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A Factor Analytic Examination of the Underlying Mechanisms of Delay Discounting

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Abstract

People tend to prefer smaller-but-sooner over later-but-larger rewards, indicating the subjective value of a reward is discounted as a function of time. This phenomenon is referred to as *delay discounting* and represents a facet of impulsivity that is associated with reward processing. Despite the empirical literature surrounding delay discounting, the underlying mechanisms are not yet well established. The current study investigated whether delay discounting belongs more to one grouping – personality traits or cognitive functioning – than the other. Additionally, neuroimaging metrics (i.e., cortical thickness) was also examined, as it has the potential to mediate these pathways to delay discounting. Data from the Human Connectome Project was used for the current study and included behavioral and neuroimaging data on 1,051 healthy young adults. Exploratory and confirmatory factor analysis (EFA and CFA, respectively) were used to investigate proposed relationships between personality and cognitive variables and delay discounting and examine the extent that neuroimaging variables mediate the relationship. Results from the exploratory factor analysis revealed support for two separate latent constructs of cognition and personality. A progression of CFA models in structural equation modeling demonstrated evidence for the relationship between cognition and delay discounting, while personality appeared to have little explanatory power in understanding delay discounting. Results from the analysis examining cortical thickness in a selected brain region of interest did not provide evidence for a mediative relationship between cognition and delay discounting. This study helps to clarify and explain the construct of delay discounting and highlights the importance of cognition in reward-based decision-making.

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History of Delay Discounting

Given the choice, certain people may choose a smaller, immediate reward over a larger, delayed reward. The tendency to devalue future outcomes, coined as *delay discounting,* is associated with reward processing and decision-making (Odum, 2011). Additional terms for the same concept include *time discounting* and *temporal discounting* (Frederick, Lowenstein, & O'Donoghue, 2002). The concept of delay discounting is central to behavioral economics and dates back to 1834, at which time the Scottish economist, Dr. John Rae, introduced the theory of "intertemporal choice," i.e., a process by which people make decisions about what to do at various points in time (Frederick et al., 2002). Rae's theory suggested that there is a relative value to two or more outcomes at various times, such that immediate rewards are more tangible than later rewards (Rick & Loewenstein, 2008). The theory of intertemporal choice was later elaborated on by American economist Paul Samuelson, who proposed the Discounted Utility Model (Frederick, Loewenstein, & Donaghue, 2002). The central assumption of Samuelson's model was that the varied motives underlying intertemporal decisions can be reduced into a single parameter called the "discount rate."

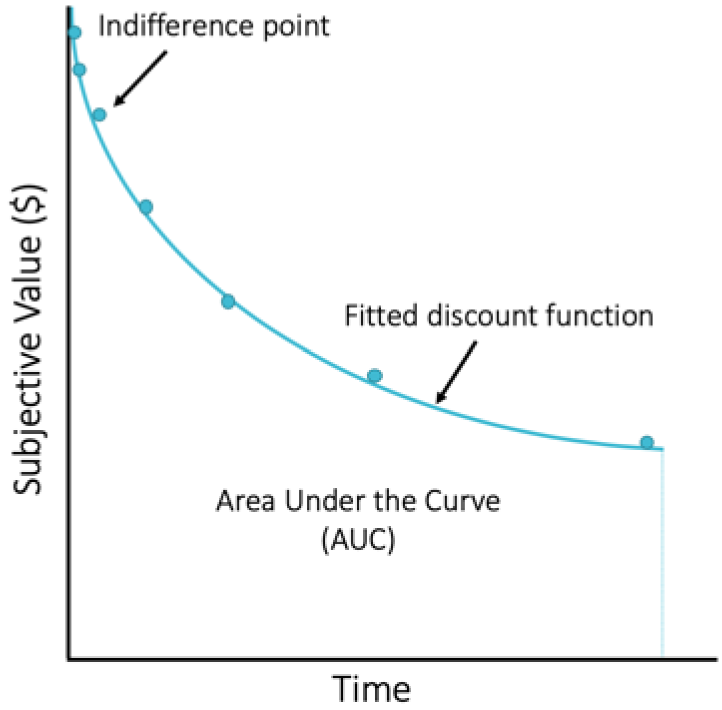
A major limitation of Samuelson's Discounted Utility Model, however, is that it assumes the discount rate for each person is invariant across different types of outcomes/rewards and is stable over time. Thaler (1981) found that discounting rates of students varied based on 1) the duration of the delay (i.e., time to wait for outcome), 2) size of the reward (i.e., $50 vs. $500), and 3) whether the outcome was a gain or loss, e.g., students were more likely to wait for a reward but less willing to pay very much to delay a fine. Building on Thaler's findings, Loewenstein and Prelec (1992) proposed that a person's discounting rate follows a hyperbolic

function, likely representing a person's "decreasing impatience." The hyperbolic discount function, as measured by various laboratory discounting tasks, appears to be the most widely accepted measure of one's discounting rate. Chabris et al. (2008) suggested that even a brief delay discounting task in a laboratory setting may be the single best predictor of real-world behaviors related to impulsivity (e.g., smoking, alcohol use, exercising, saving money). For example, although laboratory tasks of delay discounting and field behaviors show weak-to-modest correlations (i.e., $r = 0.28$ at most), the relationship is still more robust than other individual-level variables (e.g., age, sex, depressive symptoms, education, cognitive ability), suggesting that delay discounting is an important variable.

Construct of delay discounting. Unlike a number of psychological constructs, delay discounting involves only a few factors, including the concept of reward, duration (time), and a simple decay function. Broadly speaking, delay discounting tasks aim to find the point at which two rewards – one relatively immediate and one delayed – have approximately the same subjective value. The "indifference point" represents the point at which the value of the smaller-but-sooner reward is equivalent to the larger-but-later reward (see **Figure 1**). For example, if someone equally prefers to receive $100 today or $500 in a year, their indifference point for $500 in a year is $100. This person is said to discount more than someone whose indifference point in the same situation is $300. This information is used to quantify the extent to which a person discounts.

Figure 1

Sample Discounting Curve Based on Data Points.



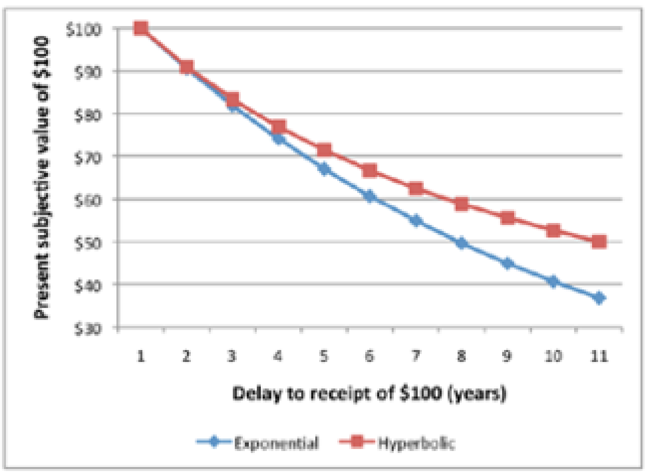
Initially, this was calculated using an exponential function introduced by Samuelson (1937), who presented it as an assumption about the measurement of utility. As previously mentioned, one assumption of an exponential function, however, is that the delay discount rate for a person remains constant over time, e.g., the same discount rate would apply to a choice between outcomes available a year from today versus a year and a week from today. As research in delay discounting progressed, this was found not to be an accurate reflection of realistic discounting behavior. Loewenstein and Elster's (1992) formative book, "Choice over Time," demonstrated that a hyperbolic function fit better to discounting behavior than an exponential function. The hyperbolic discount function is typically expressed as:

$$V = \frac{A}{1 + kD}$$

Where *A* is the magnitude of the delayed reward, *V* is the current subjective value of the reward, *D* is the delay to the reward, and *k* is a free parameter that refers to the discount rate (i.e., higher *k* values indicate that delayed rewards are devalued more quickly than smaller *k* values) (Mazur, 1987). A hyperbolic function suggests that a person's discount rate decreases as a delay to reward increases (whereas one's discount rate would be unchanged regardless of the duration of delay for an exponential function). **Figure 2** illustrates the comparison between exponential and hyperbolic discount functions with the same discount rate (10%), and shows that in the hyperbolic function, the extent of discounting becomes less steep as the delay increases.

Figure 2

Exponential and Hyperbolic Discount Functions.



Note. This table shows exponential and hyperbolic discount functions for a delayed reward of $100, with k = 0.10. Taken from Angott, A. M., 2010.

Assessing delay discounting. Typically, delay discounting is measured by questionnaires (either paper-and-pencil or computer-presented) and involve either fill-in-the-blank forms or binary forced-choice. For fill-in-the-blank forms, the participant is given two options: 1) the magnitude of and the delay to the reward are specified by the experimenter, or 2) one value

(either the magnitude or the delay) is missing. The participant is asked to fill in the blank in a way that they would be indifferent to the two options. For example:

> *Please fill in the number that would make you indifferent between the following two options:* A. Win $100 immediately. B. Win $____ one year from now.

The fill-in-the-blank method, however, may not accurately reflect real-world tendencies, and Frederick et al. (2003) demonstrated that people rather may be applying rigid rules to determine their response (e.g., multiplying the amount in option A by 3). Due to these problems, the preferred method in many studies is to use a series of forced-choice questions between a variety of smaller-but-sooner and larger-but-later rewards. There are a variety of ways to do this, and one way is to hold the larger-but-later reward constant (e.g., $200 in one year) while increasing or decreasing the smaller-but-sooner reward incrementally ($100 now; $94 now; $90 now) (Johnson & Bickel, 2002). If the participant continues to choose the smaller-but-sooner reward until $90, then their indifference point for $200 in one year is somewhere between $94 to $90. Another method described by Li (2008) assessed how happy participants would be if they received $100 after various delays, making ratings on a scale from 0 (“not happy at all) to 100 (“very happy”).

Clinical Implications

Adaptive function. Many theories suggest that the devaluing of future outcomes is related to uncertainty, investment, and risk, and, in some cases, has an adaptive function. For instance, discounting the delay of future rewards may be a response to risks associated with waiting, such as the decreased probability of receiving a reward over time related to loss and potential exposure to threat (Frost & McNaughton, 2017). With food, for example, there is an increased likelihood of the food spoiling as time passes or someone else consuming the food

first. On the other hand, there is also an adaptive function for less discounting of future rewards, and data show that many people are often willing to accept delays of days, weeks, months, and even years to maximize the reward amount (regardless of whether rewards are real or hypothetical) (Johnson & Bickel, 2002; Madden, Begotka, Raiff, & Kastern, 2003). One framework suggests that biases in decision-making likely arise from adaptation to an environment that was previously useful but is no longer appropriate (Huys et al., 2016). Given the different scenarios, there is no single ‘optimal’ rate of discounting as it is likely context-dependent and would vary based on outcome, risk, and duration of the delay (Zentall & Smith, 2014).

Maladaptive behavior. Delay discounting can become maladaptive when a person consistently chooses the sooner-but-smaller reward over the later-but-larger outcome and continues to make this choice, i.e., ‘choosing impulsively’ (Monterosso & Ainslie, 1999). A decision made without considering the consequences of the outcome is considered to be reflective of impulsive decision-making and poor self-control (Moeller et al., 2011). Impulsive choice, as measured by delay discounting, has been associated with a variety of socially important problems, such as alcohol abuse (Lim, Cservenka, & Ray, 2017), cigarette smoking (Bickel, Odum, & Madden, 1999), cocaine use (Heil, Johnson, Higgins, & Bickel, 2006), pathological gambling (Alessi & Petri, 2003), risky sexual activity (Story, Vlaev, Seymour, Darzi, & Dolan, 2014), obesity (Fields, Sabet, & Reynolds, 2013), future air quality (Berry, Nickerson, & Odum, 2017), and even texting while driving (Hayashi, Fessler, Friedel, Foreman, & Wirth, 2018). A study by Hampton, Asadi, and Olson (2018) showed higher discounting rates predicted lower income later in life; however, it is important to note this study, and other similar studies of income and discounting rates, have been mostly comprised of White Americans.

Although the association between the rate of delay discounting and real-world behavioral disorders strongly suggests a relationship between delay discounting and impulsivity, laboratory measures of impulsivity often show mixed results when comparing self-report measures of impulsivity with performance on a delay discounting task (Lane et al., 2003). One reason for this lower-than-expected relationship may be because impulsivity is thought of as a multidimensional construct, whereas behavioral tasks often tap into a single aspect of impulsivity (Lane et al., 2003). These equivocal results highlight the need for further research between behavioral measures of impulsivity (i.e., delay discounting) and self-report test data.

Perspectives of Delay Discounting

Cognitive. One theoretical debate in the literature is whether delay discounting is most influenced by cognitive functioning (i.e., cognitive control, working memory) or enduring personality traits (i.e., self-discipline, sensation-seeking). Support for the cognitive perspective includes research that has demonstrated delayed discounting depends on search processes for identifying potential future outcomes and/or imagined expectations (i.e., episodic future thinking; Schacter, Addis, & Buckner, 2007). Kurth-Nelson and colleagues (2012) suggest that this search process of potential outcomes involves three assumptions: 1) evaluation of outcomes involves a search process, 2) a value is assigned to an outcome proportionally to how easy it is to find, and 3) outcomes that are less delayed are typically easier for the search process to find. Their theory provides an explanation for why improving cognitive resources (e.g., working memory) may help slow discounting by improving the efficiency of the search process. Additionally, Miyake et al. (2000) separated executive functions into three different, but still related, functions: 1) “shifting,” 2) “updating,” and 3) “inhibition,” all of which can be intuitively linked to the construct of delay discounting. In particular, “updating” refers to working memory,

which requires monitoring, evaluating, and revising information held in temporary storage (Baddeley & Hitch, 1974), and, of all the cognitive processes of executive functioning, updating or working memory has been most closely associated with delay discounting (Bickel, Yi, Landes, Hill, & Baxter, 2011; Wesley & Bickel, 2014). The cognitive aspect of executive function has also been described by Diamond (2013) as “top-down mental processes needed when you have to concentrate and pay attention” (p. 1). Diamond (2013) also argues that executive functions are essential for nearly every aspect of life, including quality of life, school readiness, school and job success, marital harmony, and public safety (i.e., crime, reckless behavior, violence).

Correlational studies have demonstrated that higher cognitive skills have been associated with better self-control and lower discounting rates (Mischel & Grusec, 1967). In a sample of healthy adults, Finn and colleagues (1999) investigated the link between delay discounting and working memory capacity (i.e., the ability to keep information “on-line” for short periods of time) and found that adults with lower working memory capacity demonstrated decreased executive control of their inhibition system, leading to steeper rates of discounting. Additionally, the authors suggest that delay discounting emerges from the correlation between delay and the ease of identifying future rewarding outcomes. Lindberg and colleagues (2014) provide a compelling argument that pathological aging would lead to poorer delay discounting performance. For example, the authors describe general impairments in decision-making and impulsivity that are associated with neurodegenerative disorders, as well as executive dysfunction (e.g., working memory) which often precedes decline in other cognitive domains (Lindberg, Puente, Gray, Mackillop, & Miller, 2014).

Imposing a cognitive load (i.e., decreasing cognitive resources) has also been shown to 'impair' or steepen the rate of discounting. For example, individuals tend to show steeper (i.e., more impulsive) delayed discounting when they concurrently perform a cognitively demanding task (Van Dillen, Papies, & Hofmann, 2013). In addition to depleting these cognitive resources, delay discounting can also be modulated by training working memory (i.e., increasing cognitive resources), which in turn slow (i.e., improve) discounting rates (Bickel, Yi, Landes, Hill, & Baxter, 2011). Researchers have also demonstrated steeper delay discounting may occur in the context of pathological cognitive processes. For example, Thoma, Maercker, and Forstmeier (2017) found that older adults with mild cognitive impairment and mild Alzheimer's disease demonstrated poor delay discounting, likely due to structural and functional decline in brain regions that mediate self-control (e.g., dorsolateral and medial prefrontal cortices). It has been concluded that cognitive control is crucial in the stages of decision-making that involve weighing choices and reinforcement learning, both of which have been shown to be important for delay discounting (Kurth-Nelson, Bickel, & Redish, 2012).

Personality. A common definition of a personality trait is a "relatively enduring pattern of thoughts, feelings, and behaviors that reflect the tendency to respond in certain ways under certain circumstances" (Roberts, 2009). Steeper discounting rates have been conceptualized as a potential indicator of trait impulsivity (Bickel, Odum, & Madden, 1999). In this context, impulsivity can be defined as a tendency to make rapid, maladaptive decisions (Dalley, Everitt, & Robbins, 2011). Past research has indicated inconsistent relationships between personality measures and delay discounting, which may be a result of these studies being limited to relatively small and homogenous student samples (e.g., Daly et al., 2009; Hirsh, Morisano, & Peterson, 2008; Ostaszewski, 1996). For instance, studies with small sample sizes (i.e., lower

power) generally have decreased replication probability (i.e., when “real” effects are replicated with a certain level of probability), due to issues in accounting for variability and measurement error (Miller, 2009). Although limited in scope, previous research has demonstrated that steeper discounting has been associated with higher levels of neuroticism (Manning et al., 2014), less empathy (Kirby et al., 1999), and less agreeableness (Miller, Lynam, & Jones, 2008).

The primary model used in personality research is the Five Factor Model (FFM; Costa & McCrae, 1992; Goldberg, 1993). The ‘Big Five’ is composed of trait characteristics 1) Openness to Experience, 2) Conscientiousness, 3) Extraversion, 4) Agreeableness, and 5) Neuroticism. Impulsivity has typically been associated with four out of the five FFM domains, the exception generally being Agreeableness (Asad et al., 2012; Badgaiayn & Verma, 2014; Verplanken & Herabadi, 2001). Individuals low in Conscientiousness tend to be careless, inpatient, and lacking meticulousness (Whiteside & Lynam, 2001). Individuals high in the Neuroticism domain have a propensity toward negative emotions, including feeling tense, anxious, and irritable, and it has been proposed that impulsive behavior (i.e., steeper delay discounting) may provide sudden relief from prolonged unpleasant emotional states which people with elevated neuroticism tend to experience (Heatherton & Baumeister, 1991). People high in the Extraversion domain tend to be sensation seeking, adventurous, and bold (Zuckerman, 1994), similar to the domain of Openness to Experience, in which people tend to prefer novel and intense experiences (Soto & John, 2009). Nicholson and colleagues (2005) administered the Neuroticism-Extraversion-Openness Personality Inventory-Revised (NEO-PI-R; Costa & McCrae, 1992) and the Risk Taking Index (Nicholson et al., 2005) to a sample of 2,401 university students. Nicholson et al. (2005) found that risk-taking was positively associated with Extraversion ($\beta = 0.26$, $p<.001$) and Openness to Experience ($\beta = 0.36$, $p<.001$), while Agreeableness ($\beta = -0.31$, $P<.001$),

Conscientiousness ($\beta = -0.20$, $P<.001$), and Neuroticism ($\beta = -0.18$, $p<.001$) were inversely associated to risk-taking. Compared to the other personality domains, the relationship between Extraversion and delay discounting has been more variable, with several studies indicating greater extraversion is related to more impulsive discounting (e.g., Ostaszewski, 1996), while other studies show the opposite (e.g., Da Silva, De Faveri, & Matsushita, 2017). Interestingly, Hirsh, Morisano, and Peterson (2008) examined how personality and cognitive ability interacted to predict discounting dates and found that the level of Extraversion predicted higher discounting rates but only at the low end of the cognitive distribution.

Personality traits may impact discounting rates by moderating the relationship between the "fast" impulsive visceral system that responds to immediate rewards versus the "slow" deliberate system that considers delayed rewards (Manning, Hedden, Wickens, Whitfield-Gabrieli, Prelec, & Gabrieli, 2014). Evidence from neuroimaging studies evaluating this competition perspective have demonstrated an association between brain activation in response to immediate rewards in subcortical reward regions and activation in the prefrontal and neocortical regions in response to delayed rewards (Manning et al., 2014). This finding is generally intuitive, such that the prefrontal cortex has a hypothesized role in the self-control necessary to select delayed rewards (Figner et al., 2010). Personality may, therefore, be an important mechanism that can predict the rate of discounting.

Further evidence to support the role of personality in delay discounting is its stability over time. For example, Ohmura and colleagues (2006) demonstrated that level of performance on delay discounting tasks was relatively stable over three months, and Kirby (2009) showed delay discounting was stable at one year. Another way to assess the intraindividual stability of delay discounting over time is to examine test-retest reliability. Simpson and Vuchinich (2000)

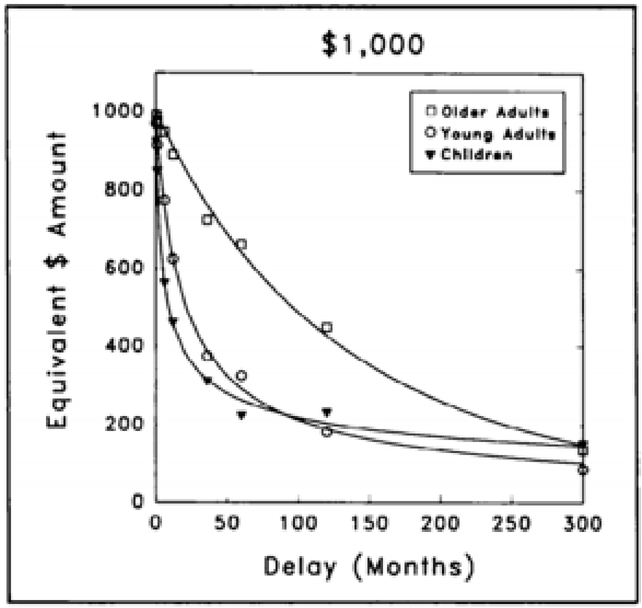
found strong test-retest reliability ($r = .91$) with an interval of one week using a hypothetical money task involving $1,000 in a sample of college students. Kirby (2009) found that test-retest reliability remained robust up to an interval of one year ($r = .71$) using a monetary choice questionnaire in a sample of 46 college students. Strong test-retest reliability over time has supported the notion that the rate of delay discounting for individuals is relatively stable and enduring.

For the purposes of this study, it is important to note that intelligence and personality are sufficiently distinct constructs. Of the Big Five factors, only Openness to Experience has been consistently found to be moderately associated with intelligence (Ackerman & Heggestad, 1997; DeYoung, Peterson, & Higgins, 2005; Moutafi, Furnham, & Crump, 2006) and is more associated with a variety of intellectual traits, including curiosity and creativity, compared to the other four factors (Goldberg, 1993). Although Conscientiousness has been positively associated with academic performance, this is a trait that less intelligent people can possess in order to compensate in a competitive environment (Moutafi et al., 2006).

The literature also includes studies that focus on a developmental perspective of delayed discounting. For example, although short-term stability has been demonstrated in adults, there are broader nomothetic shifts in rate of discounting across the lifespan. For example, Green, Fry, and Myerson (1994) found that children reduced the value of delayed rewards at a faster rate than did young adults, and young adults reduced the value of delayed rewards at a faster rate than did older adults (see **Figure 3**).

Figure 3

Delay Discounting Across Children, Young Adults, and Older Adults.



Note. This figure shows data from children, young adults, and older adults for the delayed, fixed-amount reward of $1,000. A steeper line indicates more discounting (i.e., devaluing a future reward). Image taken from Green, Fry, & Myerson, 1994.

Shared/dual mechanism perspective. Another perspective suggests that delay discounting may be best conceptualized as a construct that involves both cognitive and personality factors. For example, delay discounting can be operationalized in a similar manner as the “hybrid” construct of executive function, a broad construct that operates as a cognitive and personality trait. In the case of delay discounting, the shared mechanism relates to the “behavioral” aspect of executive function, also coined ‘behavioral disinhibition.’ Behavioral disinhibition is defined as “an inability to inhibit impulses toward behaving in socially undesirable ways” (Wilson, Thomas, & Iacono, 2015, p. 280) and is observed as “under-controlled” behavior. Behavioral disinhibition can also be seen in dementing disorders, particularly those involving the frontal lobes. Delay discounting may share similarities with newer generation executive function tasks, such as the

Iowa Gambling Task (IGT; Bechara et al., 1994), which was developed out of concern over the ecological validity of existing tests of executive function, such as the Trail Making Test (Tombaugh, 2004) and Wisconsin Card Sorting Test (Grant & Berg, 1948), as well as the emerging realization that decision-making and emotional processes were highly associated (Lerner, Li, Valdesolo, & Kassam, 2015). Behavioral disinhibition is often characterized as a generalized vulnerability to externalizing disorders, such as problematic substance use, antisocial behavior, academic problems, childhood disruptive disorders (defiant disorder, conduct disorder, attention-deficit/hyperactivity disorder), and precocious sexual activity (Young et al., 2009; Wilson, Thomas, & Iacono, 2015). Similarly, delay discounting also relates to risky and problematic behaviors that stem from poor self-control. For example, Bobova and colleagues (2009) found that young adults with higher discounting rates (i.e., more impulsivity) had a greater risk of disinhibited behavior as manifested by alcohol dependence, childhood conduct disorder, and adult antisocial disorder. Additionally, those with greater discounting rates also were associated with lower working memory capacity, higher trait impulsivity, and lower intelligence (Bobova, Finn, Rickert, & Lucas; 2009).

Behavioral disinhibition is posited to occur as an interaction between bottom-up (reward-based) mechanisms and the failure of top-down (inhibitory mechanisms) (Wilson, Thomas, & Iacono, 2015). In this way, delay discounting may reflect this same process contingent on the interplay of bottom-up and top-down processing, which are two distinct and competing systems (Steinberg, 2008). For example, neurobiological models suggest brain networks implicated in delay discounting include the limbic “bottom-up” brain areas (i.e., emotion-based drive; urge for rewarding experience) and the “top-down” frontal and prefrontal regions which regulate executive function and decision-making (Giedd et al., 1999). These findings also align with the

'dual brain pathology' theory proposed by Tebartz van Elst et al. (2003), which proposes a combination of prefrontal hypometabolism and limbic hypermetabolism associated with impulsivity and aggression.

Consistent with developmental literature, top-down regions mature at a later period than other brain regions (Giedd et al., 1999), and this asymmetric development may be related to the commonly observed phenomenon that children and adolescents make riskier choices than adults (Leshem, 2016; Green, Fry, & Myerson, 1994). In other words, impulsive delay discounting may be, in part, a consequence of bottom-up processes outcompeting top-down regulatory mechanisms (Ochsner et al., 2009; LeDoux, 2000). In the example of poor delay discounting, the bottom-up system conceptually maps onto the sensation-seeking trait, whereas the top-down system reflects cognitive difficulties with planning/decision-making.

Mediating brain variables. Within the neuroimaging literature, delay discounting has been correlated with several indices of brain structure and function. Two meta-analyses examining functional MRI (fMRI) studies of delay discounting (Wesley & Bickel, 2014; Carter, Meyer, & Huettel, 2010) suggest regions activated by delay discounting tasks include a self-reflective/future-oriented network (e.g., medial prefrontal cortex, posterior cingulate, lateral and medial temporal lobe, and the temporoparietal junction; collectively referred to as the default mode network), a reward network (e.g., ventral striatum, insula, ventral tegmental area, orbitofrontal cortex), and a cognitive control network (e.g., anterior cingulate cortex, dorsolateral prefrontal cortex). Recent fMRI research has also demonstrated an association between delay discounting and activation in mesolimbic dopamine projection regions. For instance, studies have found activity in the nucleus accumbens and medial prefrontal cortex to correlate with decisions involving immediate rewards, while activation in lateral cortical regions, e.g.,

dorsolateral prefrontal cortex and posterior parietal cortex, was associated with all (i.e., immediate and future) rewards (McClure et al., 2004; McClure et al., 2007). McClure and colleagues (2004) suggest that the differentiation for immediate versus longer delays is intuitive, such that longer delays should provoke activation in cortical regions involved in cognitive control (i.e., dorsolateral prefrontal cortex).

A recent study, also using data from the Human Connectome Project (1,038 adult participants), characterized regional gray matter volume and delay discounting and found several right- and left-hemispheric volumes associated with delay discounting (see **Table 1)**.

Table 1

Correlations Between Regional Gray Matter Volume and Delay Discounting

Rank	**Hemi**	**Region**	***r***	***p***
1	L	Entorhinal Cortex	0.151	1.00E-07
2	R	Middle Temporal Gyrus	0.141	1.00E-06
3	L	Middle Temporal Gyrus	0.14	1.00E-06
4	R	Entorhinal Cortex	0.125	1.00E-06
5	R	Fusiform Gyrus	0.107	0.001
6	L	Lateral Occipital Cortex	0.101	0.001
7	R	Inferior Temporal Gyrus	0.098	0.002
8	L	Precentral Gyrus	0.098	0.002
9	L	Postcentral Gyrus	0.095	0.002
10	L	Precuneus	0.094	0.003
11	L	Inferior Temporal Gyrus	0.089	0.004
12	R	Banks of Superior Temporal Sulcus	0.087	0.005
13	L	Lateral Orbitofrontal Cortex	0.087	0.005
14	R	Lateral Orbitofrontal Cortex	0.086	0.006
15	L	Insula	0.083	0.008
16	L	Transverse Temporal Gyrus	0.082	0.008
17	R	Superior Frontal Gyrus	0.08	0.01
18	L	Temporal Pole	0.079	0.011
19	R	Parahippocampal Gyrus	0.077	0.014
20	R	Precentral Gyrus	0.075	0.016

Note: Table taken from Owens et al. (2017). Significant partial correlations of gray matter volume with area under the curve ($200 and $40,000 trials), controlling for gender, age, income, and total intracranial volume.

Only two studies have examined cortical thickness and delay discounting and, in particular, only in adolescent (Pehlivanova et al., 2018) and elderly populations (Drobetz et al., 2014). Pehlivanova and colleagues (2018) found diminished cortical thickness in brain networks involving the ventromedial prefrontal cortex, orbitofrontal cortex, temporal pole, and temproparietal junction that was associated with a delay discounting task. Drobetz et al. (2014) demonstrated positive correlations between delay of gratification (i.e., ability to postpone immediate rewards in favor of later and better rewards) and the dorsolateral prefrontal cortex, ventrolateral prefrontal cortex, and the left mid-anterior cingulate cortex.

Gaps in the literature. Although decades of research on delay discounting has been established, the underlying mechanisms with respect to whether delay discounting is a personality trait or cognitive variable has not yet been adequately studied using factor analysis. Furthermore, prior studies involving a delay discounting task typically have relatively small sample sizes due to practical reasons (e.g., budget, time constraints). The brain-behavior relationship between delay discounting and cognitive and personality variables has not yet been extensively studied. As noted above, this will be the first study to investigate the association between delay discounting and cortical thickness in a large sample of healthy young adults. Of particular interest, and in need of further investigation, is the role of the orbitofrontal cortex, given variability in the literature which suggests it to be either part of the bottom-up (e.g., Xie, Nie, & Yang, 2018) or top-down (e.g., Stanger, Budney, & Bickel, 2013) network.

Present Study

Objective and Hypotheses

The proposed study aims to explore and determine the relative contributions of personality, cognition, and neuroimaging to the phenomenon of delay discounting in healthy adults. I have three objectives and hypotheses regarding the present study. Details regarding model fit indices and comparison of models will be included in the Statistical Plan section.

Objective 1: The first study objective is to assess how well my proposed latent variables can be represented by the data. These latent variables include the following: (1) executive function (EF) and (2) personality (comprised of lower-order latent variables of Neuroticism, Conscientiousness, and Openness to Experience). Indicator variables will include three of the relevant age-adjusted standardized scores from the NIH Toolbox battery (List Sorting, DCCS, Flanker test), the *2*-Back accuracy score from the *N-Back* task, and 46 item-level responses from the relevant domains of the NEO-FFI (12 from Neuroticism, 12 from Conscientiousness, 12 from Extraversion, and 10 from Openness to Experience). Establishment of a measurement model will be a step-wise process, beginning with an omnibus model in which all indicators will comprise a single latent variable. The EFA will be used to inform my model for CFA.

Hypothesis: I anticipate that, for the omnibus model in which all indicators load onto a single latent variable, that model fit will be poor. Next, I hypothesize that personality items and performance on EF tests will load onto two respective latent factors broadly representing EF and personality. Regarding the indicator variables that represent a latent construct of executive function, I hypothesize that the DCCS, Flanker test, *N*-back task, and the List Sorting test will emerge as a factor, consistent with evidence from the literature, and that a latent personality construct will emerge with a four-factor solution, consistent with literature indicating

independent factors of Neuroticism, Conscientiousness, Extraversion, and Openness to Experience will emerge (see **Table 2 and Figure 4**). Lastly, associations between the 5 latent variables (Neuroticism, Conscientiousness, Extraversion, Openness to Experience, EF) will be examined, and bidirectional arrows that reach statistical significance ($p < 0.05$) will be retained for the measurement model. Significance at $p < 0.05$ will also be used to evaluate the association between the latent variable and any given proposed indicator (e.g., NEO items). The effect of household income (an ordinal variable with 8 levels, a proxy for socioeconomic status) will be controlled for by setting paths between household income and executive function and personality indicators.

Table 2

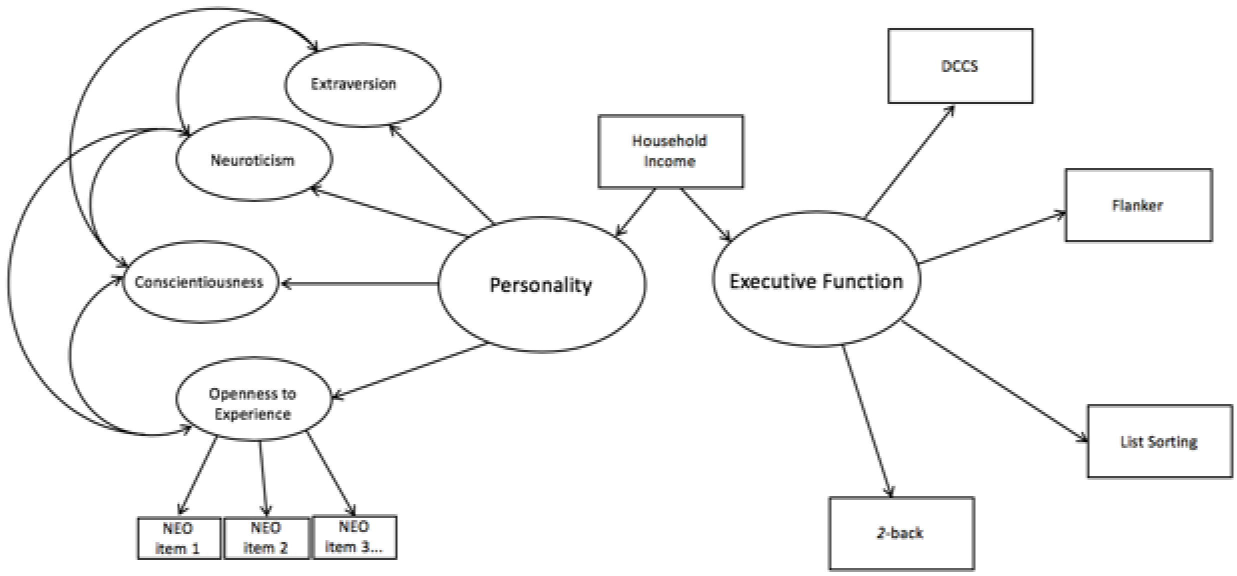
Hypothesized Factor Loadings for Cognitive and Personality Variables

Executive Function	**Personality**
Dimensional Change Card Sort	
Flanker Inhibition and Attention Test	
List Sorting Working Memory Test	
N-Back task	
	Extraversion
	Neuroticism
	Openness to Experience
	Conscientiousness

Note: Personality is the second-order construct while NEO domains (Neuroticism, Openness to Experience, and Conscientiousness) are lower-order latent variables.

Figure 4

Confirmatory Factor Analysis – Two Factors.



Objective 2: To test my measurement model, I will add the delay discounting variable (i.e., area under the curve for the $40,000 task trials). When delay discounting is added to the model, I hypothesize that the path from Extraversion to delay discounting will not survive statistical significance ($p < 0.05$), given its variable relationship with discounting noted in past research studies. Next, I will begin with a base structural model and add one path at a time between latent variables to indicate directional influences (i.e., from EF to delay discounting, EF to each latent variable of personality, personality to delay discounting, and from each personality variable to EF and delay discounting. To test whether personality or cognitive (i.e., EF) is best explaining delay discounting, I will control for one variable at a time. For example, I will add paths between Neuroticism, Openness to Experience, Extraversion, and Conscientiousness to EF, with a path from EF to delay discounting. If EF remains a robust predictor of delay discounting, then I can assume that EF best explains delay discounting. If the path between EF and delay discounting loses significance, then I will add a path from each personality variable, one at a time, to EF (see **Figure 5)**. The same process will be completed with personality variables, while

controlling for EF (see **Figure 6**). If beta weights and alpha values suggest that EF and personality share the variance in delay discounting, then the shared/dual mechanism hypothesis will be supported. **Figure 7** is my hypothesized final structural model with paths from personality and EF to delay discounting.

Hypothesis: I hypothesize that significant ($p < 0.05$) standardized beta weights will support the paths from EF and personality variables to delay discounting. I also hypothesize that personality will emerge as the more robust predictor of delay discounting when controlling for EF, and likewise that the path from EF to delay discounting will no longer reach significance ($p < 0.05$) when controlling for personality.

Figure 5

Measurement Model – Personality and Delay Discounting, Controlling for EF.

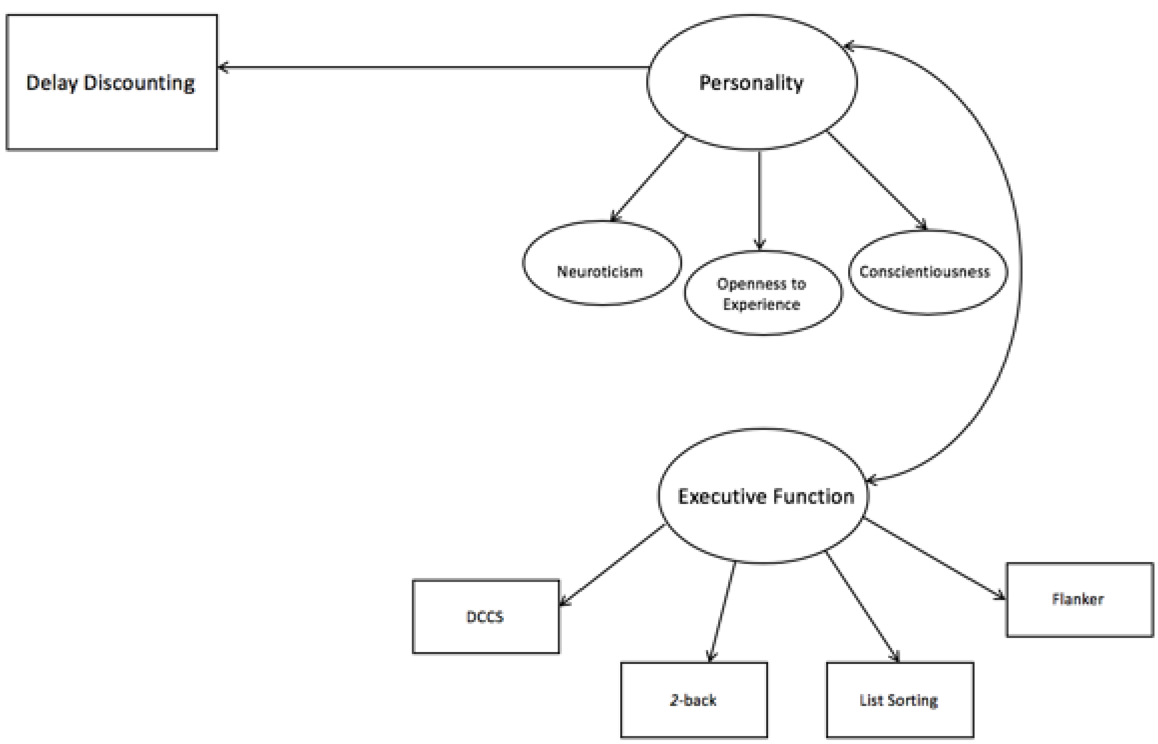


Figure 6

Measurement Model – EF and Delay Discounting, Controlling for Personality.

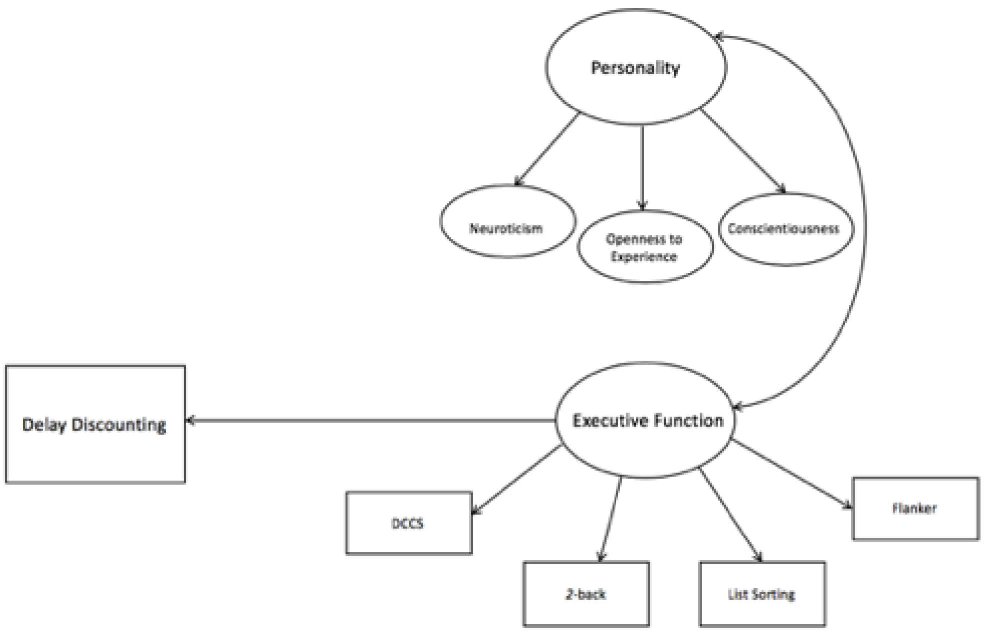
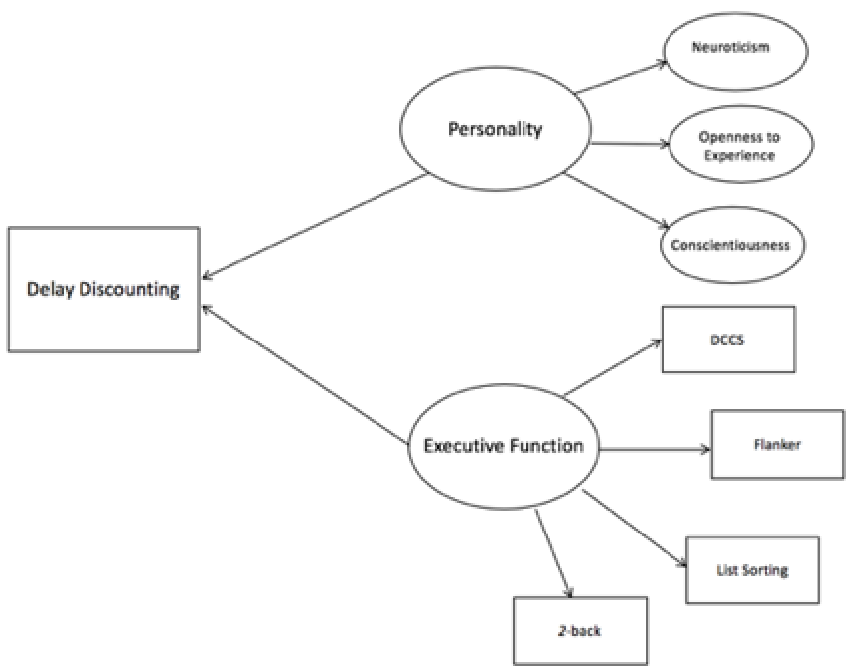


Figure 7

Measurement Model of Delay Discounting.



Objective 3: To test whether neuroanatomic variables (i.e., cortical thickness) are mediating the relationship between personality or EF and delay discounting, the single ROI for each subset (i.e., EF and personality) will be added to the measurement model in a mediation analysis fashion. To test for mediation, I will specify two indirect effects, one between personality variables/EF and the brain ROI, and the other between the brain ROI and delay discounting (see **Figures 8** and **9**). The direct (e.g., personality to delay discounting) and indirect paths (e.g., personality to the brain ROI) will be compared by 95% confidence intervals from bootstrapping along with *p*-values for each mediation model (Woody, 2011). To test the fit between EF and the executive control ROI, and personality and the default mode ROI, I will switch the position of the ROIs and compare model fit (i.e., before and after the switch) to test the hypothesis that the given ROIs actually better mediate the latent construct they are matched with relative to the construct they are not theoretically linked with. Change in Akaike's information criterion (AIC) will be used to assess and compare model fit.

Hypothesis 4. I hypothesize that brain regions relevant to delay discounting will mediate the relationship between delay discounting and personality variables and EF, consistent with the literature.

Figure 8

Personality and Delay Discounting, Mediated by Brain ROI.

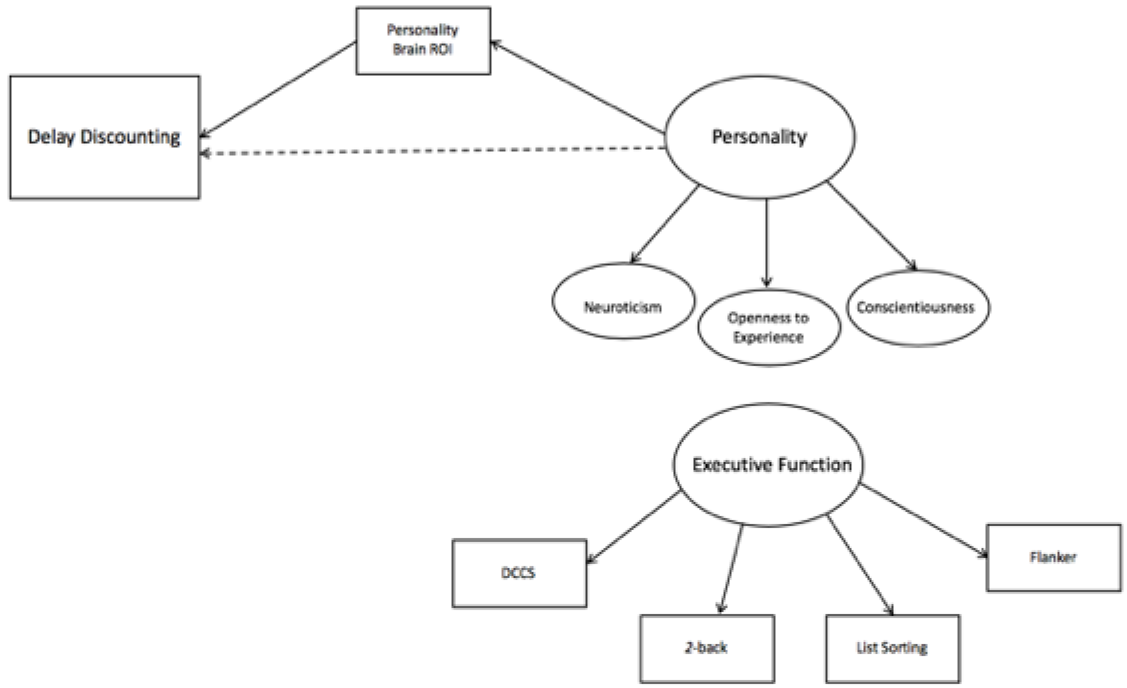
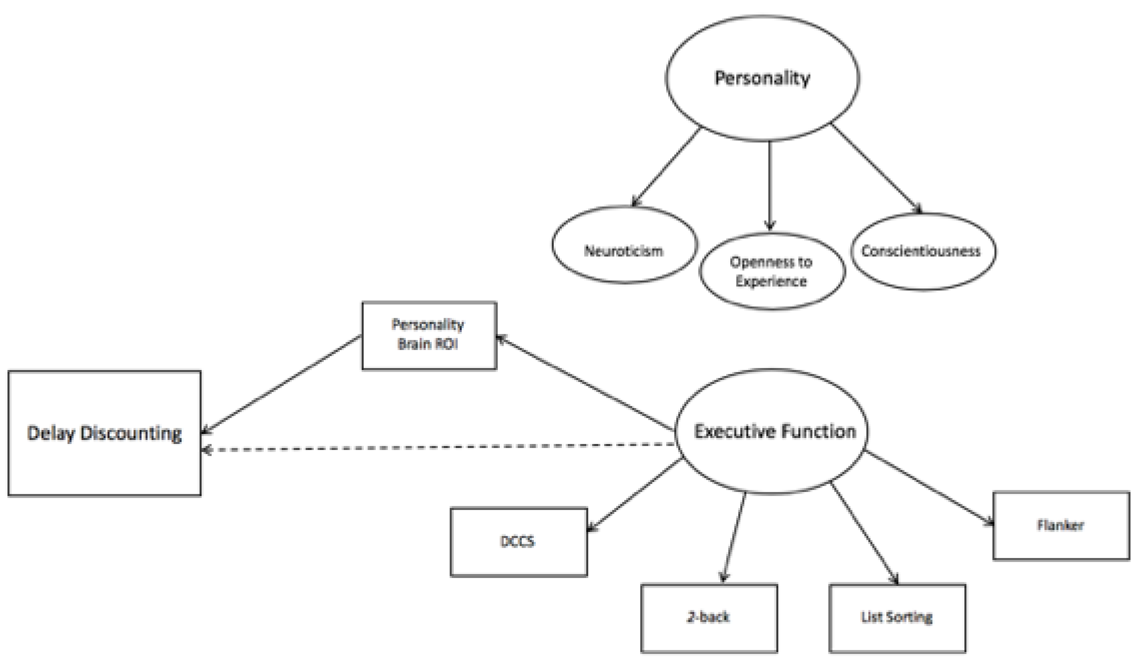


Figure 9

EF and Delay Discounting, Mediated by Brain ROI



Participants

The Human Connectome Project (HCP) consortium is a multisite project led by Washington University, University of Minnesota, and Oxford University. It was a systematic effort to "map macroscopic human brain circuits and their relationship to behavior in a large population of healthy adults" (Van Essen et al., 2013). The current study included 1,206 young adults (ages 22-35 years) from the HCP consortium from the 1200 Subjects release (please visit for more details: https://www.humanconnectome.org/study/hcp-young-adult). The primary participant pool comes from healthy individuals born in Missouri to families that include twins, based on the Missouri Department of Health and Senior Services Bureau of Vital Records. Additional recruitment efforts were used to ensure that participants broadly reflected the ethnic and racial composition of the U.S. population as represented in the 2000 decennial census. The HCP consortium opted to define 'healthy' broadly, in an effort to capture a wide range of variability in healthy individuals with respect to "behaviors, ethnic, and socioeconomic diversity" (Van Essen et al., 2013). The target number of participants was limited to 1,200 due to budget constraints as well as logistical constraints associated with the number of scans feasible to carry out in a three-year period on a single dedicated 3 Tesla (3T) scanner.

Procedures

Formal data collection. Recruitment, data collection, and brain imaging acquisition protocols for the HCP Young Adult study were described in detail by Van Essen et al. (2013) and available on-line at: https://www.humanconnectome.org/storage/app/media/documentation/s1200/HCP_S1200_Release_Reference_Manual.pdf. The study took place at Washington University in Saint Louis, Missouri. A review and signature of the informed consent document was completed by all

participants at the beginning of the study. Participants completed cognitive and behavioral assessments and magnetic resonance imaging (MRI) of their brain during two sessions lasting a total of several hours. Day 1 also included a mental status exam, breathalyzer test, blood draw, several self-report measures (relating to sleep quality, parental history, etc.), and cognitive testing using the National Institutes of Health (NIH) Toolbox (www.nihtoolbox.org). Also taking place on Day 1 was mock scanner practice, as well as three scan sessions involving several types of brain MRI scans. Day 2 included a diffusion imaging scan followed by a second combined resting-state and task-fMRI session. The total duration of the standard four scan sessions was about four hours, not including set-up time. If any scan was judged as unusable, an additional session was attempted to be scheduled during the initial or follow-up visit in order to reacquire the scan.

Screening interview. Initial telephone screening consisted of a questionnaire to determine whether prospective participants met the Human Connectome Project (HCP) inclusion criteria. If at least three family members, including one twin pair, met the inclusion criteria and expressed willingness to participate, each person was asked for verbal informed consent and given a more extensive telephone interview. The extensive phone interview consisted of the Semi-Structured Assessment for the Genetics of Alcoholics (SSAGA, Bucholz et al., 1994). A link to the complete questionnaire can be found at: https://niaaagenetics.org/coga_instruments/phaseI/ssagaI/ssagai.pdf). The SSAGA was designed to “assess the physical, psychological, and social manifestations of alcohol abuse or dependence and other psychiatric disorders” (Bucholz et al., 1994, p. 565). It is a polydiagnostic instrument that assesses somatization disorder, alcohol, nicotine, marijuana and drug abuse/dependence, anorexia, bulimia, adult attention-deficit/hyperactivity disorder, depression, mania, dysthymia,

antisocial personality disorder, posttraumatic stress disorder, panic, agoraphobia, social phobia, and obsessive-compulsive disorder using DSM-III-R and DSM-IV and at least one other of the following diagnostic systems: Feighner RDC (Research Diagnostic Criteria) and ICD-10. Many disorders can be scored for DSM-III diagnosis as well. See **Figure 10** for an example of the items on the questionnaire.

The SSAGA also covers general demographic information, medical history information, information about tobacco use, and suicide attempts, and it contains a psychosis screener to identify individuals requiring clinical follow-up for diagnosis. The SSAGA has the interviewer plot a “life chart” of diagnoses to elaborate on comorbidity, the course of the respondent’s substance use as this relates to other psychiatric problems. This instrument was used to confirm the absence of significant previously documented psychiatric illness and to obtain information about subthreshold psychiatric symptoms. According to Van Essen et al. (2013), no participants who passed the initial telephone interview screening had been subsequently excluded during the SSAGA. On average, approximately 6-7 families were screened in order to identify one family with a twin pair and at least one other sibling who met all inclusion criteria and who were willing to participate. Of the 1,206 participants, 336 participants were monozygotic twin pairs and 206 participants were dizygotic twin pairs as determined by genotyping (if available) or self-report.

Exclusion/inclusion criteria. Siblings of individuals with severe neurodevelopmental disorders (e.g., autism), documented neuropsychiatric disorders (e.g., schizophrenia or depression), or neurologic disorders (e.g., Parkinson’s disease) were excluded from the study. Also excluded were individuals with illnesses such as diabetes or high blood pressure, as they may negatively impact neuroimaging quality. Twins born prior to 34 weeks’ gestation and non-twins born prior to 37 weeks’ gestation were excluded, reflecting the higher incidence of

prematurity in twins. The HCP young adult consortium included individuals ages 22 to 35 years who could give valid informed consent. Additionally, individuals were included who are smokers, are overweight, or have a history of heavy drinking or recreational drug use without having experienced severe symptoms. Out of 1,206 participants, a total of 1,046 participants were included in the present study due to data availability, and all 1,046 participants had complete data for variables relevant to the present study. Participant demographics for the current study are shown in **Table 3**.

Figure 10

SSAGA Interview. Selected questions from Module I: Depression.

Now I'm going to ask you some questions about your mood.

RDCI	I1	Have you ever had a period of at least <u>one week</u> when you were bothered most of the day nearly every day by feeling depressed, sad, blue, or irritable?	NO......................1 YES....................5
	I2	Have you ever had a period of at least one week when you lost interest or enjoyment in almost everything, even things you usually liked to do?	NO......................1 YES....................5

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***********************************
* IF I1 AND I2 BOTH CODED 1, SKIP *
* TO J1, P.59.   OTHERS CONTINUE. *
***********************************
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	I3	Have you been feeling depressed, uninterested in things or unable to enjoy almost everything for at least one week during the past 30 days?	NO...(SKIP TO I4)......1 YES....................5
DEP3RA1		A. For how long have you felt this way?	__ __ __ WEEKS
DEP3RA2		B. Have you been feeling depressed, sad or blue nearly every day?	NO......................1 YES..(SKIP TO I4)......5
		C. Have you lost interest or enjoyment in most things nearly every day?	NO......................1 YES....................5
	I4	Think about your most <u>severe</u> period of feeling depressed, uninterested in things or unable to enjoy most things. When did it begin?	__/__ __/__ MO YR
		A. So you were ___ years old?	AGE ONS: __/__
DEP3RA1 DEP3RA2		B. How long did that period last?	__ __ __ WEEKS
		C. Were you feeling depressed, sad, or blue nearly every day during this period?	NO......................1 YES...(SKIP TO BOX)....5
		D. Had you lost interest or enjoyment in most things nearly every day during this period?	NO......................1 YES....................5

CHECK TALLY SHEETS E, F, AND G. IF 3 OR MORE CHECKS FOR DSM-III-R SYMPTOMS, CONTINUE. OTHERS SKIP TO I4K.

		E. During this most severe period were you using street drugs or drinking more than usual?	NO....(SKIP TO K)......1 YES....................5
		F. Did you have another period of feeling depressed, uninterested in things or unable to enjoy most things when you were not drinking more than usual or using street drugs?	NO....(SKIP TO K)......1 YES....................5

Table 3

Participant Demographics

Characteristic	Value	%
N	1046	--
Age, years (*M, SD*)	28.8 (0.11)	--
Education, years (*M, SD*)	14.9 (0.05)	--
Handedness (*M, SD*)*	66.2 (1.40)	--
Male	482	46
Race		
White	787	75
Black/African American	143	15
Asian/Nat. Hawaiian/Pac. Islander	63	6
Am. Indian/Alaskan Nat.	2	<1
More than one	26	2
Unknown/Not reported	18	2
Household Income		
<$10,000	72	7
$10,000 - $19,999	82	8
$20,000 - $29,999	136	13
$30,000 - $39,999	126	12
$40,000 - $49,999	108	10
$50,000 - $74,999	220	21
$75,000 - $99,999	142	14
≥$100,000	163	15

Participants are from the HCP 1200 Release dataset
*Handedness of participant is a numerical value that ranges from -100 to 100 and was assessed using the Edinburgh Handedness questionnaire (Oldfield, 1971). Negative numbers indicate that a subject is more left-handed than right-handed, while positive numbers indicate that a subject is more right-handed.

Measures

Neuroimaging. All HCP subjects are scanned on a customized Siemens 3T “Connectome Skyra” at Washington University, using a standard 32-channel Siemens head coil. Based on HCP piloting, an optimized fMRI protocol was established (both resting-state and task-evoked) on the Connectome Skyra (Ugurbil et al., 2013). Structural MRI images included high resolution T1-

and T2-weighted images. The T1-weighted images had a spatial resolution of 0.7mm isotropic voxels (FOV = 224 mm, matrix = 320, 256 sagittal slices, interleaved), repetition time (TR) of 2400ms, and an echo time (TE) of 2.14ms. The total acquisition time for this scan was 7 minutes and 40 seconds. The T2-weighted images had a spatial resolution of 0.7mm isotropic voxels (FOV = 224mm, matrix = 320, 256 sagittal slices, interleaved), TR = 3200ms, and TE = 565ms. A complete list of all the HCP MRI protocols can be found at: https://humanconnectome.org/storage/app/media/documentation/s1200/HCP_S1200_Release_Appendix_I.pdf

Per Glasser et al.'s (2013) description, FreeSurfer, an open source software package for processing, analysis, and visualization of neuroimaging data (see: https://surfer.nmr.mgh.harvard.edu), was used to automatically segment subcortical gray matter structures (see Fischl et al., 2002). In contrast to subcortical data, cortical data was constructed with a surface-constrained method, as a cortical surface is most easily manipulated and analyzed as a 2D surface (Glasser et al., 2013). Glasser et al. (2013) describes in detail that, "cortical areas are spaced farther apart across the surface than they are in the volume because of cortical convolutions. Functionally distinct areas may be separated by only a few millimeters in volume across sulcal banks or gyral blades" (p. 106). The Connectivity Informatics Technology Initiative (CIFTI) file format was created to include combinations of cortical surface data and subcortical gray matter data modeled in volumetric parcels. The term "grayordinates" is used to describe the spatial dimension of the combined coordinate system (Glasser et al., 2013). Right and left standard cortical surface meshes and subcortical volumes are used to create the grayordinate space. The benefit of the CIFTI grayordinate space is that it has more precise spatial correspondence across subjects than data aligned using whole brain volume. The cortical gray

and white matter were segmented according to Desikan et al.'s (2006) atlas based on gyral and sulcal patterns. All procedures related to neuroimage processing, reconstruction, segmentation, and extraction of data were performed by HCP investigators. Cortical thickness, surface area, and volume for each ROI were readily available for use for statistical analyses. See Glasser et al. (2013) for further details on the CIFTI/grayordinate cortical surface data. For the current study, cortical thickness, calculated as the shortest distance between the white matter and the pial surface, is the preferred neuroanatomic variable, given its alterations across the lifespan as a consequence of raining, experience, and disease (Meyer et al., 2013). Additionally, the "radial unit hypothesis" (Rakic, 1988), suggests that cortical thickness is driven by the number of neurons within each cortical column, which reflects how cortical neurons are organized in the brain rather than simply indicating the density of gray matter tissue (Menary et al., 2013).

Regions of interest. The parcellated left and right regions of cortical thickness are referred to as "regions of interest" or ROIs. Two subsets of ROIs, one for personality factors and one for executive function, were based on the empirical literature of mapping intrinsic connectivity networks of the brain, consistent with a more contemporary, network representation of brain function (Yeo et al., 2011; Smith et al., 2009). I selected 12 left and right ROIs per network, which are the common brain areas in the default mode network (i.e., cortical midline structures and parietal regions important for self-reflection and autobiographical knowledge; Grecious et al., 2003; Raichle & Snyder, 2007) or executive control network (i.e., frontal network crucial to working memory and cognitive control; Smith et al., 2009; Seeley et al., 2007). In the current study, the default mode network is hypothesized to be theoretically linked to personality whereas the executive control network is thought to reflect cognition. See **Table 4** for the *a priori* list of selected ROIs corresponding to each intrinsic connectivity network.

Table 4

Regions of Interest Corresponding to Intrinsic Connectivity Networks

Executive Control	Default Mode
L Caudal Anterior Cingulate	L Inferior Parietal Lobule
R Caudal Anterior Cingulate	R Inferior Parietal Lobule
L Caudal Middle Frontal	L Medial Orbitofrontal
R Caudal Middle Frontal	R Medial Orbitofrontal
L Lateral Orbitofrontal	L Middle Temporal
R Lateral Orbitofrontal	R Middle Temporal
L Rostral Anterior Cingulate	L Posterior Cingulate
R Rostral Anterior Cingulate	R Posterior Cingulate
L Rostral Middle Frontal	L Precuneus
R Rostral Middle Frontal	R Precuneus
L Superior Frontal	L Supramarginal
R Superior Frontal	R Supramarginal

Note: L = left hemisphere; R = right hemisphere

Next, the subset of ROIs will be correlated with delay discounting, and the single most robust ROI with the most promise for model building will be selected from each subset.

Delay discounting task. The discounting task in the HCP protocol involves identifying indifference points where a person is equally likely to choose a smaller reward sooner versus a larger reward later. Delays were fixed and reward amounts were adjusted on a trial-by-trial basis determined by the participants' choices in order to identify indifference points. This approach was validated and demonstrated reliable estimates of delay discounting (Estle et al., 2006). The area-under-the-curve discounting measure (AUC) provides a valid and reliable summary measures of how steeply an individual discounts delayed rewards (Myerson et al., 2001).

The following description of the delay discounting task is adapted from the Human Connectome Manual (https://www.humanconnectome.org/storage/app/media/documentation/s1200/HCP_S1200_Release_Reference_Manual.pdf). In the HCP delay discounting task, participants are presented with

two choices on each trial – a smaller amount “today” or a larger amount at a later point in time. Participants make choices at each of 6 delays (1 month, 6 months, 1 year, 3 years, 5 years and 10 years) and for two delayed amounts ($200 and $40,000). For each combination of delay and amount of delayed reward (e.g., $200 in 1 month or $40,000 in 6 months), participants make 5 choices, and the value that would have been used for the immediate amount in a 6th choice is taken as the indifference point for that condition. The participants make all five choices for a particular combination of delay and amount before moving on to the next combination of delay and amount. The order is as follows:

Delayed amount ($200 or $40,000) dollars: Today vs. 6 months; Today vs. 3 years; Today vs. 1 month; Today vs. 5 years; Today vs. 10 years; Today vs. 1 year. The first choice at each delay is between the delayed amount ($200 or $40,000) and an immediate amount equal to half the delayed amount (e.g., $100 today or $200 in 1 month, $20,000 today or $40,000 in one month). The size of the adjustment after the first choice is always ½ the amount of the immediate value on the first choice (e.g., a change of $50 if the first immediate amount is $100). If the subject chooses the immediate amount, then the immediate amount is reduced on the next choice (e.g., $50 today versus $200 in 1 month). If the subject chooses the delayed amount, then the immediate amount is increased (e.g., $150 today versus $200 in 1 month). The amount of change on each subsequent choice is half the amount of the prior change (e.g., $25 on the 3rd trial), regardless of whether the subject chooses the immediate or the delayed amount. This procedure rapidly hones in on the amount of immediate gain that is close to the subjective value of the delayed gain. This design means that for all the choices with $200 dollars as the delayed amount, the first choice will always be between $100 today, and $200 in the specified time period. The second choice will always increment or decrement the immediate value by $50. The third choice

will always increment or decrement the immediate value by $25. The fourth choice will always increment or decrement the immediate value by $12.50. The fifth choice will always increment or decrement the immediate value by $6.25. The "sixth" choice value, which is never presented to the subject, but is entered in the database, is always an increment or decrement of $3.125 from the immediate value on the 5th choice. Similarly, for all the choices with $40,000 dollars as the delayed amount, the first choice will always be between $20,000 today, and $40,000 in XX time period. The second choice will always increment or decrement the immediate value by $10,000. The third choice will always increment or decrement the immediate value by $5,000. The fourth choice will always increment or decrement the immediate value by $2,500. The fifth choice will always increment or decrement the immediate value by $1,250. The "sixth" choice value, which is never presented to the subject, but is entered in the database, will always be an increment or decrement of $625 from the immediate value on the 5th choice. Thus, for the $200 or $40,000 amount, there are 6 values (1 month, 6 months, 1 year, 2 years, 3 years, 5 years, 10 years).

An area under the curve was computed for each of the two amounts as described below.

- Area under the curve for $200 = ((1+SV1mo.2)/(120*200)) + ((SV1mo.2+SV6mo.2)/(48*200)) + ((SV6mo.2+SV1yr.2)/(40*200)) + ((SV1yr.2+SV3yr.2)/(10*200)) + ((SV3yr.2+SV5yr.2)/(10*200)) + ((SV5y r.2+SV10yr.2)/(4*200))
- Area under the curve for $40,000 = ((1+SV1mo.4)/(120*40,000)) + ((SV1mo.4+SV6mo.4)/(48*40,000)) + ((SV6mo.4+SV1yr.4)/(40*40,000)) + ((SV1y r.4+SV3yr.4)/(10*40,000)) + ((SV3yr.4+SV5yr.4)/(10*40,000)) + ((SV5y r.4+SV10yr.4)/(4*40,000))

The AUC measure for each of the two amounts ($200 and $40,000) was computed and higher values for AUC are indicative of higher valuation of future gains (i.e., higher AUC values indicate lower levels of impulsivity). The steeper the discounting (i.e., the lower the subjective value of delayed rewards), the smaller the AUC will be. The AUC can vary between 0.0

(steepest possible discounting) and 1.0 (no discounting). An important note is that in this case the AUC is calculated from actual data points rather than from a curve to fit the data.

Confounding variables.

Socioeconomic status. Past studies have found an association between higher discounting rates and lower socioeconomic status. The importance of incorporating socioeconomic status while examining discounting behaviors came to light following the famous “Marshmallow Test,” conducted by Walter Mischel and Ebbe Ebbesen (1970). Mischel and Ebbesen found that children who displayed willpower by waiting to eat the first marshmallow fared better later in life (e.g., higher standardized test scores), as noted in their follow-up study in 1990 (Shoda, Mischel, & Peake). However, subsequent studies by other researchers failed to replicate this finding. For instance, Watts, Duncan, and Quan (2018) replicated this test in a larger sample that was more representative of the general population. The authors found that being able to delay gratification was in large part shaped by a child’s socioeconomic background, and that in turn, was also what was behind the children’s long-term success. Therefore, I controlled for household income by including it in my measurement model, as income is a suitable proxy for socioeconomic status (APA, 2007). In this study, household income is an ordinal variable, with eight levels ranging from one (less than $10,000 annual household income) to eight (more than $100,000; see **Table 3**).

Age. Rate of discounting can change as a function of age (see **Figure 2)**; however, the current study includes participants within a highly restricted age range (e.g., 22 to 35 years). The extent that age may interact with delay discounting is unclear. An initial step was to use a data visualization technique of the regression of age upon the delay discounting variable and examine

the R-square value for the linear and quadratic nature of the relationship to see if age should be stratified into groups (e.g., 22 to 25, 26 to 29, etc.).

Personality inventory. On the second day of the study, participants completed the Neuroticism-Extraversion-Openness Five-Factor Inventory (NEO-FFI; Costa & McCrae, 1992), a self-report measure that assesses five domains that best explain personality: Neuroticism, Conscientiousness, Openness to Experience, Extraversion, and Agreeableness. These domains were developed through examination of adjectives in the English language that have been used to describe traits/characteristics of people. Raymond Catell's influential research (1945) applied factor analysis to people's ratings of personality and identified 16 common factors of personality. Further decades of research indicated the taxonomy of personality could be best described through a five-factor solution (e.g., Borgatta, 1964; Norman, 1963) also called the "five-factor model," or FFM, or "The Big Five." Currently, the FFM may be the most widely accepted method of describing personality trait structure (McCrae & Costa, 2008).

To reduce participant burden, the NEO-FFI consists of 60 items selected from the more extensive 180-item NEO Personality Inventory (NEO-PI; Costa & McCrae, 1989) and 240-item NEO Personality Inventory – Revised (NEO-PI-R; Costa & McCrae, 1992). The NEO-FFI items were selected from the NEO-PI and NEO-PI-R items that demonstrated the strongest correlations with each domain factor score and based on factor structure and internal consistency (Rosellini & Brown, 2011). As expected, the longer NEO questionnaires (NEO-PI-R and NEO-PI) have better psychometric properties than the shorter forms (e.g., NEO-FFI) (Costa & McCrae, 2004). As noted above, The NEO-FFI incorporated 12 items relating to each of the five domains (i.e., 60 total items) of Neuroticism, Conscientiousness, Openness to Experience, Extraversion, and Agreeableness. For example, Extraversion facets include warmth, assertiveness, gregariousness,

positive emotions, activity, and excitement-seeking (please see **Table 5** for a comprehensive description of each of the five domains of personality).

Table 5

List of the Five Factor Model Domains, Definitions, and Example Behaviors

Five Factor Model Domain	Definition	Example Behavior for Low Scorers	Example Behavior for High Scorers
Openness to Experience	The tendency to appreciate new art, ideas, values, feelings, and behaviors.	Prefers not to be exposed to alternative moral systems; narrow interests; inartistic; not analytical; down-to-earth	Enjoys seeing people with new types of haircuts and body piercings; curious; imaginative; untraditional
Conscientiousness	The tendency to be careful, on-time for appointments, to follow rules, and to be hardworking.	Prefers spur-of-the-moment action to planning; unreliable, hedonistic; careless; lax	Never late for a date; organized; hardworking; neat; persevering; punctual; self-disciplined
Extraversion	The tendency to be talkative, sociable, and to enjoy others; the tendency to have a dominant style.	Preferring a quiet evening reading to a loud party; sober; aloof; unenthusiastic	Being the life of the party; active; optimistic; fun-loving; affectionate
Agreeableness	The tendency to agree and go along with others rather than to assert one's own opinions and choices.	Quickly and confidently asserts own rights; irritable; manipulative; uncooperative; rude	Agrees with others about political opinions; good-natured; forgiving; gullible; helpful
Neuroticism	The tendency to frequently experience negative emotions such as anger, worry, and sadness, as well as being interpersonally sensitive.	Not getting irritated by small annoyances; calm; unemotional; hardy; secure; self-satisfied	Constantly worrying about little things; insecure; hypochondriacal; feeling inadequate

Table adapted from Diener and Lucas (2018).

Responses on the NEO-FFI use a Likert scale, and participants responded by marking on each item whether they *strongly disagree, disagree, neutral, agree, or strongly agree* to a proposition about themselves. The scores were derived by coding each item (strongly disagree = 0, disagree = 1, neutral = 2, agree = 3, and strongly agree = 4. Items were also reverse coded and summed into each of the five subscales (Neuroticism, Conscientiousness, Openness to experience, Extraversion, and Agreeableness). Sample items on the NEO-FFI include: “I really enjoy talking to people,” “I like to be where the action is,” and “I am seldom sad or depressed.”

Administration time of the NEO-FFI can take as little as 10-15 minutes. The NEO-FFI item-level data for the three relevant domains of personality (Neuroticism, Conscientiousness, Openness to Experience) will be used for the exploratory and confirmatory factor analyses.

Costa and McCrae (1992) reported adequate internal consistencies of the NEO-FFI ranging from 0.68 to 0.86 for each of the five factors, with test-retest correlations ranging from 0.75 to 0.83. Robins and colleagues (2001) reported even better temporal stability across the five domains in a sample of 107 undergraduate students at one point in time and then two weeks later, with test-retest reliabilities of 0.86 (Extraversion, Agreeableness), 0.88 (Openness to Experience), 0.89 (Neuroticism), and 0.90 (Conscientiousness). The NEO-FFI has demonstrated good convergent and discriminant validity. Forrester and colleagues (2016) administered the NEO-FFI and the Fundamental Interpersonal Relations Orientation – Behavior (FIRO-B; Schutz, 1979) instrument to 219 students engaged in business courses at an American university in the southeast and ranged in age from 20 – 52 years (M = 26.7 years). Results showed adequate correlations in the expected direction between Extraversion and ‘Expressed Inclusion’ ($r = 0.21$, $p < .01$), Neuroticism and ‘Expressed Affection’ ($r = -0.209$, $p < .01$), and Agreeableness and ‘Expressed Affected’ ($r = 0.302$, $p < .01$; Forrester, Tashchian, & Shore, 2016). Regarding convergent validity of the FFM and psychopathology, Costa and McCrae (1992) examined the association between the NEO-PI and psychopathology as assessed by the Personality Assessment Inventory (PAI; Morey, 1991). The authors found positive associations between Neuroticism and depression ($r = 0.40$), schizophrenia ($r = 0.51$), and anxiety ($r = .63$), and between Openness to Experience and mania ($r = 0.37$) and features of antisocial personality disorder ($r = 0.38$). Additionally, negative associations between Extraversion and depression ($r = -0.38$),

Agreeableness and paranoia (r = -0.52), and Conscientiousness and depression (r = -0.27) were expectedly found as well (Costa & McCrae, 1992).

The NEO-FFI domain scores also demonstrate good external validity (i.e., relate to "real-world" behavior). For instance, Barrick and Mount (1991) found that people higher in Conscientiousness showed consistent positive relationships with three job performance criteria (job proficiency, training proficiency, and personnel data) across five occupational groups (professionals, sales, managers, police, and skilled/semi-skilled). Additionally, Paunonen and Ashton (2001) sampled 717 undergraduate students and found that higher scores on the Conscientiousness scale significantly predicted (r = 0.21, p < .01) final course grades, an objective measure of academic performance. The FFM domains also relate to problematic behaviors, for example, Ruiz, Pincus, and Dickinson (2003) examined NEO-PI-R scores and alcohol-related behaviors and found that people with high neuroticism (r = 0.26) and low conscientiousness (r = -0.33) were significantly associated with risky drinking.

Cognitive measures. Participants completed a set of measures from the NIH Toolbox (http://www.nihtoolbox.org/) on visit Day 1, which took about 2 hours and included 19 subdomains within the broad domains of cognitive, emotional, motor, and sensory function (Weintraub, et al., 2013). Below are the NIH Toolbox tests that were selected for the current study, based on an expected relationship with delay discounting. Age-adjusted scaled scores for stratified age ranges (18-29, 30-39) were used for all NIH Toolbox measures (see Casaletto et al., 2015 for more details about the normative sample). The age-adjusted scaled scores (M = 100, SD = 15) for the NIH Toolbox measures will serve as the data for my exploratory and confirmatory factor analyses. See **Table 6** for a summary of the selected NIH Toolbox tests and their psychometric properties. Additionally, one relevant in-scanner task, the *N-Back* Working

Memory Task, was also selected for the analysis. There were no standardized scores available for this task, and therefore each participant's percentage accuracy on this task will be used for data analysis. The use of different scales, e.g., age-adjusted standardized scores from the NIH Toolbox measures and percentage accuracy on the *N-Back*, may pose an issue for exploratory and confirmatory factor analyses. For this reason, indicator loadings will be examined to inspect whether scalar variance may be influencing results.

Table 6

Psychometric Properties of the Selected NIH Toolbox Measures

Test	**Test-Retest Reliability (ICC)**	**Convergent Validity**	**Discriminant Validity**
Card Sort	0.88	-0.51	0.14
Flanker	0.80	-0.48	0.15
Picture Sequence	0.77	0.69	-0.08
List Sorting	0.77	0.58	0.30
Oral Reading	0.91	0.93	0.19

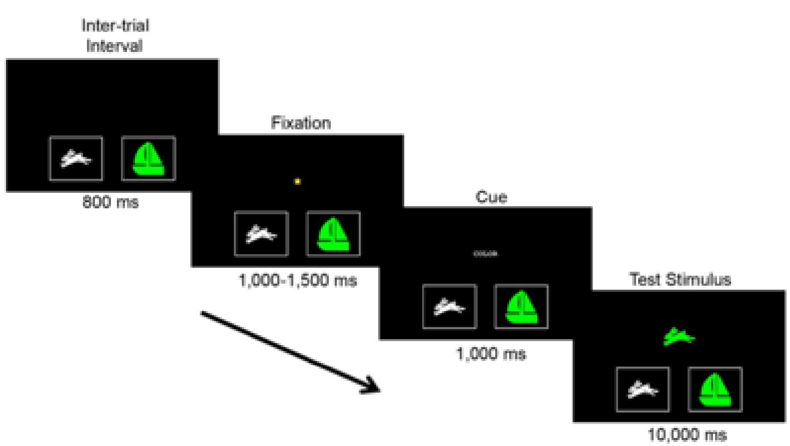
Validation sample included 268 adults (ages 20-85). Table taken from Weintraub et al., 2013.

Dimensional Change Card Sort Test. The Dimensional Card Sort Task (DCCS; Zelazo, 2006) is a measure of executive function that primarily taps into cognitive flexibility, attention, and working memory. In this task, two target cards are presented that vary across two dimensions (e.g., shape and color). Participants are required to sort the series of test cards (e.g., blue trucks and yellow balls), first according to one dimension (e.g., color), and then according to the other (e.g., shape). There are 4 trial conditions, administered in the following order: practice, pre-switch, post-switch, and mixed trials. The dimension for sorting is indicated by a cue word on the screen, and participants respond to each trial by using a key press. Participants received feedback on their performance during practice trials only and were required to accurately sort 3 out of 4 practice items in order to proceed. Once the criterion was met for the

first sorting dimension, participants were trained on the second dimension. If they did not meet this criterion, they could receive 2 more practice trials (limit was 3 total). If both trials were successfully completed, the test trials were administered. See **Figure 11** for visualization of a practice trial sequence for the DCCS (Zelazo et al., 2014). A pre-switch block of 5 trials was administered in which participants needed to sort by the same dimension (e.g., color) that was used in the preceding practice block, and then 5 post-switch trials were administered requiring the participant to sort by the other dimension (e.g., shape). Lastly, “mixed” trials were administered which required participants to switch back and forth between dimensions and consisted of 50 trials, including 40 “dominant” and 10 “non-dominant” trials presented in a pseudorandom order. The dominant dimension was always the sorting dimension used in the post-switch block (e.g., shape). The total administration time for this task is around 4 minutes (Weintraub et al., 2013).

Figure 11

Dimensional Change Card Sort Test.



Caption: A sequence of practice stimuli from the Dimensional Change Card Sort test (DCCS). This image is taken from Zelazo et al.’s (2014) description of the DCCS which was adapted for computerized use as part of the NIH Toolbox Cognition Battery.

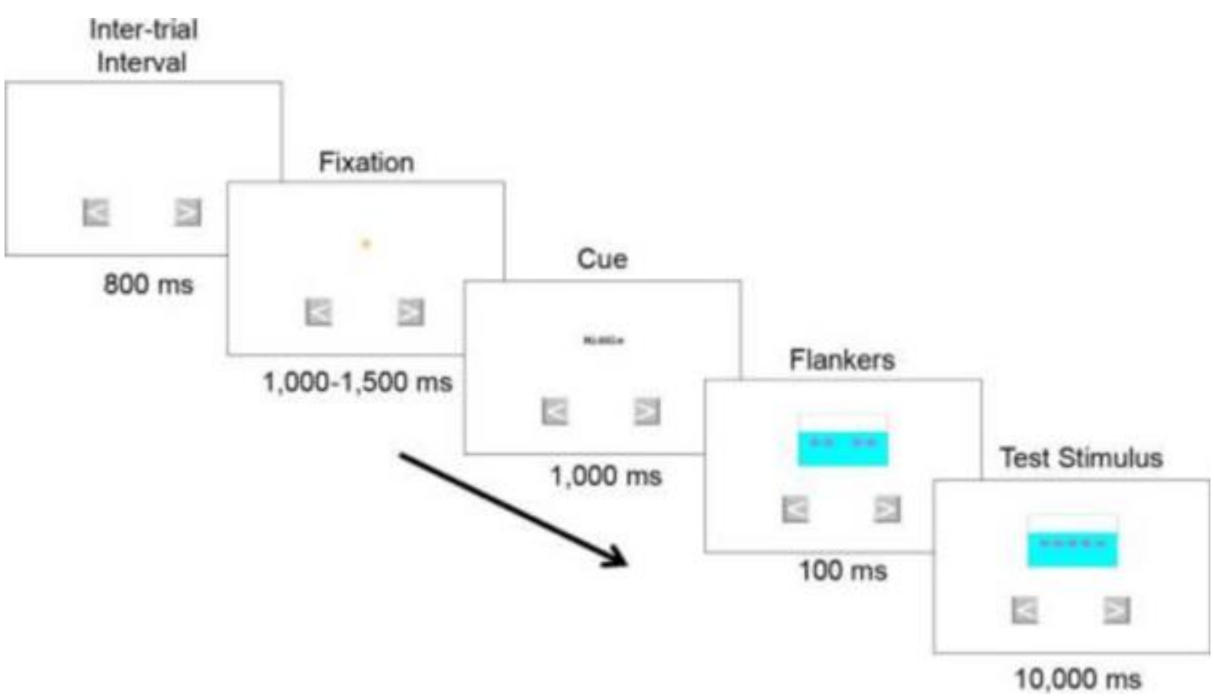
As described in Zelazo et al. (2013), the scoring algorithm integrated accuracy and reaction time, such that when accuracy levels are >80%, reaction time score and accuracy score were combined. If accuracy levels were ≤80%, the final computed score was equal to the accuracy score only (NIH Toolbox DCCS Technical Manual). Test-retest reliability was good over a period of 1-3 weeks (ICC = 0.88) across the adult sample. The Color-Word Interference Inhibition subtest from the Delis-Kaplan Executive Function Scale (D-KEFS; Delis, Kaplan, Kramer, 2001) was used to assess convergent validity and was found to be moderately correlated (r = 0.51), suggesting adequate convergent validity (Weintraub et al., 2013). Discriminant validity was assessed using the Peabody Picture Vocabulary Test, 4th Edition (PPVT-4; Dunn & Dunn, 2007). Participants' DCCS scores demonstrated a lack of or weak relationship to scores on the PPVT-4 (r = 0.14), indicating good discriminant validity.

Flanker Inhibitory Control and Attention Test. The Flanker Inhibitory Control and Attention Test (i.e., the flanker test), is a version of the Erikson flanker task (Erikson & Erikson, 1974) which was adapted from the Attention Network Test (ANT; Fan, McCandliss, Sommer, Raz, & Posner, 2002). In the current flanker task, participants were required to indicate the left-right orientation of a stimulus while inhibiting attention to an incongruent stimulus surrounding it (i.e., the 'flankers'), typically two on either side (Zelazo et al., 2014). The version created for the NIH Toolbox includes both fish (easier) and arrows (more difficult) as the flankers. On some trials, the orientation of the flanking stimulus is congruent with the orientation of the target stimulus, and on others is incongruent. The incongruent trials provide a measure of inhibitory control performance in the context of visual selective attention, also considered a measure of executive function (e.g., Fan et al., 2002). There are 40 trials and the average time to complete the task is 4 minutes. The flanker test consisted of a practice block, a fish block, and an arrows

block. Participants were given 4 practice trials (2 congruent and 2 incongruent) and were required to respond correctly on at least 3 out of the 4 to advance to the test trials. They could receive up to 2 additional practice trials if they did not meet this criterion. Test trials consisted of a block of 25 fish trials (16 congruent and 9 incongruent) presented in a pseudorandom order (with 1-3 congruent trials preceding each incongruent trial). Participants preceded to the arrows block with an identical structure to the fish trials (25 trials with 16 congruent and 9 incongruent). The test takes approximately 3 minutes to administer. See **Figure 12** for a visualization of a practice fish trial. Similar to the DCCS scoring algorithm, accuracy and reaction time were factored together, with reaction time being a more relevant measure of adult performance on this task (Zelazo et al., 2013).

Figure 12

Flanker Inhibitory Control and Attention Test.



Caption: A sequence of practice stimuli from the Flanker Inhibitory Control and Attention Test. This image is taken from Zelazo et al.'s (2014) description of the flanker test which was adapted for computerized use as part of the NIH Toolbox Cognition Battery.

Test-retest reliability was good over a period of 1-3 weeks (ICC = 0.8) across the adult sample (Weintraub et al., 2013). The Color-Word Interference Inhibition subtest from the D-KEFS (Delis, Kaplan, Kramer, 2001) was used to assess convergent validity, and was found to be moderately correlated (r = -0.48), suggesting adequate convergent validity (Weintraub et al., 2013). Discriminant validity was assessed using the PPVT-4 (Dunn & Dunn, 2007), and performance on the flanker task was weakly associated with scores on the PPVT-4 (r = 0.15), indicating good discriminant validity.

Picture Sequence Memory Test. The Picture Sequence Memory Test (PSMT) is a measure of episodic learning and memory (Dikmen et al., 2015). Episodic memory is a person's unique memory of a specific event and includes information about recent or past events and experiences (e.g., where you parked your car yesterday) (Tulving, 2002). The PSMT requires new learning of sequences of pictures of objects/activities. The sequence lengths used in this task exceeded immediate normal working memory span and multiple learning trials were used to specifically target episodic memory. In addition to episodic memory, the PSMT also relies heavily on verbal skills (i.e., verbal comprehension of instructions, verbal responses, etc.) (Dikmen et al., 2015). Administration involved a series of color pictures presented in a fixed order while the content of each picture is orally described. Once described, the picture is minimized and moved to its fixed position in the sequence, and the next picture is presented without delay. This continues until all pictures in a sequence have been displayed and placed in position. Next, the pictures are placed in a random spatial array and the participant must move each picture from the center to its correct location to replicate the correct sequence. Exposure to each picture was approximately 5 seconds. Therefore, a 15-item sequence would take

approximately 1.25 minutes, though how long the participant took to perform the task varied. To orient participants to the task, two to three practice sequences were administered first. **Figure 13** shows a practice trial involved a four-step practice sequence with a “Circus” theme. Test trials involved administration of one of three equivalent forms of the task, which were randomly assigned: “Working on the Farm,” “Playing in the Park,” and “Going to the Fair.” Participants were administered 15-picture sequences with additional pictures added to the end of the sequence on the 2nd and 3rd trials in the case of ceiling score on the first trial. Three trails with recall were administered after each exposure.

Figure 13

Picture Sequence Memory Test.

Caption: A sequence of practice stimuli from the Picture Sequence Memory Test. This image is taken from Dikmen et al.’s (2015) description of the test for computerized use to measure episodic memory as part of the NIH Toolbox Cognition Battery.

Performance on the PSMT was measured by the cumulative number of correct adjacent pairs of pictures remembered correctly over the 3 earning trials, regardless of the number of pictures in the sequence. Adjacent pairs are two pictures placed in the correct consecutive and ascending order (e.g., pictures placed in the order 3-4 and 5-6 would be correct, whereas pictures placed 1-3 or 5-10 would not receive credit. Total administration time, on average, was about 10 minutes. Delayed recall of trials was not examined due to significant time constraints of the length of the NIH Toolbox Battery.

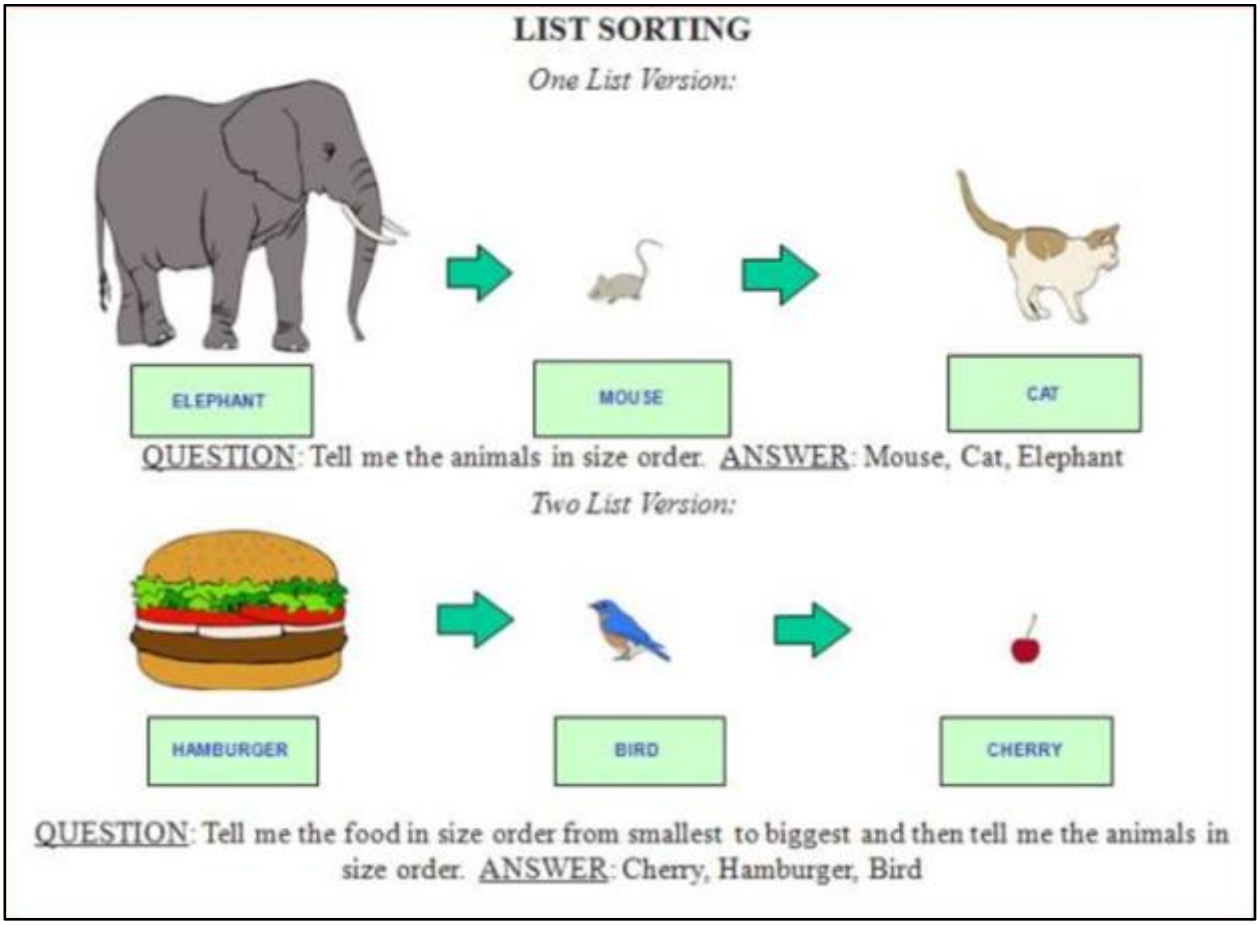
Test-retest reliability was good over a period of 1-3 weeks (ICC = 0.77) across the adult sample (Weintraub et al., 2013). Convergent validity was evaluated by comparing the performance on the Brief Visuospatial Memory Test-revised (BVMT-R; Benedict, 1997) and the Rey Auditory Verbal Learning Test (RAVLT; Rey, 1964). Correlational analyses found a moderate association ($r = 0.69$), suggesting adequate convergent validity (Weintraub et al., 2013). Discriminant validity was assessed using the PPVT-4 (Dunn & Dunn, 2007), and performance on the PSMT was weakly associated with scores on the PPVT-4 ($r =- 0.08$), indicating excellent discriminant validity.

List Sorting Working Memory Test. The List Sorting Working Memory test (i.e., List Sorting test) was adapted from Mungas' List Sorting Task, the Spanish and English Neuropsychological Scales (Mungas et al., 2005). It is a measure of working memory that requires participants to sort and sequence stimuli (Tulsky et al., 2015). Participants are presented with a series of stimuli (i.e., illustrated pictures of an animal or a piece of food), each of which is both visually and auditorily presented by the computer. A picture of each stimulus is presented for 2 seconds while the name of the stimulus is simultaneously being read via a computerized voice. The participant is required to remember each stimulus in a series, mentally reorder them from smallest to largest, and then recite the names of the stimuli in order. In the "1-list" component, only one type of stimulus is presented (e.g., "food" or "animals"). The string is increased by a single item (up to a maximum of a seven-item string) if the participant continues to correctly recall the list order. For the 2-list trials, the participant is required to sort the stimuli by category prior to sequencing in size order, requiring dual sorting and sequencing of the information. Similar to the 1-list trials, the string of items increases after each correct trial (also a maximum of a seven-item string). The task is discontinued when the participant provides

incorrect responses on 2 trials with the same number of items or when the participant correctly sequences all 7 items. See **Figure 14** for a sample visualization trial for 1-list). The test takes approximately 7 minutes to administer.

Figure 14

List Sorting Working Memory Test.



Caption: A sequence of practice stimuli from the List Sorting Working Memory test. This image is taken from Tulsky et al.'s (2014) description of the List Sorting test which was adapted for computerized use as part of the NIH Toolbox Cognition Battery.

Test-retest reliability was good over a period of 1-3 weeks (ICC = 0.77) across the adult sample (Weintraub et al., 2013). Convergent validity was evaluated by comparing the performance on the Letter-Number Sequencing task from the Wechsler Adult Intelligence Scale,

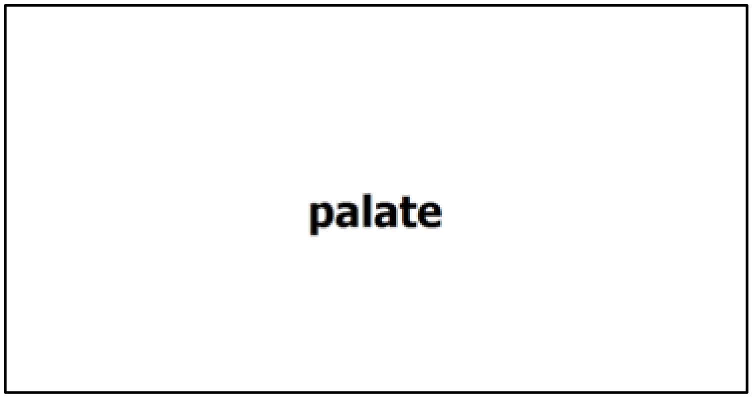
4th Edition (WAIS-IV; Wechsler, 2008) and the Paced Auditory Serial Addition Test (PASAT; Gronwall, 1977). Correlational analyses found a moderate association (r = 0.58), suggesting adequate convergent validity (Weintraub et al., 2013). Discriminant validity was assessed using the PPVT-4 (Dunn & Dunn, 2007), and performance on the List Sorting test was weakly associated with scores on the PPVT-4 (r = 0.3), indicating good discriminant validity.

Oral Reading Recognition Test. The Oral Reading Recognition Test (i.e., the Oral Reading test), is a “proxy” measure for a range of cognitive, educational, and socioeconomic factors, as the ability to accurately pronounce low-frequency words has been used as an estimate of overall intelligence (Grober & Sliwinski, 1999). The Oral Reading test measures ability to pronounce words that occur infrequently and have irregular orthography (e.g., ‘brought,’ ‘rhythm’). For more details about development of the Oral Reading test and the selection of words, please see Gershon et al., 2014). Participants and examiners were seated in front of different computer screens. The examiner adjusts the starting point based on the participant’s educational level. The examiner then tells the participant to look at the word presented on the computer and to read it aloud as best they can. The examiner then codes the response as correct or incorrect based on the accepted pronunciation(s) listed on their screen. Examiners are trained on correct word pronunciation. See **Figure 15a** for a sample item as viewed by the participant and **Figure 15b** for the corresponding examiner screen that provides the correct pronunciation(s) of the word. Words varied between 2-14 letters. Testing continues until a .3 standard error level of accuracy is obtained or 25 items are administered, with a median of 20 items administered in 4 minutes.

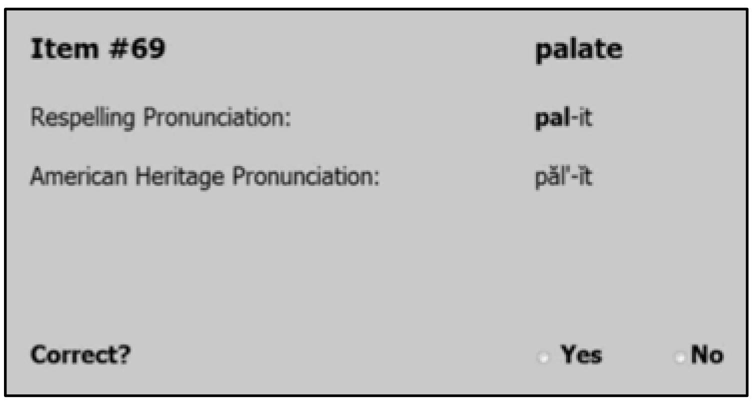
Figure 15

The Oral Reading Recognition Test.

A



B



Caption: This sample item of the NIH Toolbox Oral Reading Recognition Test was taken from Gershon et al.'s (2014) description of the test for computerized use. During this test, a word is presented on the participant's screen (A), while the examiner views a screen with the phonetic key and scoring template (B).

Test-retest reliability was excellent over a period of 1-3 weeks (ICC = 0.91) across the adult sample (Weintraub et al., 2013). Convergent validity was evaluated by comparing the performance on the Wide Range Achievement Test-4th edition (WRAT-4; Wilkinson & Robertson, 2006). Correlational analyses found a strong association (r = 0.93), suggesting excellent convergent validity (Weintraub et al., 2013). Discriminant validity was assessed using

the BVMT-R (Benedict, 1997) and the RAVLT average (Rey, 1964), and performance on the Oral Reading test was weakly associated with scores ($r = 0.19$), indicating good discriminant validity.

N-Back task. The *N-Back* task is a sequential memory task used extensively in research studies and has been conceived of as a measure of working memory. The task typically involves multiple processes, such as the encoding of incoming stimuli, as well as monitoring, maintenance, and updating of the stimuli, and matching the current stimulus to the preceding item *n* positions back in the sequence. The nature of the task requires simultaneous storage and processing of the stimuli, which likely led to its label as a measure of working memory (Jaeggi, Buschkuehl, & Meier, 2010). There are various versions of the *N-Back* test in the literature.

Of importance, the *N-Back* task has not yet received sufficient empirical validation to be referenced as a putative measure of working memory (Kane, Conway, Miura, & Colflesh, 2007). For example, Oberauer (2005) found weak-to-modest relationships between the *N-Back* task and widely-accepted working memory tasks (e.g., span tasks, etc.). This weaker relationship may be explained by complex span tasks requiring ‘serial recall’ that involves the *retrieval* of items, whereas the *N-Back* demands *recognition* via discrimination of target items from foils. These two aspects of remembering may only be minimally related to one another, despite both being important aspects of fluid intelligence (Kane et al., 2007). Another explanation why the *N-Back* task may not robustly relate to span tasks is that *N-Back* tasks are typically visually presented, whereas span tasks, such as the digit span task, tend to be auditorily presented. Miller et al. (2009) examined the validity of the *N-Back* task and found that *N-Back* accuracy significantly correlated with a test of psychomotor processing speed (i.e., Trail Making Test – Part A; Army Individual Test Battery, 1944), but did not significantly correlate with digit span forward,

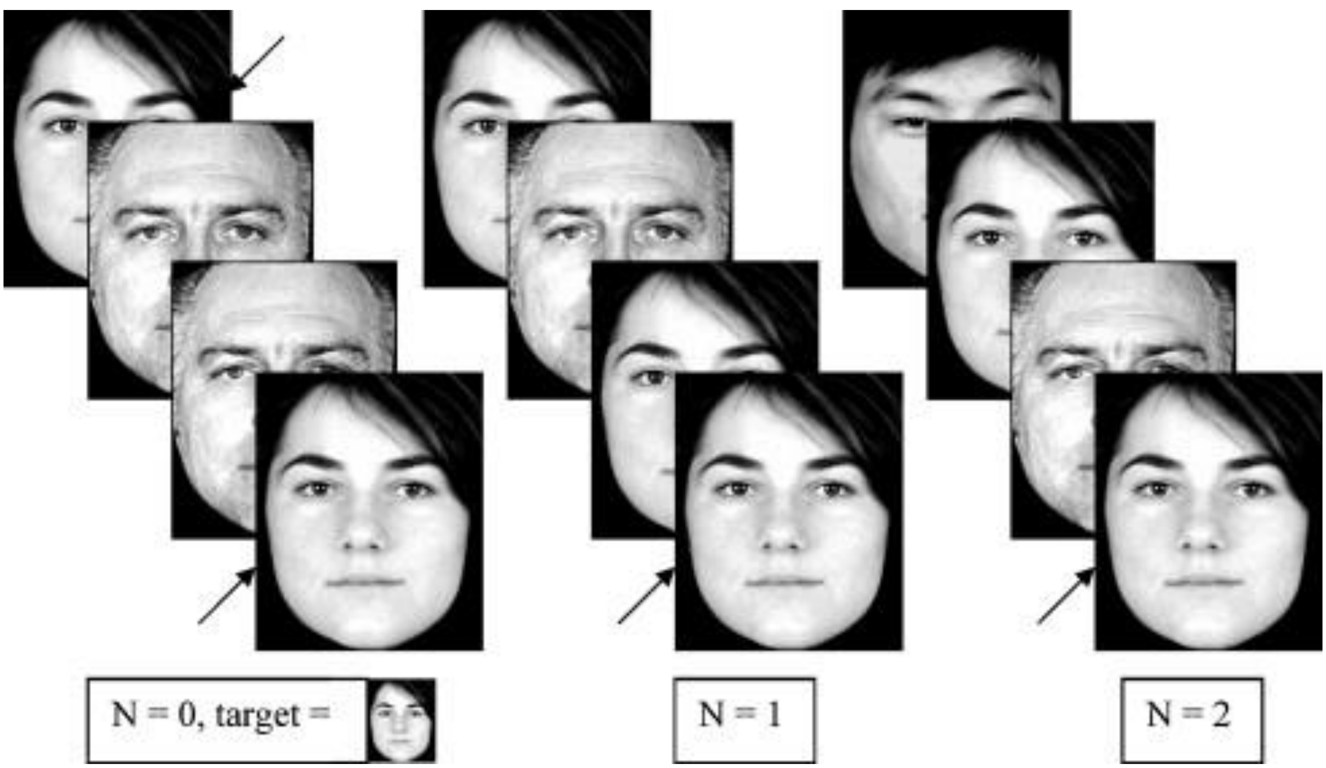
backward, or Stroop word or color reading (Stroop, 1935). Consistent with these findings, Parmenter and colleagues (2006) found that the *N-Back* task loaded on a common factor of speeded information processing, whereas digit span forward and backward loaded together on a non-speeded working memory factor. Regarding its use, Miller and colleagues (2009) recommend that the *N-Back* task may be useful for measuring cognitive function, and particularly information processing speed, but that it may not be an appropriate measure of pure working memory. With these findings in mind, the *N-Back* task will be used as a measure of executive function and as a broad measure of cognitive functioning, and less as a measure of working memory. Reliability studies of the *N-Back* task have been variable, ranging between r = 0.02 and r = 0.91, though higher task levels (2- and 3-back) generally result in reliable estimates that exceed 0.80 (Jaeggi, Buschkuehl, Perrig, & Meier, 2010). Jaeggi and colleagues (2010) administered the *N-Back* to 116 participants and found that split-half reliability coefficients for accuracy of the visual 2-Back task (as used in the current study) was 0.85, indicating good reliability.

In the current study, participants completed the *N-Back* test in the fMRI scanner. Participants were presented with 4 trials that consisted of pictures of places, tools, faces, and body parts, all of which were relatively neutral (i.e., low emotion) stimuli (Barch et al., 2013). Within each trial, the 4 different stimuli types were presented in separate blocks, and half of the blocks used a 2-Back task (i.e., “high working memory load”) and half was a 0-back task (i.e., low working memory load). Participants were instructed to press one button for every picture. Correct responses were indicated when the participants matched the cued picture to the current picture (e.g., “0-Back,”) or the same picture that was presented 2 trials back (e.g., “2-Back”). For matching pictures, participants pressed the one button with their right index finger. For non-

matching pictures, participants pressed a different button with their right middle finger. There were no available images of the *N-Back* task used in the present study; however, see Figure 10 for an example visualization of a similar *N-Back* task involving faces. There were 10 items per trial lasting 2.5 seconds each (the stimulus is presented for 2 seconds, followed by a 500 millisecond inter-task-interval. In total the task took about 5 minutes to complete. Consistent with past literature, the average percentage correct (i.e., accuracy) across 2-Back trials was selected for analysis (Meule, 2017). See **Figure 16** for a sample visualization of this task.

Figure 16

Visualization of a Sample N-Back Task.



Caption: This sample item of an *N-Back* task involving faces was taken from Mayer and Murray (2012). During this test, pictures of faces, tools, places, and body parts were projected onto the participant's screen while they were inside the MRI scanner. Note that this example *N-Back* task involves a 1-back trial, which the current study omitted.

Statistical Plan

Data cleaning. Preliminary descriptive analyses (mean, standard deviation, range, skewness, kurtosis) were performed on the predictor and indicator variables to test for relevant assumptions of normality (i.e., skewness and kurtosis values falling between -3 and 3; see **Table 7)**. Cases with missing data were excluded in a listwise fashion to enable the use of modification indices and bootstrapping. For delay discounting, the AUC for the $40,000 task was favored for the current study's data analysis as the variable is more normally distributed with more optimal skewness and kurtosis values.

Table 7

Descriptive Statistics (N = 1,051) of the Relevant Study Variables

Variable	Mean	SD	Range	Skewness	Kurtosis
DD-AUC $200	0.26	0.20	0.02-0.98	1.31	1.58
DD-AUC $40,000	0.51	0.28	0.02-0.98	-0.03	-1.21
Cognitive Variables					
Card Sort (DCCS)	102.43	9.89	58-123	-0.3	0.62
Flanker	101.83	10.01	70-124	-0.35	-0.36
List Sort	103.31	13.23	60-141	0.05	0.02
Picture Sequence	105.12	16.5	135-78	-0.14	0.42
Oral Reading	107.13	14.81	60-138	-0.45	0.46
2-Back (Acc%)	83.61	10.68	37-100	-0.98	0.68
Personality Variables					
NEO-Conscientious	34.49	5.91	11-48	-0.37	0.23
NEO-Agreeableness	32.01	4.88	13-45	-0.23	0.23
NEO-Neuroticism	16.58	7.39	0-43	0.41	0.33
NEO-Openness	28.39	6.25	10-47	0.23	-0.20
NEO-Extraversion	30.67	5.97	10-47	-0.29	0.17

Delay Discounting Area under the curve discounting for $200 trials
Delay Discounting Area under the curve discounting for $40,000 trials
Cognitive variables are age adjusted standard scores (M=100, SD=15)
2-Back data are mean percentage accuracy for all 2-Back targets
NEO-FFI scores are raw values (higher value indicates greater association with the personality trait)

Exploratory factor analysis. Separate exploratory factor analyses (EFA) will be conducted on personality and cognitive variables, using the Statistical Package for the Social

Sciences (SPSS; version 21). EFA was chosen as the appropriate statistical method as the objective of the current study is to assess the construct of delay discounting. Additionally, the number of cases in the current study (i.e., 1,051) indicates an excellent sample size for a factor analysis (Comrey, 1973). Maximum likelihood extraction (MLE) with oblique rotation will be used as it is most appropriate for normally distributed data and allows for correlation among variables (Tabachnick & Fidell, 2007). If the factor correlation matrix falls below the Tabachnick and Fiddell (2007) threshold of .32 (i.e., less than 10% overlap in variance among factors), then an orthogonal matrix may be indicated.

Prior to the extraction of factors, several tests will be run to assess the suitability of the data for factor analysis. These tests include Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Williams, Brown, & Onsman 2012). The KMO index ranges from 0 to 1, with a minimum value of 0.60 indicating suitability for factor analysis (Tabachnick & Fidell, 2007). The Bartlett's Test of Sphericity should be significant at the $p < 0.05$ level for factor analysis to be considered suitable (Tabachnick & Fidell, 2007). Next, the number of factors will be determined using multiple criteria, as recommended by Costello and Osborne (2005). The present study will use Kaiser's criteria, which states that eigenvalues above 1.0 should be included for further consideration (Kaiser, 1960). Additionally, the cumulative percentage of variance extracted should be at least 50% (Hair, Anderson, Tatham, & Black, 1995). Oblique rotation will be performed to aid in the interpretation of factors and correlations between factors. Additionally, visual inspection of communality values will be conducted to confirm the appropriateness of factor analysis, with values greater than 0.40 indicating suitability. Variables will be assigned to factors after visual comparison of factor loadings in the rotated component matrix. According to accepted standards in the field, primary factor loadings

should exceed 0.40, while secondary factor loadings should be below 0.30 (Tabachnick & Fidell, 2007). If co-loading occurs, theory-based considerations will take precedence over data-driven considerations (Tabachnick & Fidell, 2007).

Confirmatory factor analysis. Confirmatory factor analysis (CFA) uses an *a priori* model to determine whether the covariance of the data aligns with the proposed theoretical model. A model with poor fit indicates that the variables do not covary in a way that would support the *a priori* theoretical model. For the present study, CFA in structural equation modeling (SEM), along with path analysis using maximum likelihood estimation, will be used in R (htpp://www.R-project.org/) version 3.5.2 to evaluate the nature and extent of the relationships between variables and delay discounting. The progression of structural models will be monitored using a combination of indices of model fit. These indices may include the adjusted chi-square (Cmin/*df*), the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and changes in Akaike information criterion (AIC).

For the present study, a Cmin/*df* value (chi-square value divided by degrees of freedom) close to 2 indicates good model fit (Tabachnick & Fidell, 2007), with smaller values indicating better model fit. Importantly, given the large sample size of the present study, a Cmin/*df* value as high as 5 may also be acceptable according to Wheaton, Muthen, Alwin, and Summers (1977). The CFI statistic assumes that all latent variables are uncorrelated (i.e., null model), and compares the sample covariance matrix with this null model. The values for this statistic range between 0.0 to 1.0, with values closer to 1.0 indicating good model fit. A cutoff of CFI at or above 0.95 is recognized as indicating good model fit (Hu & Bentler, 1999). The RMSEA index was first developed by Steiger and Lind (1980) and indicates how well the model, with unknown chosen parameter estimates, would fit the populations covariance matrix, i.e., RMSEA favors

parsimony such that it will choose the model with the fewest number of parameters (Hooper, Coughlan, & Mullen, 2008). An RMSEA value between 0.08 to 0.10 indicates mediocre model fit, with smaller values (<0.08) indicating better model fit (MacCallum et al., 1996). Consideration of all three indices will be used to make conclusions about model fit as no measure on its own is considered a "gold standard" (Brown, 2006).

Correlation coefficients that reach statistical significance ($p < 0.05$) will be assessed to indicate the bidirectional strength of association between variables. Standardized β coefficients at or below statistical threshold ($p < 0.05$) were also noted to indicate the strength of influence (directional pathway) of a latent variable onto another latent variable. Furthermore, standardized β coefficients at or below $p < 0.05$ were used to evaluate the paths between latent and indicator variables (i.e., how well the indicator variable represents the underlying latent construct). For the final structural model, bootstrapping with 5,000 samples will be completed to calculate 95% confidence intervals and p-values in order to quantify the relative contribution of personality and EF on delay discounting.

Regarding comparison of the progression of my models, the Akaike information criterion (AIC; Akaike, 1974) can be used as a fit index to compare models that are non-nested or non-hierarchical (Hooper, Coughlan, & Mullen, 2008). The AIC, like RMSEA, is a form of parsimony fit index and thus penalizes for model complexity. Smaller values suggest a good fitting, parsimonious model; however, the absolute value of AIC is not interpretable. Therefore, the model with the lower AIC value indicates superior model fit relative to the other (Hooper, Coughlan, & Mullen, 2008).

Lastly, to test for mediation of brain variables, I will include two regions of interest of cortical thickness and add to the structural model. The mediated effect will be the product of

indirect effect A and indirect B (i.e., AxB). This will undergo bootstrapping with 5,000 samples to calculate 95% confidence intervals and *p*-values for each mediation model. A significant *p*-value ($p < 0.05$) will indicate mediation.

Results

Data Cleaning

There were 1,206 participants released in the Human Connectome Young Adult Study. A subset of participants was retained for the current study based on data availability of variables of interest. As previously noted, the Area Under the Curve (AUC) for the $40,000 condition was retained for analyses. Cases with missing data were excluded in a listwise fashion, to reduce bias in the parameter and standard error estimates. Upon inspection, demographic, cognitive, and personality variables were normally distributed based on skewness and kurtosis values (skewness and kurtosis values falling between -1.0 and 1.0), as well as visual inspection of histogram plots. The dependent variable, delay discounting, had a kurtosis value of 1.21, well within the conservative criterion of -2.0 to 2.0 (George & Mallery, 2010). Of the 24 neuroanatomical variables, nine had kurtosis values of over three (maximum = 6.48). Removal of outliers was considered, however, there were no variables with absolute values of over three standard deviations. A linear regression was performed between age and the AUC summary measure to investigate whether discounting rates changed as a function of age. Model summary statistics showed that age accounted for less than 1% of the variance of delay discounting ($R = 0.14$, $R_2 = 0.00$, $p = 0.911$). Therefore, the current sample was not stratified into age groups, as there was no substantial relationship between age and discounting. The final sample consisted of 1,051 participants (487 men) with a mean age of 28.69 years (SD = 3.62, range = 22-35 years; see **Table 8**).

Table 8

Participant Demographics of the Final Sample

Characteristic	Value	%
N	1051	--
Age, years (*M, SD*)	28.7 (3.62)	--
Education, years (*M, SD*)	14.9 (1.78)	--
Handedness (*M, SD*)*	66.4 (43.8)	--
Male	487	46
Ethnicity		
Hispanic/Latino	92	9.1
Not Hispanic/Latino	947	88
Unknown/Not reported	12	1.1
Race		
White	792	75.4
Black/African American	151	14.4
Asian/Nat. Hawaiian/Pac. Islander	61	5.8
Am. Indian/Alaskan Nat.	2	0.2
More than one	26	2.6
Unknown/Not reported	18	1.7
Household Income		
<$10,000	72	6.9
$10,000 - $19,999	82	7.8
$20,000 - $29,999	136	12.7
$30,000 - $39,999	126	12.0
$40,000 - $49,999	108	10.2
$50,000 - $74,999	220	21.2
$75,000 - $99,999	142	13.8
≥$100,000	163	15.4

*Handedness of participant is a numerical value that ranges from -100 to 100 and was assessed using the Edinburgh Handedness questionnaire (Oldfield, 1971). Negative numbers indicate that a subject is more left-handed than right-handed, while positive numbers indicate that a subject is more right-handed.

Exploratory Factor Analysis

An exploratory factor analysis (EFAs) was performed with cognitive and personality variables using the Statistical Package for the Social Sciences (SPSS; version 21). The EFA was

an iterative process and initial results were used to inform the final models. A factor correlation matrix revealed coefficients above 0.32 (i.e., more than 10% overlap in variance among factors), indicating suitability for the use of an oblique rotation. Maximum likelihood extraction with oblique rotation was used to confirm that the data were factorable. The Kaiser-Meyer Olkin value was 0.63 and Bartlett's test for sphericity reached statistical significance ($p < 0.001$, χ^2 $(df = 15) = 807.59$), supporting the factorability of the correlation matrix. Results of the exploratory factor analysis for personality and cognitive variables revealed a one-factor solution each based on eigenvalues and visual inspection of the scree plot. Variables with lower loadings were sequentially removed. Next, decisions for variable inclusion were based on total cumulative percentage of variance, with a minimum threshold set at 50%. See **Tables 9** and **10** for a summary of the iterative EFA process for cognitive and personality variables, respectively. The amount of cumulative percentage of variance extracted for each three-factor solution exceeded the minimum acceptable threshold of 50%. The results of this analysis suggest that the three cognitive variables and three personality variables may be meaningfully represented as latent factors. To ensure suitability as two factors, the final primary factor loadings (see **Tables 11 and 12**) exceeded 0.40, and there were no secondary factor loadings, as only a single factor was selected. A correlation matrix with the selected variables is presented in **Table 13**.

Table 9

Exploratory Factor Analyses for Personality Variables

Personality Variables Entered	**EFA Results**
Neur, Open, Cons, Agr, Ext	*1-factor solution (38% of total variance explained):* • Ext, Neur, Cons, Agr
Neur, Cons, Agr, Ext	*1-factor solution (47% of total variance explained):* • Ext, Neur, Cons, Agr
Neur, Cons, Ext	*1-factor solution (55% of total variance explained):* • Neur, Ext, Cons

Abbreviations include: N = Neuroticism; O = Openness to Experience; A = Agreeableness; C = Conscientiousness; E = Extraversion

Table 10

Exploratory Factor Analyses for Cognitive Variables

Cognitive Variables Entered	**EFA Results**
DCCS, Flanker, Reading, PSMT, List, *N-Back*	*1-factor solution (39% of total variance explained):* • Reading, PSMT, List, *N-Back*
Reading, PSMT, List, *N-Back*	*1-factor solution (49% of total variance explained):* • Reading, PSMT, List, N-Back
Reading, List, N-Back	*1-factor solution (58% of total variance explained):* • Reading, List, *N-Back*

Abbreviations: Neuroticism (Neur); Openness to Experience (Open); Conscientiousness (Cons); Extraversion (Ext); Agreeableness (Agr); Dimensional Change Card Sort Test (DCCS); Flanker Inhibitory and Attention Test (Flanker); Oral Reading Recognition Test (Reading); Picture Sequence Memory Test (PSMT); *N-Back* Working Memory Test (*N-Back*)

Table 11

Factor Loadings for Cognition

Cognitive	
Oral Reading	0.63
List-Sort	0.54
N-Back	0.68

Table 12

Factor Loadings for Personality

Personality	
Neuroticism	-0.73
Conscientiousness	0.57
Extraversion	0.46

Table 13

Correlation Matrix

	Neuroticism	Conscientiousness	Extraversion	Reading	List-Sort	*N-Back*
Neuroticism	1.00					
Conscientiousness	-0.39**	1.00				
Extraversion	-0.34**	0.27**	1.00			
Reading	-0.06	-0.15**	-0.07*	1.00		
List-Sort	-0.12**	-0.43	-0.02	0.34**	1.00	
N-Back	-0.15**	-0.08**	0.03	0.42**	0.37**	1.00

** p <.01; * p < 0.05

Neuroimaging variables. To find two distinct neuroanatomical regions of interest for the personality and cognitive variables, a bivariate correlation analysis was performed with 24 neuroanatomical regions that corresponded to one of two intrinsic connectivity networks: (1) Executive Control and (2) Default Mode (see **Table 14**). The Executive Control network is thought to reflect cognitive functioning (Disbrow et al., 2014), whereas the Default Mode network is thought to be associated with personality and self-referential thinking (Coutinho, Sampaio, Soares, & Goncalves, 2012). A bivariate correlation was performed between delay discounting and each of the 24 (12 left and 12 right) neuroanatomical regions to determine the single most robust neuroanatomical variable from each network. For the Default Mode network (reflecting personality), results of the correlation analysis revealed a moderate relationship between delay discounting and the right posterior cingulate cortex (r = 0.122, p < 0.001). The

next most robust correlation within this network was the left precuneus ($r = 0.073$, $p = 0.03$). For the Executive Control network, a small association was observed between delay discounting and the left lateral orbitofrontal cortex ($r = 0.064$, $p = 0.04$). The second most robust correlation, though nearly equivalent, was the right lateral orbitofrontal cortex ($r = 0.063$, $p = 0.04$). Based on the size of the associations with delay discounting, the right posterior cingulate cortex and left lateral orbitofrontal cortex were included as mediation variables in the structural model.

Table 14

Regions of Interest Corresponding to Intrinsic Connectivity Networks

Executive Control	**Default Mode**
1. L Caudal Anterior Cingulate	1. L Inferior Parietal Lobule
2. R Caudal Anterior Cingulate	2. R Inferior Parietal Lobule
3. L Caudal Middle Frontal	3. L Medial Orbitofrontal
4. R Caudal Middle Frontal	4. R Medial Orbitofrontal
5. L Lateral Orbitofrontal	5. L Middle Temporal
6. R Lateral Orbitofrontal	6. R Middle Temporal
7. L Rostral Anterior Cingulate	7. L Posterior Cingulate
8. R Rostral Anterior Cingulate	**8. R Posterior Cingulate**
9. L Rostral Middle Frontal	9. L Precuneus
10. R Rostral Middle Frontal	10. R Precuneus
11. L Superior Frontal	11. L Supramarginal
12. R Superior Frontal	12. R Supramarginal

Abbreviations: L = left hemisphere; R = right hemisphere
Note: Regions in bold were selected for mediation analyses.

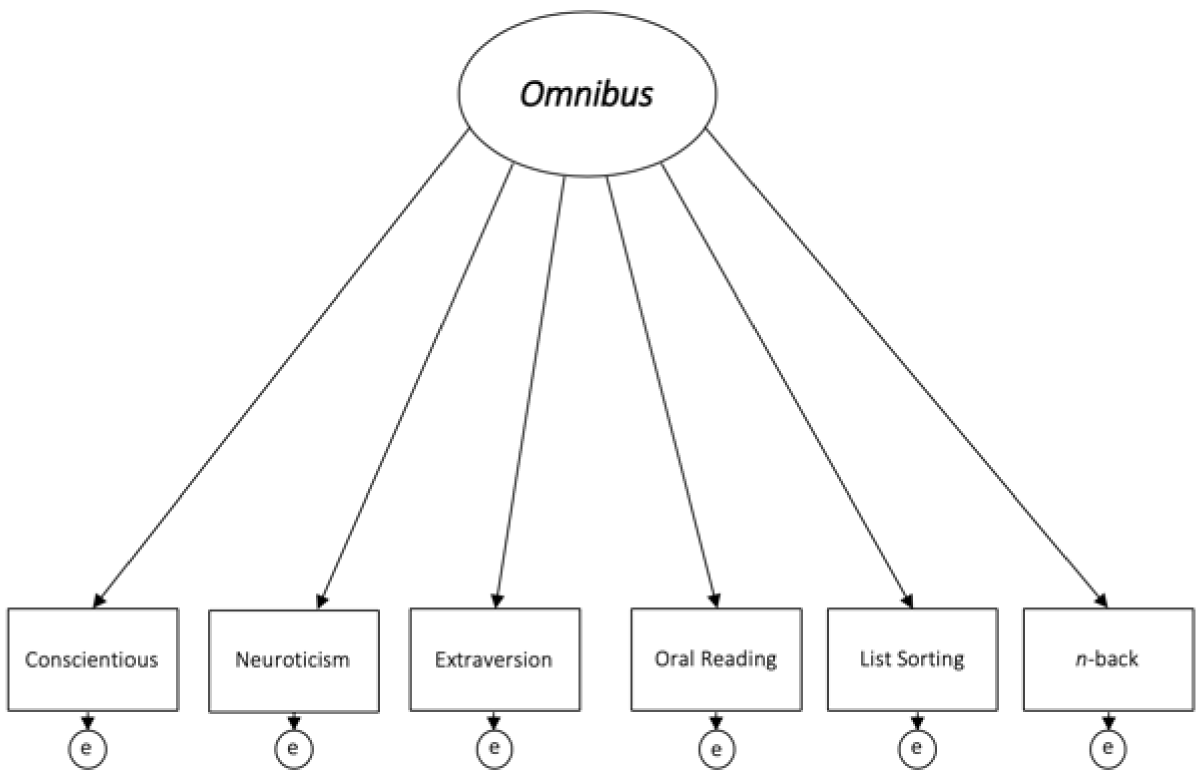
Confirmatory Factor Analysis.

Measurement models. Cognitive and personality data ($N = 1,051$) were used for confirmatory factor analyses (CFAs) using R (version 4.0.0, R Core Team, 2020). The CFAs were informed by prior exploratory factor analyses, indicating two factors comprised of cognitive and personality variables. A progression of measurement models was created to

represent the relationships between the two hypothesized latent variables (i.e., cognition and personality) and their indicators. Establishment of a measurement model was a stepwise process, beginning with an *omnibus* model in which fit was tested with all indicators as part of a single latent variable (**Figure 17**). Model fit of this *omnibus* model was poor, as would be anticipated (Cmin/*df* = 51.90; CFI = 0.42; RMSEA = 0.22).

Figure 17

Measurement Model – Omnibus.

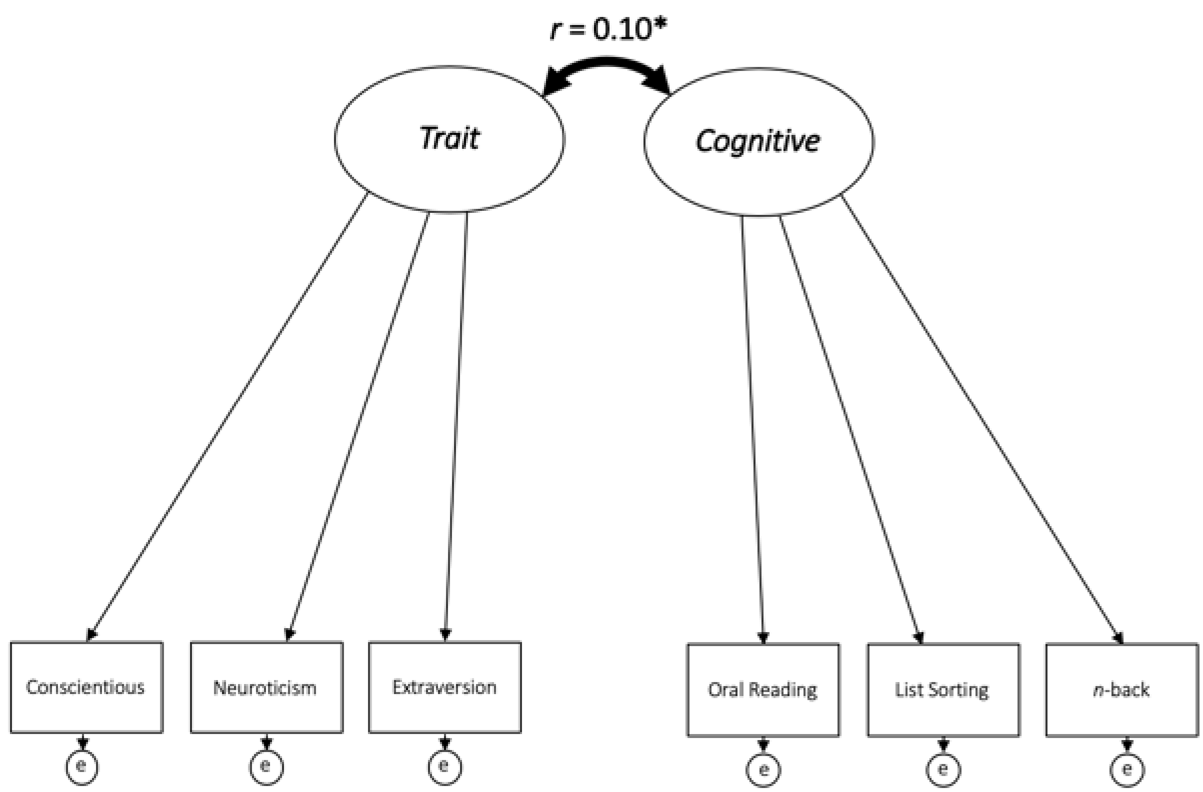


Next, separating the single (omnibus) latent variable into two related latent variables, broadly representing cognition and personality (**Figure 18)**, resulted in improved model fit indices (Cmin/*df* = 9.77; CFI = 0.91; RMSEA = 0.09; ΔAIC = -386.94). Cognitive and

personality latent variables were significant but weakly associated ($r = 0.10$, $p = 0.04$). In this model, all indicators significantly loaded onto their respective latent variables, at the $p < 0.001$ level (range: $\beta = 0.45$ to 0.77).

Figure 18

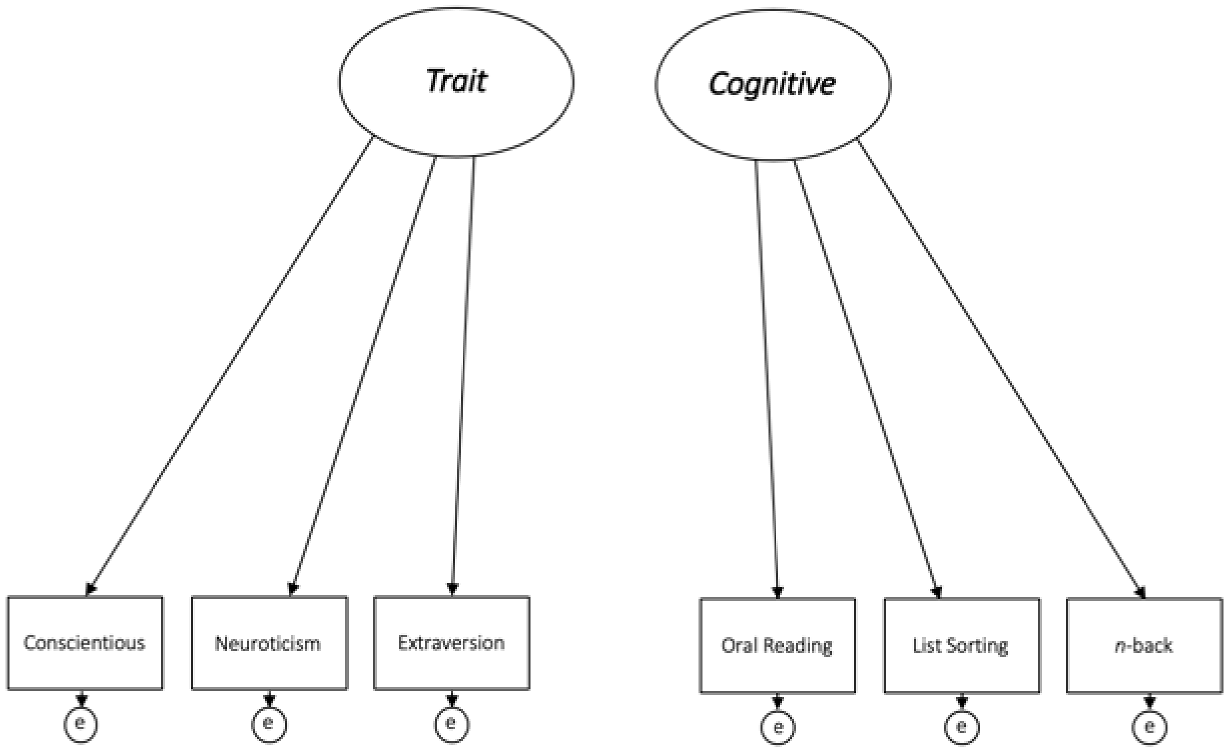
Measurement Model: Two Factors Allowing for Correlation.



The correlation between the two latent variables (**Figure 19**) was removed, resulting in essentially unchanged model fit indices (Cmin/df = 8.99; CFI = 0.91; RMSEA = 0.08, ΔAIC = 0.78). In this final model, all indicators significantly loaded onto their respective latent variables, at the $p < 0.001$ level (β range: 0.48 to 0.71).

Figure 19

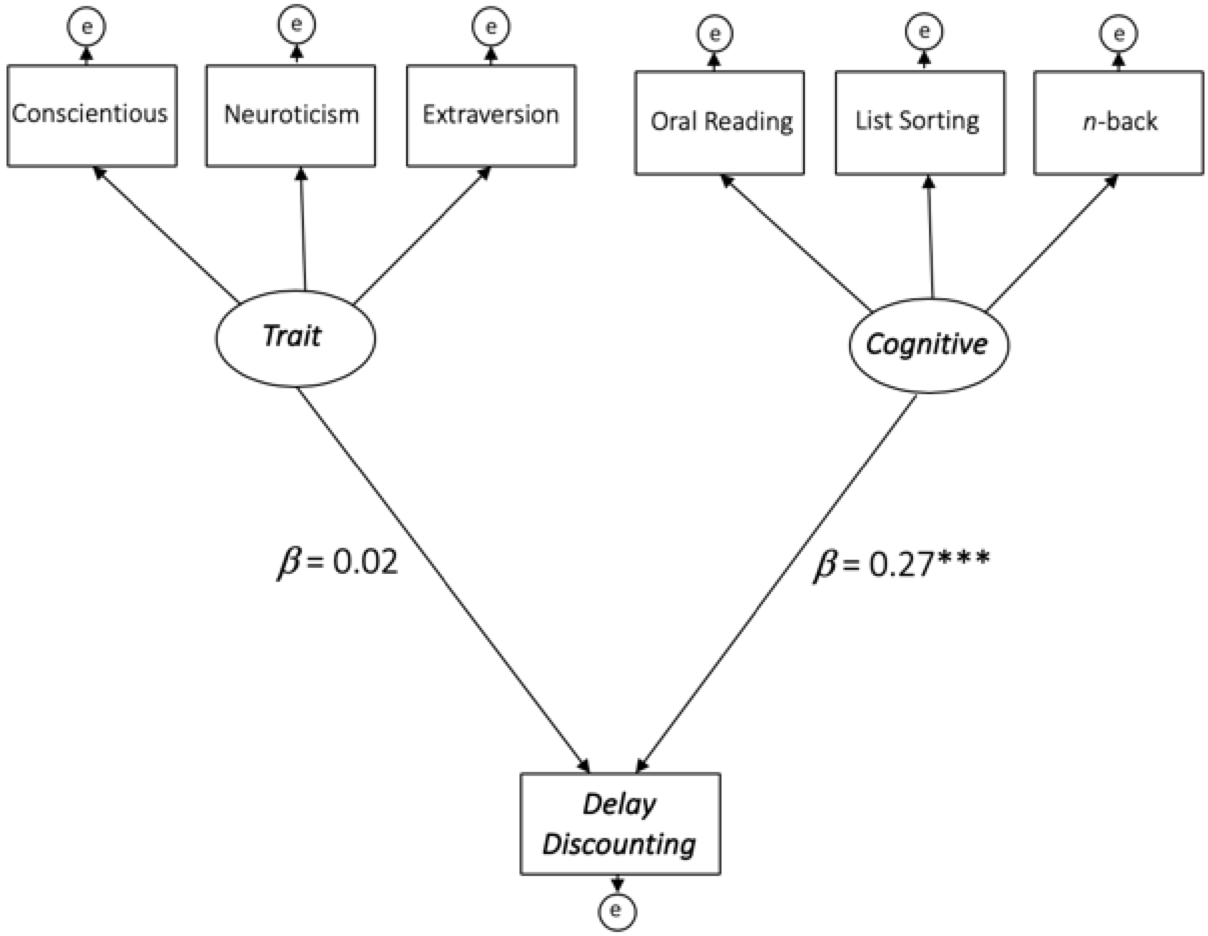
Measurement Model: Two Factors.



Structural Models. A series of structural models was created to assess the relationship between the latent variables (i.e., cognition and personality) and delay discounting (**Figure 20**). The association of the two latent variables to one another was set to zero per the principle of parsimony. Model fit indices were essentially unchanged compared to the final measurement model (Cmin/*df* = 7.97; CFI = 0.90; RMSEA = 0.08). The latent variable of cognition showed a significant modest association ($\beta = 0.27$, $p < 0.001$) with delay discounting. In contrast, the latent variable of personality was not significantly associated with delay discounting ($\beta = 0.02$, $p = 0.61$).

Figure 20

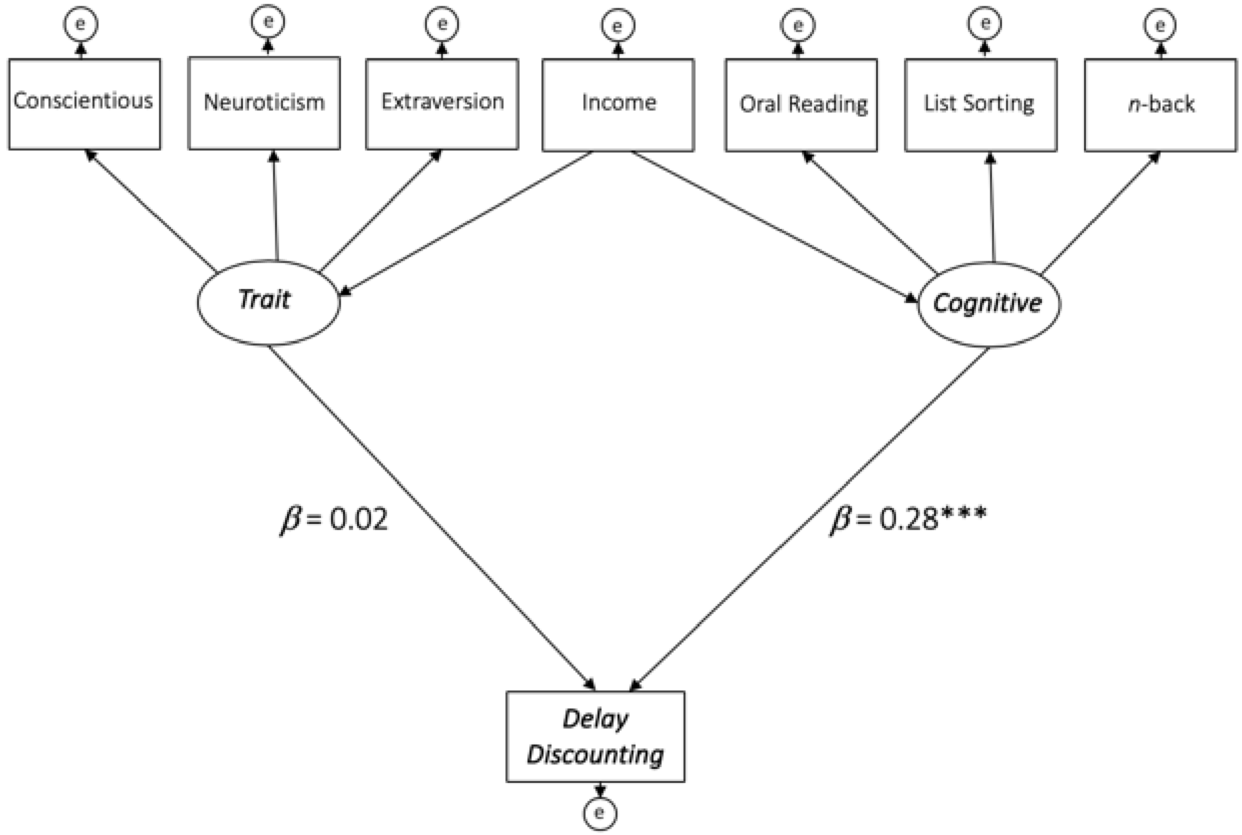
Structural Model – Cognition and Personality.



In the next step, a path was added to include household income as a covariate **(Figure 21)**, which resulted in a modest improvement in model fit (Cmin/*df* = 6.15; CFI = 0.90; RMSEA = 0.07). The latent cognitive variable showed a significant association ($\beta = 0.28$, $p < 0.001$) with delay discounting, though largely unchanged relative to the previous model. The latent variable of personality was again not significantly associated with delay discounting ($\beta = 0.02$, $p = 0.633$).

Figure 21

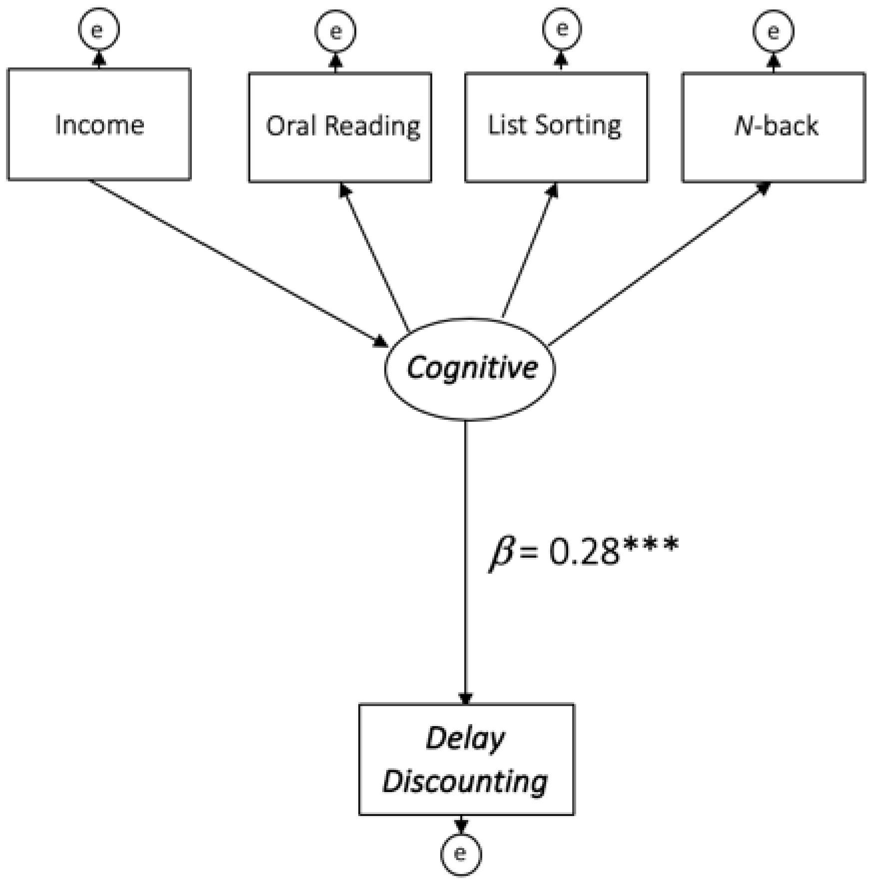
Structural Model – Cognition and Personality with Income as Covariate.



Finally, model fit improved after retaining the latent cognitive variable and income as a covariate and removing the latent personality variable (**Figure 22**; Cmin/*df* = 5.50; CFI = 0.96; RMSEA = 0.07; ΔAIC = -8461.98). As expected, the latent variable of cognition remained significantly associated with delay discounting (β = 0.28, $p < 0.001$).

Figure 22

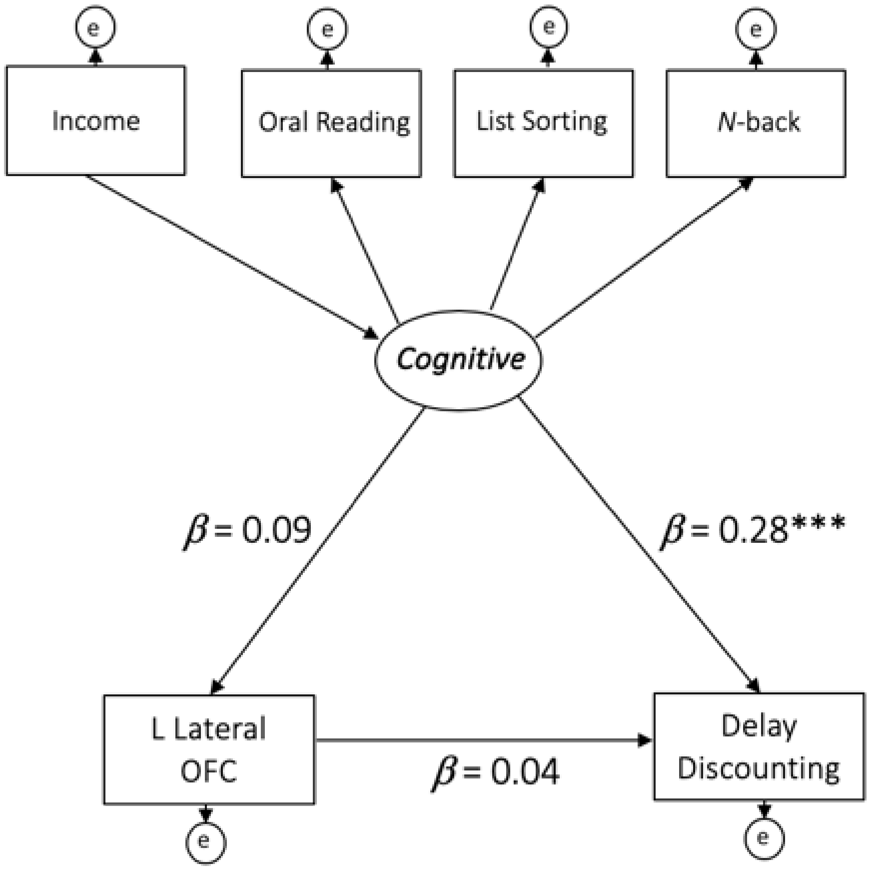
Final Structural Model: Cognition with Income as Covariate.



Mediation Analysis. Cortical thickness of the lateral orbitofrontal cortex (OFC) was included to test for mediation between cognition and delay discounting **(Figure 23)**. Although model fit improved (Cmin/*df* = 3.48; CFI = 0.96; RMSEA = 0.05), the relationship between the mediating variable (i.e., lateral OFC) and delay discounting was not significant (β = 0.04, p = 0.22). Therefore, although overall model fit improved, the addition of the lateral OFC was not indicated as an appropriate mediator of the relationship between the cognitive latent variable and delay discounting.

Figure 23

Structural Model: Addition of OFC as Mediator.



Discussion

The current study used exploratory and confirmatory factor analyses to model the contributions of personality characteristics and cognitive functioning in delay discounting. This study was the first to apply structural equation modeling in a large sample (N > 1000) of healthy adult participants to better understand delay discounting. The primary aims of this study were (1) to use EFA and (2) CFA in SEM to model the contributions of cognitive functioning and personality with delay discounting. The final aim of the study was (3) to test whether neuroanatomical variables mediated the relationship between cognitive and/or personality variables.

Regarding the first aim of the study, exploratory factor analysis yielded two latent constructs of cognition and personality. The three-variable solution of cognitive variables was unexpected given that the three executive function measures (Card Sort, Flanker, and *N-Back*), out of six cognitive variables, did not load onto one factor. The decision to include primarily measures of executive function for the present study was in response to prior research demonstrating a relationship between executive function and delay discounting (e.g., Bickel et al., 2011; Finn et al., 1999; Wesley & Bickel, 2014). Despite this, the final cognitive model included the Oral Reading, List-Learning, and *N-Back* task. Given the variety of areas these three measures tap into (crystallized abilities, working memory), it is possible that the model reflected a *g* factor, or broad general intelligence, rather than a specific cognitive domain (Spearman, 1904). Therefore, the model that emerged from my data was different from the proposed cognitive framework for discounting, which was primarily related to executive function and reflected a 'search process.' Given that my model of cognition reflected general intelligence rather than executive function, I was unable to assess the veracity of discounting as it relates to executive function. Interestingly, this finding aligns with other research that supports that general intellect may be more critical for explaining discounting behaviors than executive function. For instance, Shamosh and colleagues (2008) investigated the extent working memory and tests of intelligence (i.e., *g* factor) accounted for variance in delay discounting, and found that the majority of the variance was explained by general intelligence rather than working memory. Furthermore, Wilson and colleagues (2011) found that the relationship between ADHD and discounting in children was attenuated after controlling for intelligence level.

The latent construct of personality that emerged from my data included three of the five NEO domains. Each of these three domains have aspects that inherently relate to discounting,

including sensation-seeking (Extraversion), self-discipline (Conscientiousness), and impulsiveness (Neuroticism). In this sense, I believe this model was adequate for testing my hypothesized framework of personality. However, because only three of the five domains were selected, this construct likely reflects a more specific construct of personality. It is possible that had all five domains been selected for my model, the relationship between personality and discounting would have been improved. In light of the above, the emergence of a three-variable solution for personality variables was not unexpected given past research that has questioned the empirical and theoretical underpinnings of the five-factor model of personality (Eysenck, 1991). Additionally, past confirmatory factor analyses of the NEO-FFI have failed to support the purported latent structure of the “Big Five.” Mooradian and Nezlak (1996) sought to confirm the five-factor model of the NEO-FFI but found that only 35% of the observed variance could be explained by the five factors, while model fit indices indicated weak factor structure. Factor analyses from several studies have suggested that a 5-factor solution may not be optimal, and that 4, 3, and even 2-factor solutions are supported (Ackerman & Heggestad, 1997; Ferguson & Patteron, 1998). Additionally, a factor analytic study in a British population by Egan, Deary, and Austin (2000) found that Neuroticism, Agreeableness, and Conscientiousness loaded onto a single factor, while Openness to Experience and Extraversion did not load onto any factor. Furthermore, Egan and colleagues (2000) found that many of the items within Openness to Experience and Extraversion did not load onto their respective factors. Nevertheless, there is no one model of personality that has been agreed upon in the literature and the five-factor model is still the most extensively validated and widely used.

A progression of measurement models, from an *omnibus* latent variable model to two separate latent variables representing cognition and personality, were supported by

improvements in model fit. Model fit indices were only modestly improved when the correlation between the two latent variables was removed, suggesting that cognition and personality are distinct but related constructs. This is consistent with research that suggests personality is thought to be indirectly related to cognitive abilities through their influence on behavior and performance in academic situations (Moutafi, Furnham, & Tsaousis, 2006). For instance, many studies have consistently reported a negative association between cognitive ability and Conscientiousness (Furnham, Dissou, Sloan, & Chamorro-Premuzic, 2007; Von Stumm & Ackerman, 2013). Although this seems counterintuitive, some researchers explain the negative relationship between Conscientiousness and cognitive ability reflects a process by which individuals with lower cognitive ability develop greater levels of Conscientiousness to compensate for their cognitive disadvantage.

The second aim of the study was to establish a structural model of delay discounting with latent constructs of cognition and personality. The initial structural model demonstrated a relationship between cognition and delay discounting but did not support a relationship between personality and delay discounting. When household income was added as a covariate, overall model indices slightly improved, likely due to the modest improvement in association between cognition and delay discounting. The association between personality characteristics and delay discounting remained unchanged and continued to not be supported. Therefore, the decision was made to remove the latent variable of personality from the structural model. Model fit indices significantly improved following the removal of personality (AIC = -8461.98).

This finding did not support my hypothesis that personality, as opposed to cognitive ability, would have the most robust relationship with delay discounting. This finding was surprising given that trait-based characteristics have been found to predict goal-directed

behaviors related to impulsivity and instant gratification (Manning et al., 2014). Additionally, my reasoning for identifying personality as an important predictor was in response to research that has implied delay discounting to be a stable and pervasive individual characteristic (Odum, 2011). The explanation for the lack of support for personality in my model is potentially related to issues regarding the measurement of my construct of personality. As previously noted, my model of personality included only three domains (Conscientiousness, Neuroticism, and Extraversion), which suggests it is not fully capturing the entire construct of personality. Additionally, given the serious concerns raised regarding the use of the NEO in measuring personality, it would be premature to assert that the framework of personality is not a viable candidate for explaining discounting based on my study's findings. Further research should examine the relationship between discounting behaviors using different methods and measures of measuring personality.

In light of the above, the final structural model included the latent cognitive variable, household income as a covariate, and delay discounting. These results suggested that cognitive ability is an important predictor of delay discounting. This final model revealed an important finding that greater performance on cognitive tasks was associated with lower (i.e., less impulsive) discounting. The association between cognitive ability and discounting was consistent with research that shows higher scores on measures of intelligence are associated with less impulsive discounting (Manning et al., 2014; Shamosh & Gray, 2008). Of note, the relationship between cognitive functioning and discounting does not have clear implications for behavior. For example, Bailey, Gerst, and Finn (2019) found that intelligence moderated the relationship between delay discounting and alcohol use in young adults, such that more impulsive

discounting was associated with increased alcohol consumption for those with higher versus lower intellectual functioning.

The third aim of the present study was to investigate whether a neuroanatomical variable (i.e., cortical thickness) mediates the relationship between cognition and delay discounting. As noted in the analytic plan, 24 regions of interest (12 left and 12 right) were selected in *a priori* fashion based on two relevant intrinsic connectivity networks (Executive Control for cognition and Default Mode for personality). Bivariate correlations between the 24 regions and delay discounting revealed that the left orbitofrontal cortex (OFC) was the most robust predictor from the Executive Control network and was therefore selected for a mediation analysis. The lateral orbitofrontal cortex sits above the orbits in which the eyes are located and has extensive connections with sensory regions and limbic system structures (Rolls, 2004). Orbitofrontal cortex is thought to be involved in processing reward information, value-based decision-making, and making predictions based on newly-learned information (Torregrossa, Quinn, & Taylor, 2008). Studies have found that individuals with lesions to the OFC are more impulsive compared to people non-OFC cortex damage, as measured by cognitive and behaviors tasks (Berlin, Rolls, & Kischka, 2004). A clear example of this type of damage was seen in Phineas Gage, who in 1848 suffered an injury to his prefrontal and orbitofrontal cortices when a tamping iron rod was projected through his skull after an explosion. He survived but showed a drastic change in his personality including reductions in response inhibition and impulsivity. Regarding delay discounting, animal studies involving rodents have shown that lesions to the lateral orbitofrontal cortex were associated with decreased preference for the larger-delayed reward.

Although this region was expected to relate to delay discounting in the present study, the mediation model with cognition and delay discounting was not supported. Importantly, the

mediation variable did not pass step two of Baron and Kenny's (1986) steps for mediation, as there was no relationship between cognition and the left lateral OFC. The lack of this relationship is not unexpected given that the latent construct of cognition was thought to represent a broad *g* factor of intelligence rather than a specific cognition ability. In this case, a latent construct of cortical thickness comprised of a set of brain regions (i.e., network) may have been a more appropriate mediating variable. For instance, Jung and Haier's (2007) compelling review paper on the neural basis of intelligence suggested that variations in brain structure and function account for individual differences in intellect. The authors described this finding as the Parieto-Frontal Integration Theory (P-FIT) model. Brain regions involved in this model include the dorsolateral prefrontal cortex, anterior cingulate, inferior and superior parietal lobules, and regions within the temporal and occipital lobes (Jung & Haier, 2007). This model also relies on the fidelity of white matter integrity to efficiently communicate data from posterior to frontal brain regions. The P-FIT model suggests that sensory information is initially processed in respective temporal and occipital lobes (e.g., auditory, visual), and then travels to parietal and finally frontal regions for higher-order complex information processing (e.g., problem-solving, abstraction, inhibition). Regarding the present study, perhaps a brain network informed by the P-FIT model and comprised of frontal and parietal regions would have been a more appropriate construct to inform the relationship between cognitive ability and delay discounting.

Limitations & Future Directions

There are several limitations of the present study. First, this project used archival data from the Human Connectome Project, and as a result, the extent of the neurocognitive data was limited to the NIH Toolbox Measures and the *N*-Back working memory test. Although these tasks have adequate convergent validity with traditional neuropsychological measures, they are

used primarily in research contexts and are not for clinical use. This can be advantageous for large-scale studies where there is a need for brief assessments that measure different cognitive constructs within a large age range and without showing floor or ceiling effects. As such, these tasks are inherently not representative of a comprehensive neuropsychological evaluation. The authors of the NIH Toolbox state that their cognitive measures are best served in studies where cognition is not the targeted outcome, but rather as a covariate, e.g., examining whether "hidden" cognitive variables may be affecting treatment outcomes (Weintraub et al., 2014). As previously noted, a latent factor of executive function did not emerge from the data in the present study, rather, a general intellectual latent construct was revealed. It is possible that a construct of executive function could have emerged had there been a greater number of tasks that more closely assessed and represented this domain. For instance, a commonly used instrument that assesses executive function in clinical neuropsychological evaluations is the Tower of London (Culbertson & Zillmer, 1998). This test involves planning, strategy, and maintenance of attention in pursuit of a goal and taps into aspects of executive control (inhibition, self-monitoring, etc.) that would assume more relevance with delay discounting than the measures used in the present study.

A second limitation is that the current study did not investigate the interaction between personality and cognitive functioning. Research has found that people who are high in extraversion discount more at the low end of the cognitive distribution because they are less able to use higher-order control mechanisms to regulate their motivational impulses (Hirsh, Morisano, & Peterson, 2008). In the current study, the relationship between personality and delay discounting may have been evident if the data were stratified by high and low cognitive functioning.

Third, the delay discounting task used in the present study relied on hypothetical monetary choices. Although these are a useful analog to real-world decisions, studies investigating discounting behaviors could benefit from a combination of laboratory and real-world measures. Similarly, the present study only examined discounting as it relates to monetary choices. Odum (2011) conducted an examination of five archival studies and found that discounting rates varied across commodities but those who steeply discounted one commodity tended also to steeply discount the other one. As such, the current study's results may not necessarily generalize to discounting behaviors for other reward types (e.g., directly consumable rewards such as food). Future research should work toward clarifying shared and disparate components of delay discounting across different reward contexts.

A fourth limitation of the present study is the use of current household income as a proxy for socioeconomic status. The participants in this study were ages 22-35 years, and their current household income likely does not accurately represent their socioeconomic status given that it tends to be a time in life when income is similar across individuals as they tend to be enrolled in school or are early on in their career. Socioeconomic status is strongly shaped during childhood as an individual's environment can differ systematically by socioeconomic status (e.g., parenting style, differences in education quality). Therefore, a more appropriate measure of socioeconomic status would have been family household income during childhood. Future studies investigating delay discounting should include robust variables tapping into socioeconomic status, including childhood family income, level of education of head of household, and even more non-traditional indices such as home ownership, home size, and out-of-town vacations. Additionally, formal measures of socioeconomic status (e.g., MacArthur Scales of Social Subjective Status; Adler,

Epel, Castellazzo, & Ickovics, 2000) may be particularly useful for supplementing objective socioeconomic information.

Clinical Implications

Understanding discounting behaviors can inform almost any behavior involving delayed consequences. My primary finding was that intellectual ability is important for understanding how people make reward-based decisions. This information can help to understand how we can best influence socially important behavior (e.g., wearing one's seatbelt, receiving preventative care, maintaining a healthy diet). In addition to targeting behavior, is also important to identify who may be at increased risk for maladaptive discounting behaviors. Given the strong relationship between intellect and socioeconomic status, my current findings support that there is an important role for environmental factors in explaining rate of discounting. Another important implication is the role of assessing discounting behaviors in clinical populations in which impulsive choices are typically of concern (e.g., substance use disorders, eating disorders). A practical example may be to measure a patient's rate of discounting when they enter a substance use treatment program to identify which individuals have an increased vulnerability for relapse. After these patients are identified, clinicians could provide extra support and focus on boosting reinforcement for alternative behaviors for these individuals.

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