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Cognitive Intra-Individual Variability: The Effects of Affect in a Healthy Young Adult Sample

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COGNITIVE INTRA-INDIVIDUAL VARIABILITY: THE EFFECTS OF AFFECT IN A HEALTHY YOUNG ADULT SAMPLE

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ABSTRACT

Cognition is foundational to our experience of the world, but also to how psychologists understand dysfunctions. Cognitive impairment is a feature of a variety of mental disorders, but traditional assessment measures have key limitations in prediction and classification. A proposed alternative is cognitive intraindividual variability (cIIV), which is suggested to measure cognitive control or neural inefficiencies, fluctuating within a task, or over short periods of time. cIIV has been shown to be more sensitive in classification for a variety of conditions than overall performance, including in affective disorders. Further, some research suggests that cIIV is related to self-report cognitive abilities, and some domains of cIIV may relate to positive and negative affect. This study examined the relationship between negative and positive affect and cIIV, and cIIV and self-reported concentration ability, in an ambulatory assessment of executive functioning in a college aged sample. Sixty-two college students provided data on the TrailMaking Task, along with self-reported negative and positive affect (k = 167) and concentration ability (k = 132). Only negative affect was associated with a change in cIIV, where increased negative affect resulted in decreased cIIV. This unexpected finding, in context of past literature, suggests a variety of future directions: ascertaining whether the relationship between negative affect and cIIV is linear or curvilinear, exploring the ways affect increases or decreases cIIV on tasks which require different cognitive functions, and exploring the differences between within and across trial cIIV.

INTRODUCTION

Cognition and Cognitive Functioning

Cognition is the collection of processes which enable us to acquire, organize, and use knowledge about the world to interact with it in a meaningful way (Bender & Beller, 2013; Goldstein, 2015, p. 5). It includes a variety of mental processes and functions such as perception, attention, learning, language, memory, executive functioning (e.g. planning, decision making, error correction…), and perceptual motor skills (American Psychiatric Association, 2013; Goldstein, 2015, p. 5). These processes are foundational to our experience of, and interaction with, the world. The effect of our experiences with the world on our emotions and feelings is affect, another important process. While these processes largely go unnoticed, they are not necessarily without cost. Cognition especially requires mental and neural resources, and when those resources are stretched, performance declines (Franconeri, Alvarez, & Cavanagh, 2013, Moscovitch, 1994). Performance can decline due to the difficulty of a task, but also due to physiological changes, such as sleep deprivation (Pilcher & Huffcutt, 1996) or intoxication (Curtin et al., 2001). Sometimes, poor cognitive performance, otherwise known as cognitive impairment, is not due to context but rather to neurological or psychological problems which are context-independent.

The Importance of Cognitive Impairment

Cognitive impairment is closely related to a variety of mental illnesses, such as dementia, depression, bipolar disorder, and schizophrenia. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) classifies mental health conditions into a variety of categories, and cognitive impairment is closely related to many of these. Most

closely related to cognitive impairment are the neurocognitive disorders: delirium, major neurocognitive impairment and mild neurocognitive impairment, where it is the definitional feature (American Psychiatric Association, 2013). In mild neurocognitive impairment the boundary between normal cognitive decline that accompanies aging and cognitive impairment is especially contested and important as it is used to predict who will begin the steep descent into dementia, and other disorders which seriously impair functioning (Winblad et al., 2004). Cognitive impairment is also common to affective disorders and psychotic disorders. Affective disorders include depressive and bipolar disorders, each of which have their own section in the DSM-5. Depression is a syndrome connecting symptoms like sad mood, changes in sleeping or eating, and loss of energy and pleasure (Fried, Epskamp, Nesse, Tuerlinckx & Borsboom, 2016). Rock and colleagues (2013) conducted a systematic review and meta-analysis which indicated that cognitive impairment should be considered a core feature of depression as there are persistent deficits in both patients with current depression as well as those who have remitted from an episode when compared to controls. Bipolar disorders can include depressive episodes, but also periods of hypomania – exceptionally good mood and high energy, or mania – which can turn from good mood to irritability and include psychosis and risk taking which compromises the individual's functioning and well-being (American Psychiatric Association, 2013). In a meta-analysis of euthymic patients with bipolar disorder (patients who were not currently manic or depressed), global cognition was impaired in even after controlling for depression (Bourne et al., 2013). Broad cognitive impairment is also a hallmark of schizophrenia (Schaefer et al., 2013), a disorder characterized by psychosis, such as hallucinations or delusions, and disorganized speech and behavior (American Psychiatric Association, 2013). Cognitive impairment is also higher among those who are at high risk of developing psychotic disorders,

such as schizophrenia, regardless of whether they actually progress to a psychosis, with some forms of impairment being even more severe in those who progress to psychosis, indicating potential biomarkers of vulnerability to clinical crisis (Brewer et al., 2005). While much of mental health conception and diagnosis has focused on other symptoms of distress, cognitive impairment is a significant aspect of diagnoses spanning across the typical distinctions created to separate mental health conditions.

Limits of Traditional Cognitive Measurement

Given that cognitive impairment is broadly related to psychopathology and is an important facet of understanding clinical progression and functioning, sensitive and specific measurement is critical. Measures of cognitive impairment ideally would be able to distinguish between conditions. Traditional measurement of cognitive impairment has relied on overall performance metrics, such as error rate or time to completion of a task (e.g. Ashendorf et al., 2008). Overall performance measurements are not always sufficiently specific, such as in the case of differentiating between normal aging and the steep decline of dementia early enough for prevention, necessitating other measures as corroboration (Winblad et al., 2004).

Further, cognitive performance is more variable than overall performance metrics suggest. Arousal and increased adrenaline induced by physical exercise can improve cognitive performance (Brisswalter et al., 2002), as can environmental conditions such as the ambient lighting, noise and temperature (Hygge & Knez, 2001). But beyond the variability due to situational factors, in non-clinical populations, cognitive performance varies within individuals and within a session about half as much as it does between individuals (Nesselroade & Salthouse, 2004). Furthermore, this variability follows an inverted-U shaped curve over the

lifespan, with children and the elderly showing the highest rates of variability (Williams et al., 2005). The magnitude of this variation and its developmental change suggests important processes which mean level statistics may not adequately capture. As such, mean level comparisons may be less sensitive because they collapse individual variation and group variation (Nesselroade & Salthouse, 2004). Metrics that account for individual variation may therefore be more sensitive.

Cognitive Intraindividual Variability

Cognitive intraindividual variability (cIIV), has emerged as a more sensitive alternative to overall performance in categorizing clinical states and predicting functional change (e.g. Hultsch et al., 2000; Kaiser et al., 2008; Strauss et al., 2002). cIIV is a measure of how an individual's performance within a task of cognition, or across repeated administrations of the same task, can change over fairly short periods of time. These variations over a short time period are in contrast to intraindividual change, which denotes variation in performance across longer time durations (e.g., years) due to development or adaptation (Ram & Gerstorf, 2009). Intraindividual variability (IIV) been studied in a variety of fields aside from cognition, including affect (e.g., Eid & Diener, 1999), movement, pain, and self-perceived control (e.g., Strauss et al., 2002). By explicitly studying variability, the analyses in these studies can parse out variation due to individuals versus due to group differences. Understanding what causes those fluctuations and where they are most prominent allows that information to be used (Williams et al., 2005; Nesselroade & Ram, 2004) to classify individuals into diagnostic categories, and predict clinical outcomes, more sensitively than overall performance.

cIIV: Concurrent and Predictive Validity

cIIV correlates with decreased overall performance (Hultsch et al., 2000). Even still, when comparing the two in classifying group membership in neurodevelopmental and neurodegenerative conditions, cIIV often has greater predictive power (Hultsch et al., 2000; Strauss et al., 2002). In the domain of neurodevelopmental disorders, cIIV has been studied in Attention-Deficit/Hyperactivity disorder (ADHD), a disorder characterized by a persistent pattern of either inattention or hyperactivity and impulsivity which interferes with functioning or development (American Psychiatric Association, 2013). In ADHD, reaction time variability on a cognitive task has been shown to relate to inattention and hyperactivity-impulsivity more strongly than did errors of commission (Kuntsi et al., 2013). Similarly, while both individual overall performance and individual reaction time variability were predictive of cognitive status change in a prospective five-year study of older adults, an increase in variability was more detrimental than a lower overall performance at baseline (Bielak et al., 2010). As well as differentiating group membership, cIIV also has particular and interesting relationships with other forms of IIV in older adults. cIIV is associated with affective IIV; and in some subgroups, with inconsistency in perceived control (Strauss et al., 2002). The relationship between cIIV and IIV of perceived control is particularly interesting, as there has been evidence that cIIV is responsive to targeted feedback designed to decrease IIV in older adults (Garret et al., 2012). In older adults specifically, cIIV seems to be consciously accessible and even responsive to conscious control. In both older adults and developing children, cIIV performs differently from overall performance. These relationships begin to illustrate what might be driving cIIV and highlight potential targets for reduction of cIIV.

Affective disorders and psychosis spectrum disorders also show particular patterns of cIIV. A study comparing individuals with depression, bipolar disorder and a current depressive episode, bipolar disorder in a euthymic stage, and controls found that all three clinical groups could be differentiated from controls in their cIIV and that different indices of cIIV differentiated different groups, though the individuals with depression were least robustly distinguished from controls (Gallagher et al., 2015). Another study compared controls to individuals with schizophrenia, individuals with depression, and individuals with borderline personality disorder, a pervasive pattern of impulsivity and instability in relationships, affect, and self-image (American Psychiatric Association, 2013; Kaiser et al., 2008). cIIV robustly distinguished the individuals with schizophrenia from controls and distinguished those with borderline personality disorder and depression from controls in certain situations. However, when looking solely at mean reaction times and accuracy, those with schizophrenia were reliably differentiated, but participants with depression and borderline personality disorder were less consistently differentiated from controls (Kaiser et al., 2008). Individuals with schizophrenia consistently show increased cIIV relative to controls (e.g. Kaiser et al., 2008; Pietrzak et al., 2009; Shin et al., 2013), and this increased cIIV is stable across time (Pietrzak et al., 2009). Symptom severity in individuals with schizophrenia correlates positively with cIIV (Shin et al., 2013), where increased severity is associated with increased cIIV. cIIV may actually be a biomarker for psychosis, as it has also been documented in individuals who are considered "ultra-high risk" (UHR) for psychosis. UHR individuals show cIIV scores that do not differentiate from individuals with schizophrenia, but do differentiate from controls, even when the mean scores do not differentiate UHR individuals from controls but do differentiate those groups from individuals with schizophrenia (Shin et al., 2013). Beyond neurodevelopmental and

neurodegenerative disorders, cIIV has important relationships to affective and psychotic spectrum disorders. Accounting for cIIV above and beyond mean scores has interesting implications for transdiagnsotic understandings of psychopathology.

What Influences cIIV?

While there is sufficient evidence to support cIIV as an important part of prediction and classification, emerging research is examining what contributes to cIIV. Understanding the contexts and characteristics which exacerbate cIIV may suggest targets for remediation programs to diminish cIIV, improve overall performance, and provide insight into the mechanisms underlying cognition-related disorders. Given that in nonclinical populations, cIIV can be proportionately half of the variation between individuals, and that clinical populations show greater cIIV than non-clinical populations, decreasing cIIV may be result in meaningful improvements (Nesselroade & Salthouse, 2004; Kaiser et al., 2008). cIIV is related to executive functioning, working memory, and cognitive control (Lövdén et al., 2007). High cIIV may indicate inefficient processing at the neural level and has been associated with increased "noise" in the brain, possibly due to decreased dopamine in the synaptic cleft (MacDonald, Nyberg & Bäckman, 2006; Lövdén et al., 2007). This perspective on cIIV suggests that states which decrease neural efficiency, and interfere with executive functioning, working memory, or cognitive control, would also increase cIIV.

One potential such state would be high positive or negative affect, as emotion states are known to recruit a variety of brain areas (Phan et al., 2002), and the processing of emotion is related to increased dopamine release (Badgaiyan, Fischman, & Alpert, 2009). This possibility is also supported by the research in clinical populations, which suggests a link between affective

disorders and cIIV (Kaiser et al., 2008; Gallagher et al., 2015). Gallagher and colleagues' (2015) study show that euthymic and depressed individuals with bipolar disorder both show cIIV by some metrics. However, clinical diagnostic conditions are associated with a variety of other confounding conditions, such as medication exposure, life circumstance, and difficulties with motivation. As such, simply comparing clinical cohorts to controls does not provide conclusive information as to whether cIIV affected by emotional arousal. Some studies have explicitly explored the relations between cIIV and affect, either negative (Brose et al., 2012; Sliwinski et al., 2006) or positive and negative (Salthouse & Berish, 2005; von Stumm, 2016). The results thus far have been inconclusive. Studies which particularly focus on working memory tasks have found that reaction time variability was related to daily stress in a sample of college students and older adults (Sliwinski et al., 2006), and that day-to-day variability in accuracy was related to negative affect through motivation and subjective control of attention (Brose et al., 2012). However, reaction time variability in a task similar to the TrailMaking Task, a measure of executive control and task-switching (Sanchéz-Cubillo et al., 2009) in a sample of adults ranging from 18-91 years old did not relate to overall mood (Salthouse & Berish, 2005). This study is limited by the measure of mood, however, which treated mood as a single dimension, when evidence has long existed that positive and negative affect are not perfectly negatively correlated especially during periods of low emotionality (Diener & Emmons, 1984). Only one study has examined negative and positive affect separately, looking at their effect on day-to-day variability in accuracy in tasks of short-term memory, processing speed and working memory. This study found that positive affect influenced day-to-day variability in processing speed (von Stumm, 2016).

Another possibility is that cIIV changes with other self-reported states which are associated with depleted cognitive resources- the ability to attend to and complete multiple tasks, including tasks such as emotion regulation (Brose et al., 2012). In a study conducted with individuals diagnosed with multiple sclerosis, cIIV was positively correlated with cognitive fatigue, even when controlling for overall performance, but the reverse did not hold – when controlling for cIIV, overall performance was not associated with cIIV (Bruce, Bruce & Arnett, 2010). Similarly, in individuals with dementia, changes in beliefs about self-efficacy and perceived control negatively correlated with cIIV (Strauss et al., 2002). Again, each of these findings was largely in a clinical sample. A possible implication of these results is that individuals are aware of their diminished cognitive resources and could in fact predict when they were likely to show high cIIV. However, the study conducted by Bruce and colleagues (2010) does not quite answer that question, as it only addresses whether the participants found the tasks cognitively demanding, not how they would rate their prospective cognitive abilities. Results from Brose and colleagues (2012), suggest that subjective control of attention may be an important path which influences cIIV.

This study explored three possible sources of cIIV, all measured using state self-report: positive and negative affect and concentration, in reaction time variability of the TrailMaking Task as a measure of executive control. Further, this study checked for overall psychopathology burden as a covariate, to control for the potential variation associated with baseline affective states but did not find an effect of "trait" level psychopathology. The first aim of this study was replication of prior findings, which was explored with two separate hypotheses. The first hypothesis was that measures of variability confounded by overall performance will be greater in the more difficult task, but when the influence of overall performance is removed, variability

does not differ by task type. Further replication of previous findings tested the hypothesis that within person variability is about half of the between person variability. The second aim was to explore factors which influence cIIV in the moment. This aim was also explored with two separate hypotheses, including that increased positive or negative affect will increase cIIV in this task and that increased self-reported ability to concentrate will decrease cIIV in this task. An exploratory analysis examined whether the variation due to affect accounts for any predictive power above and beyond self-reported concentration ability.

METHODS

Participants

Archival data from 63 college students attending a state school in the Southeastern USA was used. This sample was chosen to minimize the likelihood of latent mild cognitive impairment due to aging and given the importance of age on cIIV (Williams et al., 2005), only individuals who were 18-29 years old were included. Due to technical difficulties, one participant's data was excluded, for a final $N = 62$. In exchange for participation, they were given participation credits which could be used as extra credit in their courses. Participants completed the *delta* Mental State Examination mobile application (dMSE app), on the smart device of the participant's choice.

Measures

The Brief Symptom Inventory. The Brief Symptom Inventory (BSI; Derogatis & Melisaratos, 1983) is a 53-item self-report scale which measures the nine primary symptom dimensions of the SCL-90-R (including somatization, obsessive-compulsive, interpersonal sensitivity, depression, anxiety, hostility, phobic anxiety, paranoid ideation and psychoticism). Each item is rated on a 5-point scale of distress, ranging from "not-at-all" (0) to "extremely" (4). This scale was delivered electronically using an online survey delivery platform. In this sample, the BSI had a high internal consistency (coefficient alpha = 0.96).

The Trail-Making Test. Intra-trial reaction time variability on the TrailMaking test (Trails), presented on dMSE app was the measure of cIIV. This task comes in three versions. In each version, the participant uses their finger to connect consecutive dots. In Trails version A, the dots are lettered and the participant must connect from A to B to C and so on. In Trails

version B, the dots are numbered, and the participant must connect from 1 to 2 to 3 and so on. In Trails version C, letters and numbers alternate, so the participant connects from 1 to A to 2 to B.

Affect and Concentration. Self-report state assessments, included affect and concentration, were measured using a digital slider scale coded on a scale from 0 to 100. Participants responded to a prompt asking about their current emotional state, such as "How happy are you today?", with possible answers ranging from "Not happy" (0) to "Very happy" (100). There was a total of six possible positive affect (PA) questions (i.e., hopeful, calm, appreciated, strong, happy, energetic) and seven possible negative affect (NA) questions (i.e. anxious, frustrated, afraid, sad, stressed, angry, helpless), but at each session, participants were only were presented with a random selection of five positive (PA) and five negative (NA) affect related sliders (Watson, Clark, & Tellegen, 1988). The PA composite included all six PA questions, and the NA composite included all seven NA questions. The concentration slider was given for some, but not all sessions. Given that variability would be expected across sessions, internal consistencies for each scale were computed at each session. For NA, internal consistency was fair to good at each session (coefficient alpha session 1 = 0.70; coefficient alpha session 2 = 0.87; coefficient alpha session 3 = 0.84; Cicchetti,1994). Internal consistency for PA ranged from poor to fair (coefficient alpha session 1 = 0.57; coefficient alpha session 2 = 0.79; coefficient alpha session 3 = 0.64; Cicchetti,1994), likely in part because there were fewer items on the PA scale. A similar question and response scale was given for concentration, with "Can you concentrate?" rated from "Cannot concentrate" (0) to "Steady concentration" (100).

Procedure

Participants were given a written description of the study and provided their consent. Once they did so, they were given a download link which enabled them to download the dMSE

app onto a smart device of their choosing. The dMSE app includes a variety of tasks and self-report metrics, beyond those which are of interest in this study. Participants were asked to complete the app at the time of their choosing when they would have a half hour in a quiet space, free of distraction. They were to complete the application on three separate, consecutive days, including answering the sliders, and completing the Trails task. Sixty-two participants completed the first survey, and data from three sessions is available for 50 participants, for an attrition rate of 19%. After completing the three days, they were given a final survey and compensated for their participation with course credits.

Statistical Analyses

As described by Wang and colleagues (2012) in a paper on calculating intraindividual variation, the intraindividual standard deviations ISD is the square-root of the variance of an individual's scores at different time points around their individual mean. As it is based on raw scores, it is sensitive to individual trends over time, and in cases where the distribution of means is skewed, then the ISDs and the means will artificially be correlated. Dividing the ISD^2 by the individual's mean produces the individual coefficients of variation (ICV) and accounts for the effect of overall performance.

Data Cleaning, Preparation, and Checking. In this study, the dependent variable was the individual coefficient of variation (ICV) of Trails response times. The ICV was calculated from the Trails intratrial response times by taking the squared individual's standard deviation of inter-stimulus response times and dividing that by their mean inter-stimulus response time on the given trial. The independent variables are state self-reported concentration and state self-reported positive and negative affect.

First, continuous demographic, dependent, and independent variables were examined for normality of distribution. Trails A and B error rates were skewed (skew ≥ 3) and kurtotic (kurtosis >10). The ICV of Trails B and C were both positively skewed and leptokurtic. Trails mean times and ICV scores with values greater than 3.5 standard deviations above the mean were deleted, and values from 3.0 to 3.5 standard deviations above the mean were replaced with values at 3.0 standard deviations above the mean (winsorized). Initially, this same procedure was applied to the error rates as well, but given that there was not enough range in the error rates in Trails A and B, these values only were winsorized, while Trails C error rates had enough variability to require both exclusion and winsorization. After these transformations, all meantimes and ICV variables had skew ≤ 3.0 and kurtosis < 10.0. Subsequently, zero-order correlations between the dependent variable, independent variables, clinical and demographic variables were computed to assess for any potential confounds, and none were identified. Bonferroni corrected t tests comparing mean times and error rates for all versions of Trails by gender did not find any statistically significant differences (all values of $p \geq .08$). A zero-order correlation between errors and mean response time for each version of Trails were computed to verify these metrics were not co-linear. Correlations ranged from $r = -.03$ to $r = .16$, which does not indicate co-linearity. We also compared the individual standard deviations (ISDs) of each version of Trails to the overall meantime and error rate on that version of Trails, expecting that higher ISD correlates with higher reaction times, and higher error rates. Only Trails C ISD was significantly associated with an overall Trails performance metric, as Trails C ISD was negatively correlated with error rates ($r = -.43$; $p < .001$). Individuals who made more errors on Trails C had less variability, contrary to expectations. To check for practice or fatigue effects, intraclass correlations for ICV on each version of Trails were computed across the sessions.

Trails B had the lowest stability (coefficient alpha = .24), followed by Trails A (coefficient alpha = .43), and Trails C had the highest stability (coefficient alpha = .75). Linear regressions nested by individual with session predicting cIIV and session predicting mean time showed that there were practice effects for Trails B and Trails C, where cIIV significantly decreased with more sessions. A linear regression with BSI scores predicting cIIV was run to test if "trait" level psychopathology burden was a covariate, given that cIIV has been so strongly associated with clinical state (e.g. Gallagher et al., 2015; Kaiser et al., 2008). Psychopathology burden was not found to significantly predict ICV, and therefore BSI scores were not accounted for in subsequent analyses. Individuals who completed three trials (n = 50) were compared those who completed only one (n = 7) on their Trails scores, BSI scores, mean concentration and mean affect using Bonferroni corrected t tests. No statistically significant differences were found (all p's ≥ .21).

Analytic plan. As part of our replication, we compared the cIIV for the three different Trails versions using Bonferronni corrected t tests, with the hypothesis (Hypothesis 1) that the ISDs for Trails version C, which requires inhibition, will be higher than the other Trails versions, but that accounting for the overall performance by taking the ICVs will eliminate any differences. A further replication, of Nesselroade and Salthouse (2004), required computing two new metrics: between individual variation (BIV) and mean intraindividual variability (MIIV) Means and standard deviations for each individual were computed across sessions. The standard deviation of those means is the BIV. The means of the standard deviations is the MIIV. A ratio of BIV to MIIV tested Hypothesis 2: within individual variability is about half of between individual variability. Each of the novel hypotheses were evaluated using a multilevel modeling procedure which allows nesting for subjects (random effect). First, Hypothesis 3 was that

positive or negative affect will increase cIIV and was tested with one multilevel model predicting cIIV by state negative affect, and another multilevel model predicting cIIV by state positive affect. The same procedure was repeated for state self-reported concentration, to test Hypothesis 4: that increased state concentration would decrease cIIV. The exploratory analysis was assessed using separate two-step multilevel models. Each model predicted cIIV by session and self-report concentration in the first step and added affect (either positive or negative) in the second step. The exploratory analysis predicted the second step will not be a significant improvement for either positive or negative affect.

Power Analysis and Sample Size

Power analyses for multilevel models are difficult to estimate given the number of parameters to account for. As such, an accepted way to do so is based on simulation data (Snijders, 2005). Much like other effect size calculations, a predicted effect size is added to a hypothetical model, though this hypothetical model is then run a thousand times to see in what percent of those cases would significance be found for a given value of alpha. This percentage is the power. To conduct power analyses *a priori,* as in this case, one can also run the model for varying *N* sizes, with a given predicted effect size to estimate what sample size is necessary for a desired level of power. Using R package *paramtest* (Hughes, 2017), we estimated the power for a sample of 60 with 3 sessions at b of 0.15, 0.20, 0.25 and 0.30, a range of moderate effect sizes based on the literature found on cIIV and affect. At b = 0.15, power = 0.45, b = 0.20, power = .76, b = 0.25, power = .86, and for b = 0.30, power =.97. Given that this sample has already been collected, and we have data for 62 participants, assuming the effect size is above b = 0.25 this study is sufficiently powered.

RESULTS

Descriptive Statistics

We had a total of 62 participants with a mean age of 19.82 years old (range = 18 - 23). The majority were white (80.65%, $n = 50$) and female (87.10%, $n = 54$). The average BSI score was fairly low ($M = 0.76$; $SD = 0.58$, range = 0 – 2.26), approximately "a little bit" on a scale from "not at all" (0) to "extremely" (4). The sliders showed considerably more variation. The positive affect slider composite ($M = 66.61$, $SD = 17.05$, range = 14.27 – 100.00), the negative affect slider composite ($M = 26.58$, $SD = 17.96$, range = 0.00 – 85.71) and the self-reported concentration ability slider ($M = 55.75$, $SD = 27.52$, range = 0.00 – 100.00) all seemed to indicate that participants understood how to use the sliders, and were willing to endorse a variety of mood states. All slider and performance data broken down by session is presented in Table 1. Correlations between slider data, mean times, and ICV for each version of Trails is presented in Table 2.

Table 1. Raw data by session for self-report sliders and performance on Trails.

	Session 1 *M* (*SD*)	Session 2 *M* (*SD*)	Session 3 *M* (*SD*)
Negative Affect	27.76 (15.13)	28.08 (20.36)	23.46 (18.37)
Positive Affect	65.51 (14.48)	67.88 (17.69)	66.58 (19.39)
Concentration	52.24 (26.02)	57.03 (27.77)	58.63 (29.28)
Trails A Meantime	387.97 (87.29)	373.37 (87.24)	388.31 (105.50)
Trails A ICV	1.79 (0.40)	1.81 (0.43)	1.77 (0.36)
Trails B Meantime	403.51 (98.80)	388.13 (133.51)	376.46 (111.66)
Trails B ICV	1.66 (0.57)	1.67 (0.54)	1.77 (0.46)
Trails C Meantime	716.95 (234.01)	678.62 (208.61)	681.44 (230.71)
Trails C ICV	3.53 (0.58)	3.59 (0.54)	3.75 (0.46)

Note. Mean-times are the average time to complete one connection on the TrailMaking Test in miliseconds.

Table 2. Correlations between slider data, mean times, and ICV data

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Negative Affect	—								
2. Positive Affect	-.56	—							
3. Concentration	-.32	.49	—						
4. Trails A Meantime	.05	-.13	-.18	—					
5. Trails B Meantime	.26	-.15	-.03	.32	—				
6. Trails C Meantime	.26	-.12	-.13	.30	.35	—			
7. Trails A ICV	-.18	.11	.06	-.34	.04	-.12	—		
8. Trails B ICV	-.19	.03	-.10	-.06	-.51	-.14	.01	—	
9. Trails C ICV	-.29	.08	.16	-.34	-.38	-.73	.18	.23	—

Hypothesis 1: ISDs are inflated for Trails version C by worse overall performance

This hypothesis was tested by Bonferroni corrected t tests comparing each the ICVs of each version of the Trails test to each other, and the ISDs of each version of the Trails test to each other. There was no significant difference after Bonferroni correction between the ISD of Trails A and Trails B ($t(165)= 0.73$, $p = .50$, $d = 0.06$), but there was a significant difference between the ISD of Trails A and Trails C ($t(164) = -39.22$, $p < .00001$, $d = -3.05$), and Trails B and Trails C ($t(163) = -34.11$, $p <.00001$, $d = -2.66$). This same pattern was found in the ICVs as well, where there was no significant difference between the ICV of Trails A and Trails B when the significance level was Bonferroni corrected ($t(164)= 2.49$, $p = .01$, $d = 0.19$), but there were significant differences between the ICV of Trails A and Trails C ($t(163) = -38.95$, $p < .00001$, $d = -3.04$) and Trails B and Trails C ($t(161) = -45.81$, $p <.00001$, $d = -3.60$). These results contradict the hypothesis that the ISD of Trails C is only inflated by worse overall performance. Hypothesis 1 was not supported.

Hypothesis 2: cIIV is about half the Between Individual Variation

The analyses for this hypothesis required computing the between individual variation and comparing it to the within individual variation. These comparisons were done separately for each version of the Trails test. The results are presented in Table 3. In all three tests, the within individual variation is more than half the between individual variation. Hypothesis 2 was supported.

Table 3. Comparing between and within individual variation in three versions of the TrailMaking Test.

Version	Between Individual Variation	Within Individual Variation	Ratio
A	0.11	0.09	.83
B	0.13	0.11	.84
C	0.24	0.16	.69

Hypothesis 3: Increased positive or negative affect will increase cIIV

The results of the models testing positive and negative affect, including session as a fixed factor to account for practice effects, are presented in Table 4. The first model tests negative affect. The second model tests positive affect. Session was a significant predictor in both models. Negative affect was a significant predictor of cIIV, but positive affect was not a significant predictor. However, the relationship between negative affect and cIIV went in the opposite direction predicted: increased negative affect was associated with decreased cIIV. This relationship is illustrated in Figure 1. The relationship between positive affect and cIIV is illustrated in Figure 2. Hypothesis 3 was not supported.

Table 4. Multi-level modeling of cIIV for Trails C

	B (SE)	*t*	*logLikelihood*	χ^2	$p(\chi^2)^b$
Model 1 [c]			-106.53	20.46	<.001
Session	0.12 (0.04)	3.38*			
Negative affect	-0.01 (0.002[a])	-2.87*			
Model 2 [c]			-110.41	12.71	.002
Session	0.13 (0.04)	3.74*			
Positive affect	-0.001[a] (0.003[a])	-0.38			
Model 3[d]			-89.43	7.58	.02
Session	0.11 (0.05)	2.37*			
Self-Report Concentration	0.002[a] (0.002[a])	1.35			

Note. * p <.05. [a] Given to three decimal places to show the full value. [b] Relative to the "null" model including only the random intercept. [c] k = 164, [d] k = 130

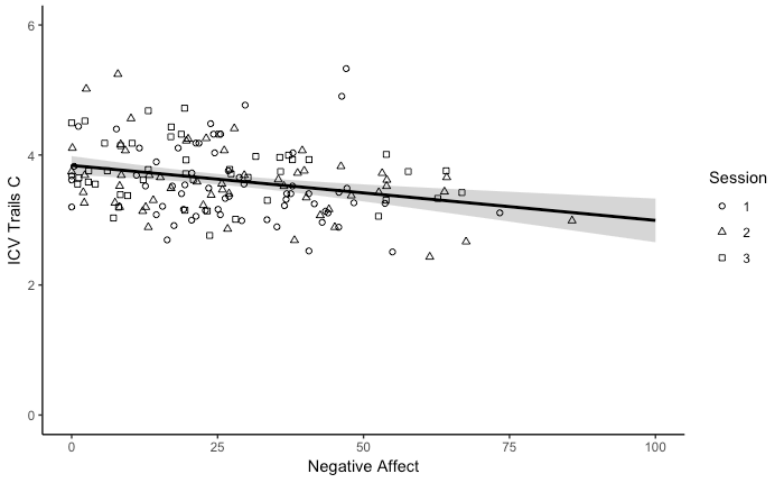

Figure 1. The relationship between negative affect and ICV for Trails C (raw data, not nested by participant).

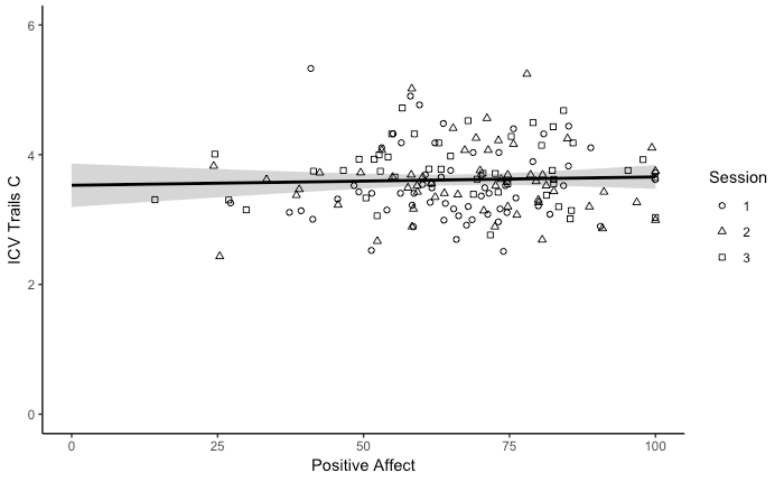

Figure 2. The relationship between positive affect and ICV for Trails C (raw data, not nested by participant).

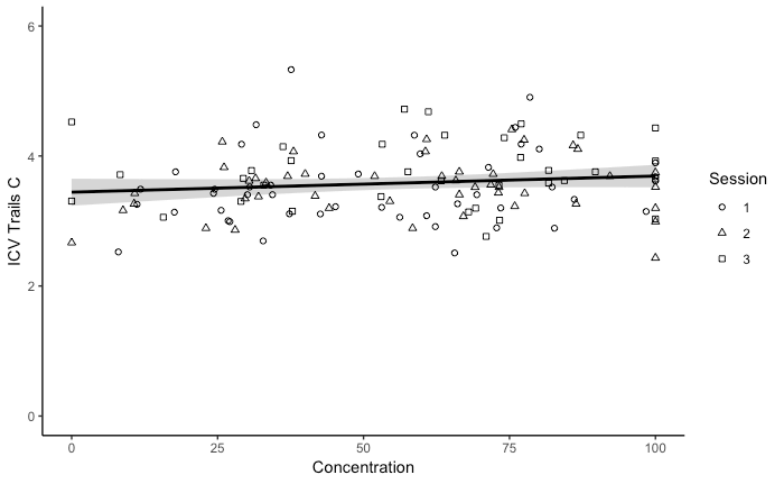

Figure 3. The relationship between self-reported concentration and ICV for Trails C (raw data, not nested by participant).

Hypothesis 4: Increased self-reported ability to concentrate will decrease cIIV

The results of the model testing self-reported concentration, including session as a fixed factor to account for practice effects, are presented in Table 4 in the row for model 3, and in Figure 3. Self-reported concentration was not a significant predictor of cIIV, though session was a significant predictor. Hypothesis 4 was not supported.

Exploratory Analyses: The effects of positive and negative affect do not add anything above the effects of subjective concentration ability

The model predicting cIIV by concentration was not significant (see Table 4 for beta weights). Adding negative affect to this model resulted in a significant contribution ($\chi^2 = 5.50$, $p = .02$), and therefore did not support the hypothesis that the effect of negative affect does not add anything above the effect of subjective concentration ability. However, adding positive affect to the original model did not result in a significant contribution ($\chi^2 = 0.07$, $p = .79$), which does technically support the hypothesis that the effect of positive affect does not add anything above the effect of subjective concentration. The hypothesis underlying the exploratory analyses was partially supported.

DISCUSSION

Review of Findings

This study examined cognitive intraindividual variability in a healthy young adult sample with the aim of exploring factors which cause increased variability in the moment. The first aim of the study was to replicate previous findings. The first hypothesis of this aim was that measures of variability which are confounded by overall performance are inflated. However, the results of this study do not support the hypothesis that ISD is inflated and ICV is not. Both measures of variability were found to be significantly higher in the hardest version of the task. The second hypothesis in the replication aim was that within individual variability is about half of between individual variability. This hypothesis was supported, and this study found that within individual variability was actually relatively more substantial than predicted by past studies (Nesselroade & Salthouse, 2004). The second aim of the study was to explore causes for increased variability within individuals. This aim was explored with two hypotheses: that increased positive or negative affect would increase variability, and that increased self-reported concentration would be connected to decreased variability. Neither of hypotheses were supported: negative affect was connected to cIIV, but in the opposite direction predicted, and subjective concentration and positive affect were not significant predictors of cIIV. The exploratory analysis comparing the relative contributions of self-reported concentration and affect was supported in part – positive affect and concentration did not add anything above concentration alone, but negative affect did. This is likely due to the fact that negative affect was the only significant predictor of the three self-report variables.

Potential Explanations for the Results of the Present Study

The lack of support for the first hypothesis can be explained mathematically. Past explanations for the benefits of the ICV argue that the ICV is more accurate than the ISD when means are skewed and means and ISD are correlated (Wang et al., 2012). In this sample, the mean interstimulus intervals were correlated with the standard deviations of the interstimulus intervals (for Trails A: $r = .46$; for Trails B: $r = .63$; for Trails C: $r = .31$; all $p \leq .01$). As such, it seems reasonable that correcting for the means is necessary. However, in this dataset, the mean intra-stimulus interval had means of 0.95 for Trails A, 0.94 for Trails B and 1.40 for Trails C. As such, dividing the squared standard deviation of the intra-stimulus interval by the mean of the intra-stimulus interval provided a very minimal correction. Dividing by values so close to one will not actually change the value of the coefficient of variation substantially. Mean inter-stimulus intervals so close to one are a function of both task administration and sample. Because the task is presented on a digital device, with a small screen, the time it takes to connect the two dots is going to be minimal. Further, the sample relies on digital natives, all in an age range where no motor impairments or reaction time impairments would be expected. The current study differs from past research on the TrailMaking Task by presenting it using an ambulatory assessment application, which allows for fine-grained analysis of the reaction time data, but that level of detail may be incompatible with previous analytic strategies. Both of the replications in this study were close conceptual replications, rather than direct replications. As such, when they fail to replicate, two questions are raised: do previous findings not generalize to the new population or methodology, or is there some concern about whether the past finding is a Type I error? Given that the past research for this hypothesis is driven by the mathematics of variation,

and that the mathematics of the calculation of the ICV in this study happen to involve dividing by one, the likely explanation is that failing to support this hypothesis is a failure to generalize.

Similarly, the replication and extension of past findings that within individual variation is about half of between individual variation — finding an even more substantial ratio — is likely to be an effect of the assessment method. Of note, while past research has found an average ratio around half for within person variability over between person variability on tasks presented on the computer, the ratio of variability in errors on the a task similar to a paper and pencil presentation of the TrailMaking Test was .55 for versions which required connecting the same stimuli (i.e. letters or numbers) and .85 for versions which required connecting alternating stimuli (i.e. a letter then a number then a letter…) (Nesselroade & Salthouse, 2004). The ratios on the paper and pencil task similar to Trails are then more reflective of the ratios found in this study, where there is a digital presentation. It may be that requirements of the task dictates the proportion of variability which is due to between individual variation versus within-individual variation, rather than the method by which the task is delivered. However, to support that hypothesis, future research would have to focus on comparing similar tasks in similar populations, using both digital, physical, and ambulatory assessment modalities and comparing the ratios of variability between the assessment modalities. Such research has been lacking in studies of intraindividual variability. While some studies have used digital assessment (e.g. Sliwinski et al., 2006) and even computers equipped with touch screens (e.g. Lövdén et al., 2007), ambulatory assessment has largely been untested (see Salthouse & Berish, 2005, for an exception).

The second aim was to extend past research which has suggested that clinical conditions associated with overall increased positive or negative affect (e.g. depression; bipolar disorder)

are associated with increased cIIV (Kaiser et al., 2008; Gallagher et al., 2015), and to add to the burgeoning, but conflicted, literature looking at whether affect itself is a driver of cIIV (Brose et al., 2012; Salthouse & Berish, 2005; Sliwinski et al., 2006; von Stumm, 2016). The results of this study contradict previous findings that cIIV on a task based on the TrailMaking Task delivered ambulatorily was not related to mood (Salthouse & Berish, 2005). However, the current study differs methodologically from that study in two key ways: mood was measured using separate scales for positive and negative affect, and the task was more similar to the original TrailMaking Task. In the Salthouse and Berish modification of the TrailMaking Task (2005), participants were presented with four numbers or letters surrounding a number or letter on an ambulatory assessment device and instructed to tap the subsequent symbol in the ascending series. This task modification may require different components of cognitive processing (e.g. more working memory) than the presentation of the TrailMaking Task where all the numbers and letters stay present on the screen and simply have to be tapped in order. As well, as mentioned before, collapsing across emotional states may elide important differences. In fact, in the current study, negative affect was a predictor of cIIV, but positive affect was not. These methodological nuances may account for how the current results differ from past literature. Similarly, differences in the current study from recent literature which suggests that both positive and negative affect predict cIIV may account for why positive affect was not a predictor in this study. von Stumm (2016) found that in predicting variability on measures of working memory, short term memory, and processing speed with positive and negative affect, the only predictive relationship was between positive affect and processing speed. The processing speed task required comparing two strings of letters and numbers and deciding if the strings were identical, or if there was a single symbol different between the two strings. The working memory task showed the participants a

string of digits, then replaced that string with another string of equal length and required the participants to sum the two digits in every position of the string together. Trails, in contrast, is multiply determined, requiring working memory, processing speed and executive functioning (Sanchéz-Cubillo et al., 2009). Again, these findings, in light of past research, argue for the importance of precision in explaining exactly what kinds of cIIV are driven by changes in affect.

The results of the current study suggest that increased negative affect decreased cIIV. This relationship is in the opposite direction hypothesized. Past studies which found the opposite relationship between negative affect and cIIV, unfortunately, have not been similar enough to make a direct comparison, as they primarily examined day to day variability rather than within trial variability (Brose et al., 2012; Sliwinski et al., 2006). Sliwinski and colleagues (2006) did examine within trial variability in a working memory task driven by stress, but rather than looking at the ICV, they examined the tail of the distribution, and found that stress slowed down the slowest reaction times within trial. They did not find this effect for a task which only required processing speed and not working memory. Perhaps the finding in the present study is a Type II error. However, it is also worth acknowledging that the mean negative affect at each session was quite low, though there is a fair variation around that mean. An inverted U-shaped curve may best describe the relationship between negative affect and cIIV, where no negative affect results in some cIIV, as does very high negative affect, but low levels of negative affect increase the resources marshalled. Research on cognitive scope, defined at both attentional and conceptual levels, has suggested that emotions of both valence types at low levels of motivational intensity increase cognitive scope, but at high motivational intensity, both kinds of emotion narrow cognitive scope (Harmon-Jones, Gable & Price, 2012). The emotion sliders captured in the positive affect scale used in this study are of mixed motivational intensity, where the sliders on

the negative affect scale are largely of lower motivational intensity (with the exception of anger). The relation between negative affect and cIIV may thus be accounted for by low level, low motivational intensity emotions increasing cognitive performance.

Much like positive affect, self-reported concentration may not have been a predictor in this study due to methodological differences comparing to past research, or self-reported concentration may not be associated with cIIV on the kinds of cognitive functions that the TrailMaking Task evaluates. First, two of the three studies which have examined perceived cognitive control or cognitive fatigue were conducted in clinical samples, where the variability in perceived cognitive effort may be more salient than in an undergraduate sample (Bruce et al., 2010; Strauss et al., 2002). Another study found that subjective control of attention mediates between negative affect and cIIV in a working memory task (Brose et al., 2012). However, this study again looked at day to day variation, and found that days with relatively low performance were also days with low control of attention. However, overall performance on a particular day does not necessarily speak to greater variability within trial, which is the focus of the current study, and which does not seem to be impacted by subjective concentration.

Strengths and Limitations

This study has some limitations which bear acknowledging. First and foremost, there is the possibility that this study was underpowered. The power analysis was based on predicted beta weights an order of magnitude larger than the beta weights which were actually found. Given the small relations between self-reported concentration and positive affect and cIIV, the study may not have been sufficiently powered to identify these effects. Another limitation is that this study was conducted on undergraduates, who are less likely to show substantial cIIV

compared to older adults or individuals who have mild cognitive impairment. However, it is also important to understand how these processes work in younger adults. Further, undergraduates are "digital natives" and therefore more likely to be comfortable using the ambulatory assessment method which is reliant on a smart phone, and therefore less likely to have error variance in their data due to unfamiliarity with the assessment tools. The ambulatory assessment method is a strength of this study. Few studies have used ambulatory assessment in past explorations of cIIV but having computerized recording of data allows for fine-grained variance measures, such as the interstimulus interval examined here. This kind of cIIV may be qualitatively different from cIIV which examines day to day change. Further, ambulatory assessment increases ease of data gathering, especially over several days or sessions. Asking individuals to complete tasks when they want, where they want, is substantially easier than requiring them to come to the laboratory on consecutive days. For that ease, however, one trades control – it may be that the participants were less than fully concentrated on the task at hand or experienced technical difficulties, which might account for error rates higher than one would expect on a fairly simple task.

Implications and Future Directions

The results of this study have implications for the way in which cIIV is conceptualized for younger adults. First, cIIV within a trial can be measured using ambulatory assessment of the TrailMaking Test. Using computerized recordings of variability within a session and a person may be more sensitive to the variability in younger adults than variability which is measured within a person and across sessions. Measuring cIIV in a sample which is relatively homogenous for age and education (college students) requires that increased sensitivity, because there would be less expected variability on performance than in a sample with greater ranges of education or age. Future studies on cIIV in young adults ought to take advantage of this greater sensitivity.

Given the ways in which the results of the current study converge and diverge from past literature, our study highlights the importance of conceptualizing cIIV not as a monolith, but in terms of what online processes are being most evaluated by the assessment. Some aspects of cIIV may be more susceptible to increase or decrease with negative or positive affect, and others may be relatively impervious to changes in affect. Evaluating precisely which kinds of cIIV are affected by different affective states is a necessary future direction for research in this field. Mechanisms for increasing or decreasing cIIV can lead to potential interventions to minimize cIIV, but before creating those interventions, we must be sure what aspects of cIIV we will be able to effectively target. Beyond understanding which kinds of affect are related to changes in cIIV, understanding the necessary "dose" of affect to minimize cIIV is also necessary. The results of our study suggest that low levels of negative affect are beneficial to cognitive processing, and so optimizing the level of negative affect may be required. Future studies will look at the full range of negative affect to understand whether the relationship between cIIV and negative affect is linear or curvilinear. A final implication of our study is that, like cognitive performance overall, cIIV can change. While cIIV has been shown to be a marker of future cognitive performance (e.g. Hultsch et al., 2000), if it, too, is variable, then a single assessment session may be vulnerable to over- or under-estimation of risk based on the individual's current affective state. Averaging across multiple sessions may give a more accurate estimate of "true" cIIV, and ambulatory assessment methods will facilitate the gathering of that data.

Conclusion

This study examined the effect of state affect and self-reported concentration on cIIV in performance on an ambulatory adaptation of the TrailMaking task in 62 college students. Negative affect was the only mechanism of interest which predicted cIIV, however in the

opposite direction hypothesized: increased negative affect decreased cIIV. This finding is unexpected based on previous literature, however, the current study differs from past studies in several key ways: the mode of assessment and/or the task used, and the younger sample. The findings of this study highlight the importance of precision in comparing what kinds of cIIV are affected by increased affect, and the benefits of using within trial variability and ambulatory assessment in a sample of younger adults. Future studies can expand on the current findings by systematically testing the effects of affect on cIIV in different cognitive processes.

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APPENDIX. IRB APPROVAL

ACTION ON PROTOCOL APPROVAL REQUEST

Institutional Review Board
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TO: Alex Cohen
Psychology

FROM: Dennis Landin
Chair, Institutional Review Board

DATE: June 30, 2015

RE: **IRB#** 3618

TITLE: Development of Mobile Status Exam for Psychiatric Symptoms - Outpatient

New Protocol/Modification/Continuation: New Protocol

Review type: Full __X__ Expedited ____ **Review date:** 5/29/2015

Risk Factor: Minimal ___X_____ Uncertain _____ Greater Than Minimal_____

Approved _____X_____ **Disapproved** _____

Approval Date: 6/12/2015 **Approval Expiration Date:** 6/11/2016

Re-review frequency: (annual unless otherwise stated)

Number of subjects approved: 500

LSU Proposal Number (if applicable):

Protocol Matches Scope of Work in Grant proposal: (if applicable)_____

By: Dennis Landin, Chairman _____

PRINCIPAL INVESTIGATOR: PLEASE READ THE FOLLOWING –
Continuing approval is CONDITIONAL on:

1. Adherence to the approved protocol, familiarity with, and adherence to the ethical standards of the Belmont Report, and LSU's Assurance of Compliance with DHHS regulations for the protection of human subjects*
2. Prior approval of a change in protocol, including revision of the consent documents or an increase in the number of subjects over that approved.
3. Obtaining renewed approval (or submittal of a termination report), prior to the approval expiration date, upon request by the IRB office (irrespective of when the project actually begins); notification of project termination.
4. Retention of documentation of informed consent and study records for at least 3 years after the study ends.
5. Continuing attention to the physical and psychological well-being and informed consent of the individual participants, including notification of new information that might affect consent.
6. A prompt report to the IRB of any adverse event affecting a participant potentially arising from the study.
7. Notification of the IRB of a serious compliance failure.
8. SPECIAL NOTE:

**All investigators and support staff have access to copies of the Belmont Report, LSU's Assurance with DHHS, DHHS (45 CFR 46) and FDA regulations governing use of human subjects, and other relevant documents in print in this office or on our World Wide Web site at http://www.lsu.edu/irb*

VITA

Tovah Cowan, originally from Montréal, Québec, Canada, completed her Bachelors of Science in Psychology at Concordia University, Montréal in 2016. During her undergraduate studies, she worked in two research labs. In one, she examined the effects of Cognitive Behavioral Therapy on weight loss, in the other she examined prosocial and social cognitive development in children. Prior to attending graduate school at Louisiana State University, Tovah worked as a Research Assistant at the Prevention and Early Intervention Program for Psychosis (PEPP-Montréal) studying engagement in treatment and recovery among individuals who have had a first episode of psychosis. Tovah's interest in clinical psychology, social cognition, and psychosis led her to Louisiana State University where she is currently studying to complete her Doctor of Philosophy in Clinical Psychology under the supervision of Dr. Alex S. Cohen. Tovah's current research interests include using a multimodal approach (i.e., self-report, behavioral, and objective measures) to investigate the cognitive and affective mechanisms underlying emotional experience, social cognition, and social functioning in individuals with psychosis spectrum disorders.