as a result of dropping out, we are unable to determine the reason that most individuals did not return for the second scan; although it could be assumed that they no longer were interested, it is possible that there could be other explanations, such as having a more chaotic lifestyle (e.g., poor planning skills), finding the testing experience unpleasant, or moving out of the area. Third, because we did not systematically measure discomfort or anxiety within the scanner (e.g., with a postscan questionnaire), we are unable to conclusively determine whether this could explain why some individuals dropped out. Fourth, the use of a relatively young sample early in the illness means that the generalizability of the results to older populations is not clear. Fifth, many of the supplemental analyses (e.g., the correlation analyses presented in the Supplementary Table S1) were relatively exploratory and uncorrected for multiple comparisons, and thus should be considered preliminary and requiring replication due to the possibility of Type I error. Finally, although resting-state connectivity analyses controlled for individual differences in movement within the scanner, it remains possible that movement artificially attenuated measurements of connectivity (Power et al., 2015), thus accounting for the relationship detected between attenuated connectivity and attrition. In addition, recent data have demonstrated that the use of 12-min resting-state scans can ascertain more reliable connectivity values (Birn et al., 2013).

Conclusion

In conclusion, this study suggests that inhibitory control and head motion are related to each other and are important factors to consider when designing longitudinal fMRI studies. By evaluating these factors, investigators might be able to implement strategies to reduce attrition and/or improve the validity and generalizability of longitudinal research studies.

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No competing financial interests exist.

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