

The Hierarchical Organization of Impulse Control: Implications for Decision Making

by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
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ABSTRACT

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Abstract

The findings presented within this dissertation address the validity of current conceptions of trait impulsiveness, relationships between those traits and brain or laboratory measures of cognitive control, and links between impulsive traits and economic decisions under conditions of delay or uncertainty. The dissertation argues that impulsive traits and behavior may derive from failures of cognitive control at particular levels of abstraction within a hierarchically organized prefrontal network. The presented research affirms the multidimensional nature of impulsiveness as a construct (Chapters 2 & 3), and links individual differences in specific impulsive types to behavioral and neurobiological measures of control function (Chapters 3 & 4). The nature of motor, attentional, and non-planning impulsive types are contextualized by reference to evidence supporting a broad theory of behavioral control based on hierarchical organization of action, ranging from concrete acts to abstract plans and strategies (Chapters 1 & 6). We provide evidence linking concrete forms of urgent/motor impulsiveness to behavior and brain activation during response-related control, and more abstract and future-oriented premeditative/non-planning impulsiveness to decision control signals in more rostral PFC (Chapter 4). Finally, these findings are complemented by causal evidence from a neurostimulation study linking a contextual control network to risky decision making and attentional impulsiveness (Chapter 5).

Taken together, the results of these studies suggest that impulse control, cognitive control, and decision making share a common organization from concrete to abstract. Our reliance on diverse research techniques and confirmatory replication adds methodological rigor and provides convergent evidence linking impulsiveness to behavioral and decision control. This approach reinforces the advantages of an integrative approach across the domains of personality psychology, cognitive control, and decision making for understanding the flexible decision making and behavior.

Dedication

To my family, for a lifetime of unconditional love and support.

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1. The cognitive neuroscience of decision making: Prefrontal control of thought and action[†]

1.1 Introduction

Human thoughts and actions are notable for their flexibility. In the face of environmental uncertainty, we adaptively adjust our immediate behavior to reach our long-term goals. This flexibility carries significant computational costs: the brain must reconcile the shifting relationships among external stimuli, inhibit unimportant stimuli to focus on current goals, integrate past and present information, and project the consequences of an immediate action for future outcomes. Collectively, these psychological processes are referred to as “cognitive control” (Eysenck & Eysenck, 1978; Miller & Cohen, 2001).

Under most conditions, our cognitive control systems perform admirably, allowing us to seamlessly navigate a world full of surprises, challenges, and novel experiences. At other times, however, we find ourselves at a disadvantage, struggling to select and maintain a desired course of action in the face of distraction, temptation, and impulsive urges to act otherwise. Occasional slips of control are ubiquitous and unavoidable, but chronic deficits in the ability to control decisions and actions can be

[†]This chapter is adapted from material published as “Coutlee, C., and Huettel, S. (2012). The Functional Neuroanatomy of Decision Making: Prefrontal Control of Thought and Action. *Brain Research*, 1428, 3-12.”

problematic, and sometimes debilitating. Persistent patterns of control failure – often observed as personality traits such as impulsiveness – can derail goal-directed decision making and result in excessive risk taking, shortsightedness, or similar self-regulatory failures (Hare, Camerer, & Rangel, 2009; Platt & Huettel, 2008b) . More serious failures of cognitive control systems are implicated in disorders such as attention deficit disorder, obsessive-compulsive disorder, and alcohol or substance abuse (Dalley, Everitt, & Robbins, 2011; Nigg, 2001; Whiteside & Lynam, 2001) . Investigation of the neurobiological mechanisms underlying such failures is critical to understanding both normal and abnormal variation in control-related traits like impulsiveness, and ultimately to addressing personal and societal challenges with roots in cognitive control failure.

Research on the neural basis of cognitive control has focused on the prefrontal cortex (PFC), particularly its lateral (Brass, Derrfuss, Forstmann, & von Cramon, 2005; Koechlin & Summerfield, 2007a; Petrides, 2005) and dorsomedial (Botvinick, Cohen, & Carter, 2004; Paus, 2001; Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004; Rushworth, Walton, Kennerley, & Bannerman, 2004) aspects. Seminal early work described control processes in broad terms, based on deficits shown in animals and humans with prefrontal lesions (Franz, 1902; Milner, 1963; Shallice & Burgess, 1991a; Spaet & Harlow, 1943). The advent of human functional neuroimaging, along with parallel advances in single-unit electrophysiology, has allowed researchers to parse

cognitive control into a set of specific sub-processes associated with distinct parts of PFC (Carter et al., 2000; Johnston, Levin, Koval, & Everling, 2007; Mansouri, Buckley, & Tanaka, 2007; Smith & Jonides, 1999). New models (**Figure 1a**) integrate psychological properties of cognitive control (e.g., organizing goals at multiple temporal scales) with functional properties of PFC (e.g., connectivity with other regions; Koehlin, Ody, & Kouneiher, 2003a). Though many aspects of prefrontal organization remain unknown, the development of new models for behavioral control represents one the most active areas of research in cognitive neuroscience.

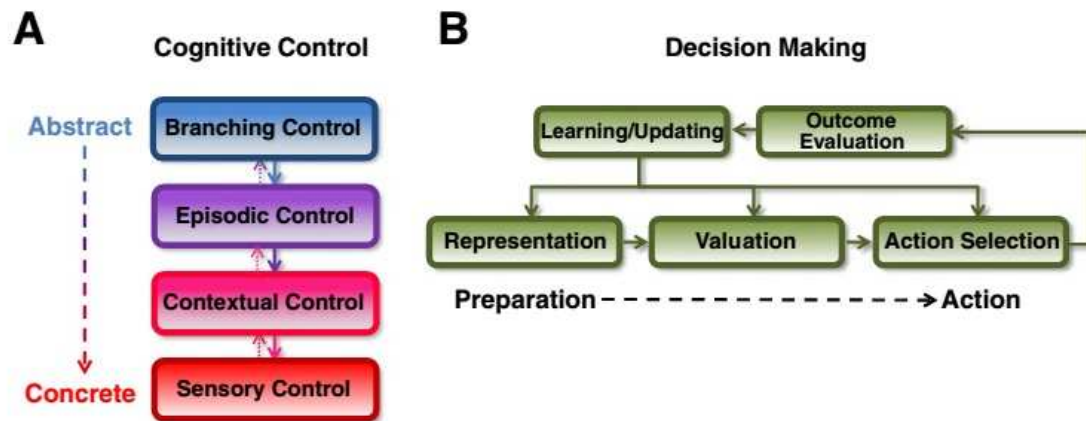


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In parallel, research on the neural basis of decision making – often described as the emerging discipline of “neuroeconomics” or “decision neuroscience” – has emphasized similar sets of psychological concepts and brain substrates. As outlined in typical reviews of this field, successful decision making requires adaptive behavior in a range of contexts: identifying a set of choice options, inhibiting the temptation of immediate or certain outcomes, integrating different variables like probability and value, and projecting the consequences of a choice for our goals (Figure 1b; Camerer, Loewenstein, & Prelec, 2005; Platt & Huettel, 2008a; Rangel, Camerer, & Montague, 2008). Brain substrates within PFC have been found to play a critical role in flexible decision making (Koechlin & Hyafil, 2007; Ridderinkhof, van den Wildenberg, Segalowitz, & Carter, 2004), in part through modulatory influences on affective and reward systems (Beauregard, Levesque, & Bourgouin, 2001; Hare et al., 2009; Knoch, Pascual-Leone, Meyer, Treyer, & Fehr, 2006a).

Despite this striking conceptual and mechanistic overlap, human neuroimaging research into decision making has proceeded in a surprisingly separate fashion from research examining cognitive control. There have been only limited attempts to incorporate models of cognitive control into decision neuroscience research (e.g., Daw, O’Doherty, Dayan, Seymour, & Dolan, 2006), with most current work describing PFC function in broad terms of “self-control” or “inhibition” (Figner et al., 2010a; Hare et al., 2009; Knoch, Pascual-Leone, et al., 2006a). Cognitive control research, in turn, has yet to

capitalize on the innovations in experimental design common to decision neuroscience, such as advanced modeling of decision behavior or reinforcement learning (Dayan & Daw, 2008; Hsu, Krajbich, Zhao, & Camerer, 2009; Pine et al., 2009). Yet, recent developments in each area suggest that conditions may be ripe for the emergence of new connections between cognitive control and decision neuroscience research.

1.2 Contrasting approaches to flexible behavior

Neuroimaging research in these two domains – cognitive control and decision making – shares a common goal of understanding the neural systems supporting flexible selection of behavior, particularly in the face of uncertainty. Yet, researchers in each area pursue this goal via independent research traditions, emphasize different sorts of psychological processes, and employ distinct experimental designs and protocols. These differences of method and tradition obscure a key similarity: these areas examine complementary action-selection mechanisms at overlapping stages in the preparation-action-feedback cycle characteristic of goal-directed behavior.

Interest in the neural basis of cognitive control emerged relatively recently from the longstanding interest in psychological processes related to executive function (Fuster, 2008). Within the context of neuroscience research, cognitive control refers to the goal-directed biasing of neural processing, as when the PFC exerts a modulatory influence on other brain regions (Miller & Cohen, 2001). Commonly studied aspects of cognitive control include resolving conflict between competing action representations,

switching of resources between concurrent tasks, and learning and implementing rules for behavior. To evoke these control processes, researchers often employ tasks which ask participants to act contrary to an overlearned tendency or to withhold a prepotent response, as in the Stroop (Egner & Hirsch, 2005), Simon (Peterson et al., 2002), and stop-signal tasks (Aron & Poldrack, 2006). Other common paradigms require participants to learn and implement experimenter-provided rules for mapping stimuli to responses, often under conditions which require flexible switching between task rules or response strategies (Bunge, 2004a). These tasks tend to emphasize experimental control of behavior, requiring participants to pursue artificial goals or respond according to rules dictated by the experimenter.

Neuroscientific research into the mechanisms of decision making has been oriented toward understanding particular phenomena, rather than psychological processes. In large part, this reflects the tradition within behavioral economic research – and, to a lesser extent, within judgment and decision making research – to treat choices themselves as the explanatory targets for models (Bateman et al., 2004; Hensher & Bradley, 1993). Thus, research in decision neuroscience frequently adopts experimental paradigms that evoke interesting choice biases, such as ambiguity aversion (Huettel, Stowe, Gordon, Warner, & Platt, 2006a), loss aversion (Tom, Fox, Trepel, & Poldrack, 2007), framing effects (De Martino, Kumaran, Seymour, & Dolan, 2006), or counterintuitive rejection of money in economic games (Sanfey, Rilling, Aronson,

Nystrom, & Cohen, 2003). Most studies require participants to make repeated and meaningful decisions, typically by linking the choice outcomes to participants' compensation. This aligns participants' personal interests with the goals of the experimenter, allowing the choices in the experiments to be used as an index of preferences within choice functions (Grether & Plott, 1979; Sen, 1971). Accordingly, research has heretofore emphasized the study of how individuals assess the desirability of each decision option and compare those options within some common neural currency (Hare, Camerer, Knoepfle, & Rangel, 2010; Smith et al., 2010), or "valuation" and "value comparison", respectively (Montague & Berns, 2002).

Three methodological differences may particularly underlie the divergence between cognitive control and decision neuroscience research. First, studies of cognitive control's neural mechanisms typically target a particular brain region (i.e., the lateral PFC), whereas studies of decision making investigate particular phenomena (e.g., temporal discounting). Second, cognitive-control paradigms generally involve the learning and execution of experimenter-defined rules mapping stimuli to actions, while participants in decision-making paradigms are provided incentives to choose according to their own personal preferences. Third, paradigms in cognitive control often (but not always) seek to minimize interindividual heterogeneity in behavior, to ensure a common process across participants, whereas decision-making studies use interindividual

variability to better understand brain function (Chiu & Yantis, 2009; McGuire & Botvinick, 2010; Venkatraman, Payne, Bettman, Luce, & Huettel, 2009).

Despite these methodological differences, both cognitive-control and decision-making experiments often target neural computations occurring within the action-selection cycle. A response inhibition task and a gambling task, for example, seem superficially dissimilar, and would typically be used to investigate different processes. These tasks share key similarities from an action-selection perspective, however: both require the representation of a controlling goal, the integration of past experience (from prior trials or individual preferences), the selection of the most goal-appropriate response, and the use of feedback to reinforce or modify future response tendencies. Accordingly, cognitive control and decision neuroscience studies address neural computations occurring throughout overlapping stages of the action-selection cycle, from goals through action to feedback. (The literatures do differ in the *domain* of control processes required, as when studying response conflict versus value comparisons.) Thus, although each literature approaches the problem of flexible action selection with different methods and traditions, there are fundamental similarities between the action-selection processes their tasks engage and between the neural computations supporting that processing.

1.3 Potential integration: Specifying control processes

From seminal neurological observations to modern functional neuroimaging, substantial evidence implicates the lateral prefrontal cortex (LPFC) in goal-directed behavior. Behavioral deficits following brain lesions have consistently implicated the PFC in the exercise of cognitive control (Kimberg, D'Esposito, & Farah, 1997; Robbins, 1996), and prefrontal patients evince deficits in decision making, motivation, planning, and simulating actions, despite often largely intact perceptual abilities (Bechara, Damasio, Damasio, & Anderson, 1994; Eslinger & Damasio, 1985; Shallice, 1982). Such cases provided early clues to the control functions supported by the LPFC, and remain experimentally important today (Badre, Hoffman, Cooney, & D'Esposito, 2009). In recent years, however, advances in functional neuroimaging have revolutionized our understanding of the mechanisms of prefrontal control. These tools allow neuroscientists to explore in detail the functional organization of cognitive control within the LPFC.

A key question within cognitive control research has been whether lateral prefrontal control processing might demonstrate some form of topographic organization. Findings from functional neuroimaging studies have provided converging evidence for a rostral-caudal axis of control processing (Badre & D'Esposito, 2007; Koechlin et al., 2003a). Control over concrete stimulus-response associations is enacted by caudal regions, such as the dorsal premotor cortex. More abstract action

representations, such as plans for simple sequences or rules for selecting action based on context, are processed in more rostral areas, such as the dorsolateral PFC. Finally, control over highly abstract plans, goals, and response strategies is exercised by the most anterior portion of PFC, the frontopolar cortex. Control processing along this rostral-caudal axis is hierarchical, such that increasingly abstract control engages additional cortical regions along the axis (Badre, 2008; Christoff & Gabrieli, 2000).

Influential examples of this rostral-caudal framework are the cascade model (Koechlin et al., 2003a) and the policy abstraction model (Badre & D'Esposito, 2009b). The cascade model argues that control processes are organized according to their degree of temporal abstraction away from the present. That is, most posterior regions of IPFC support control based on the current context (e.g., mapping actions onto stimuli as they are perceived). More anterior regions integrate current information with information carried forward from a prior context, including longer-term goals. The policy abstraction model describes an explicit hierarchy in which higher-order abstract rules manage lower-order, concrete rules for action selection. First-order policies allow for selection between multiple competing actions (least abstract), second-order policies enable selection between different first-order policies (more abstract), and so on up multiple levels of increasing abstraction. Though these two models conceptualize abstraction and control in somewhat different ways, they posit a nearly identical rostral-caudal axis supported by very similar neuroimaging results (Badre & D'Esposito, 2007; Koechlin et

al., 2003a) and by data from patients with PFC lesions (Badre et al., 2009) or schizophrenia (Chambon et al., 2008). Together, these findings present a compelling case for the organization of action selection within LPFC according to a principle of abstraction.

Such hierarchical models of action selection have been influential within cognitive control research, but they offer even greater potential advantages to researchers exploring the functional neuroanatomy of decision making. Lateral PFC activity is a common finding in decision neuroscience (Liu, Hairston, Schrier, & Fan, 2010; Mohr, Biele, & Heekeren, 2010), but functional interpretations of this processing remain rudimentary. This may be in part due to decision neuroscience's focus on behavioral phenomena and individual differences, as well as the use of more open-ended designs to evoke preference-driven behavior. While advantages in many regards, these design conventions have their drawbacks: decision neuroscience research has identified lateral prefrontal contributions to a variety of flexible, goal-driven behaviors (e.g. Bach, Seymour, & Dolan, 2009; Bhatt, Lohrenz, Camerer, & Montague, 2010; Serences, 2008), yet failed to integrate these findings within a common explanatory framework.

Hierarchical models of action selection drawn from the cognitive control literature suggest a ready antidote to the lack of structure within the decision neuroscience literature. These models provide an explanatory framework that can be

used to generate predictions regarding a variety of goal-directed behaviors, such as implementing complex or layered control, organizing sub-tasks, or optimizing behavior across response strategies. Under such conditions, IPFC activation at different levels of the rostral-caudal hierarchy should correspond to control exerted at characteristic levels of abstraction. This potential to segregate levels of control processing makes these models especially well-suited for application to decision neuroscience, where they could strengthen inferences regarding the control processes active throughout the IPFC during decision making. Researchers examining a few topics of shared interest between cognitive control and decision neuroscience are realizing these advantages, but this potential remains mostly untapped.

In the following sections, this chapter considers two points of contact between the cognitive-control and decision-making literatures: strategy switching and self-control. Each section evaluates how well current models of prefrontal function permeate that research area, and identifies key topics for future investigation.

1.4 Relational integration and strategy switching

Rules and policies that lead to good outcomes in one circumstance may not provide the same benefits at other times. Thus, adaptive behavior often requires individuals to maintain multiple plans and to shift between them to reach a particular, constant goal. The concept of “strategy switching,” though derived from decision-making research, can be linked to behavioral and neurochemical findings from the

cognitive-control literature suggesting that reward, emotion, and control mechanisms interact to balance stable and flexible responding (Braver & Cohen, 2000; Cools & Robbins, 2004; Doya, 2008; Dreisbach & Goschke, 2004; Müller et al., 2007). In particular, strategy switching in decision tasks could be subsumed within the most abstract level of cognitive control (see Section 3). Within the cascade model, for example, switching between two different response rules requires a process of branching control that holds one rule in reserve while another is engaged. This process activates rostral PFC, like other tasks that involve integrating multiple outcomes in pursuit of a higher goal (Ramnani & Owen, 2004).

Initiating a switch requires an evaluative component of control to detect circumstances justifying a change to behavior (Botvinick, Braver, Barch, Carter, & Cohen, 2001). This process reflects strategic regulation of control resources by a more abstract, superordinate evaluative system. Significant attempts have been made to integrate cognitive control and decision making accounts of the evaluative system; these suggest that PFC regions such as the dorsomedial PFC monitor for either conflicts in information processing or action outcome values (Botvinick, 2007; Rushworth & Behrens, 2008). These influential models have established a precedent within the literature that supports the integration of research from both cognitive control and decision making studies.

A canonical example of strategy switching can be seen in the shifts between exploratory and exploitative behavior. Organisms harvesting resources from a changing environment must balance an exploitative strategy that allows them to accumulate known rewards and an exploratory strategy that allows them to gather information regarding possibly more lucrative rewards (Cohen, McClure, & Yu, 2007; Montague & King-Casas, 2007). Daw and colleagues (2006) used fMRI to study voluntary transitions between exploratory and exploitative strategies. Reinforcement learning models classified participants' trial-by-trial choices as either exploitative or exploratory, with these classifications then used to identify neural correlates of these strategies. Exploitative choices were associated with activation in the ventromedial PFC, consistent with the calculation of action value (Wunderlich, Rangel, & O'Doherty, 2009). Intriguingly, exploratory decisions were associated with increased activation in bilateral frontopolar cortex and medial intraparietal sulcus. Frontopolar activation in these cases may have reflected the higher-order decision making processes necessary to pursue a strategy of exploration, in the face of greater immediate rewards through exploitation. The authors suggested that bias signals from the frontopolar cortex exert inhibitory control over the current response strategy, in order to allow for the expression of the alternate exploratory strategy.

Further investigation by Boorman and colleagues (2009) has clarified the critical role played by frontopolar cortex in selecting between response strategies. In this study,

participants made choices between two virtual slot machines. The payoff magnitude for each machine was varied randomly on every trial, so there was no advantage to tracking these amounts over time. By contrast, the probability of winning for each machine changed slowly over time, so participants could use that information to help them select which machine to play on each trial. Since the frontopolar cortex was known to be involved in switching between different response strategies, the authors suspected it might be involved in executing switches between the two slot machines. Their results supported this hypothesis, while also revealing a more specific mechanism: frontopolar cortex activation was found to encode the probability of winning on the *unchosen* slot machine, relative to the chosen machine. In other words, frontopolar cortex carried a signal about the benefits of the alternative choice strategy, relative to the current default choice strategy. Furthermore, both increased activation of frontopolar cortex and increased functional connectivity between the frontopolar cortex and parietal/premotor regions tended to predict a strategy switch on the subsequent trial. This evidence suggests that the frontopolar cortex plays both a general role in monitoring available response strategies and a specific role in implementing switches to the most beneficial strategy.

These examples from the decision-making literature support the idea that frontopolar cortex tracks the relative benefits of behavioral strategies and initiates strategic shifts based on new information. By integrating advanced behavioral learning

models common within decision neuroscience and prior work in cognitive control, these investigators were able to derive tractable neural explanations for aspects of strategy switching, an important component of goal-directed decision making. It is probably not coincidental that this topic (strategy switching) and this brain region (frontopolar cortex) provide a nexus for integration between these two literatures. The frontopolar cortex is functionally both more specific and more selective than more posterior regions of PFC; that is, its activation tends to be reliably evoked by tasks that require some sort of relational integration (Christoff et al., 2001; Kroger et al., 2002) but not by most other sorts of executive processing (Banich et al., 2000; Ford, Goltz, Brown, & Everling, 2005; Garavan, Ross, Murphy, Roche, & Stein, 2002). Thus, the observation of activation in frontopolar cortex provides clearer insight into the likely underlying functional processes, as compared to activation in other parts of PFC (Poldrack, 2006).

1.5 Inhibitory function and self-control

Successfully implementing our decisions often requires inhibition of some form of temptation (e.g., immediate outcomes, certain rewards). Anyone who has undertaken a diet, struggled with an addiction, or contemplated cheating realizes the powerful forces arrayed against our long-term goals. Accordingly, there has been substantial interest in the ability to hew to a plan and pursue a goal, particular in the face of superficially more appealing alternatives, or “self-control”. Self-control has been of particular interest to decision-making researchers because of the violations of standard

theories associated with its failures (Bickel & Marsch, 2001; Thaler & Shefrin, 1981). But, its neural instantiation poses challenges. Unlike relational integration, self-control has not been unambiguously localized to a specific aspect of PFC (Cojan et al., 2009; Kuhn, Haggard, & Brass, 2009; Sharp et al., 2010). Yet, the integration of insights from the cognitive neuroscience literature holds promise for clarifying the neuroanatomical conception of self-control processes in decision making.

Understanding how people inhibit unwanted actions has been a longstanding area of research in cognitive psychology, and now in cognitive neuroscience (Aron, 2007; Miyake et al., 2000). Canonical tasks—such as the oddball, anti-saccade, or stop signal paradigms—involve the execution of a highly automatic or practiced motor response, accompanied by intermittent signals to withhold or change that response. Successfully overcoming such pre-potent responses requires the contribution of a network of brain regions including the IPFC, as shown by converging evidence from lesion (Aron, Fletcher, Bullmore, Sahakian, & Robbins, 2003), single-unit (Sakagami et al., 2001), and functional neuroimaging studies (Liddle, Kiehl, & Smith, 2001). Regions such as the dorsolateral PFC, the anterior cingulate cortex, and the basal ganglia are often active in tasks involving self-control or response inhibition, with their engagement thought to reflect control processes related to rule or conflict monitoring and response halting (Aron et al., 2007; Bunge, 2004b; Krug & Carter, 2010). Additionally, a region of IPFC, the right ventrolateral PFC, has now been implicated in self-control under a variety of tasks

conditions, such as response inhibition, delay of gratification, and thought suppression (Cohen & Lieberman, 2010). Such research has been recently extended to establish a role for IPFC in the inhibition of a variety of automatic processes, such as in emotional regulation (Wager, Davidson, Hughes, Lindquist, & Ochsner, 2008; Winecoff, LaBar, Madden, Cabeza, & Huettel, 2010), as well as in conflict during goal-directed decision making (Hare et al., 2009).

Decision neuroscientists initially examined self-control in the context of scenarios contrasting patience with temptation. A common experimental task asks participants to choose between a small reward received immediately and a larger reward received after a time delay. Resisting the temptation to choose the immediate (but less valuable) option is hypothesized to require self-control. In a series of such experiments, McClure and colleagues (2007; 2004) identified a limbic-reward network activated by tempting options, and a prefrontal-executive network active during all decisions. Additionally, the relative level of activation between these two networks could predict participants' choices of either the tempting or patient option. This suggests that a neural system associated with cognitive control contributes when valuation requires patience (see Kable & Glimcher, 2007 for an alternative perspective).

Expanding on this literature, decision neuroscientists have begun to examine compromises between conflicting goals and desires. Hare and colleagues (2009) explicitly examined self-control's role in a familiar conflict: the decision to choose foods

based on health or taste. While undergoing fMRI, hungry participants rated images of healthy snacks and junk foods for both taste and healthiness, and then chose between such food items. Participants were sorted into two groups based on their behavior: the self-control group balanced health and taste information when choosing foods, while non-self-controllers chose based on taste alone. Imaging results demonstrated that an area of the left dorsolateral PFC was activated when participants resisted the temptation to choose tasty but unhealthy foods. Furthermore, this region was negatively functionally coupled, via an intermediate IPFC region, to the ventromedial PFC area representing the net expected value from the food choice. These results suggest a self-control mechanism based in the IPFC may modulate value representations elsewhere in the brain. Furthermore, this modulatory influence may reflect the integration of abstract long-term goals, such as a desire for health, with more primary stimulus values, such as a food's taste.

While these studies suggest a lateral prefrontal role in self-controlled decision making, neuroimaging evidence alone cannot support causal conclusions regarding brain-behavior relationships. Techniques which allow the manipulation of neural processing, such as transcranial magnetic stimulation (TMS), serve as an essential complement to measurement-based techniques such as fMRI (Paus, 2005). Figner and colleagues (2010a) applied low-frequency TMS to the dorsolateral PFC to study interactions between self-control and valuation. Research participants made choices

between small immediate or larger delayed rewards, as in prior work (Kable & Glimcher, 2007; McClure et al., 2004), after TMS disruption of processing within either the left or right dorsolateral PFC. Disruption of left dorsolateral PFC caused participants to choose impatiently, foregoing larger later rewards for smaller immediate ones. By contrast, participants' explicit valuations of these rewards were unaffected by TMS. These results suggest self-control processes instantiated in the left IPFC exert control over decisions independent of medial prefrontal/striatal valuation. Self-control of behavior may thus depend on a distinct lateral prefrontal process capable of arresting behaviors *after* the valuation stage of decision making (Luo, Ainslie, Giragosian, & Monterosso, 2009).

With a lateral prefrontal role established, self-control in decision making should now be examined within the cognitive control framework provided by the rostral-caudal hierarchical models discussed above. Self-control, like inhibitory control, is probably not a single process, but a class of processes which similarly restrain behavior (Magen & Gross, 2010). This processing could be organized according to levels of abstraction, in a manner analogous to the cognitive control models described above (see Section 3). Highly abstract planning and strategy selection might support self-control through avoidance of tempting contexts, or binding precommitment to non-tempting alternatives (e.g., joining Weight Watchers) (Ariely & Wertenbroch, 2002; Gul & Pesendorfer, 2001). Self-control that is rather less removed from temptation (e.g., driving past the candy

store) might be enacted by rostralateral PFC, while control in the face of temptation (e.g. stopping your hand in mid-reach for a candy bar) might activate more caudal PFC. Such an integrated approach makes clear and falsifiable predictions regarding neural mechanisms, and would anchor the various findings from imaging (Hare et al., 2009; McClure et al., 2007) and neurostimulation (Fecteau et al., 2007; Figner et al., 2010a; Knoch, Pascual-Leone, et al., 2006a) experiments addressing different forms of self-control.

1.6 Integrating cognitive control and decision neuroscience approaches

Cognitive control and decision making research thus address related questions: How is behavior adapted to fit changing circumstances? How are expected costs and benefits weighed to select actions? How are undesirable actions controlled or inhibited? In addressing such questions, cognitive-control models typically identify top-down, often prefrontal, executive processes which modulate target brain regions (Koechlin & Summerfield, 2007a; Miller & Cohen, 2001). Decision-making models, by contrast, translate such questions into terms of choices and value, and seek out neural responses correlated with individual preferences revealed by these choices (Rangel et al., 2008; Samanez-Larkin, Hollon, Carstensen, & Knutson, 2008). These approaches draw on distinct traditions and methods, but are clearly related, and should be understood as complementary. As the example of strategy switching illustrates, the integration of

theory and technique from cognitive control and decision making can foster unique insights into the computational mechanisms supporting behavioral control. Other topics of shared interest, such as self-control, possess great potential — yet still await the benefits of an integrative approach.

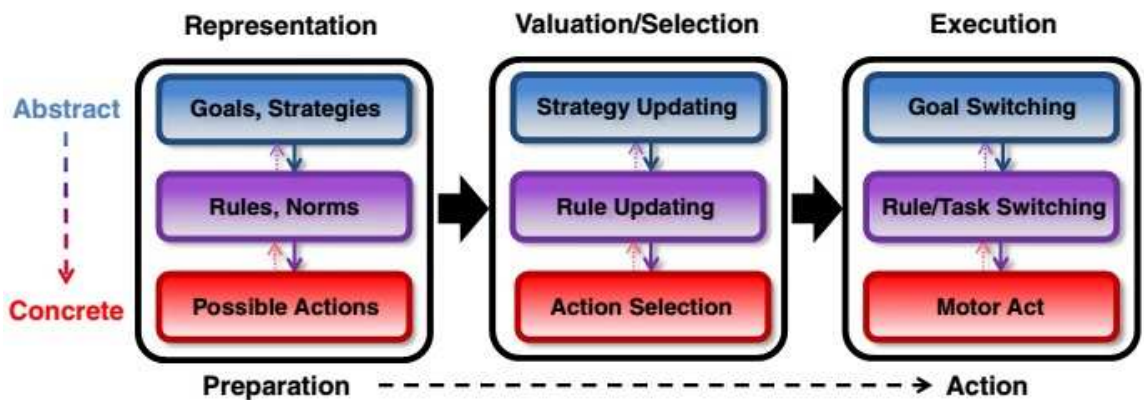


Figure 2: A schematic, integrative model of goal-directed decision making. Each stage of decision making requires control processes at multiple levels of abstraction. Competing actions, rules and strategies are selected via a value comparison process, in which cognitive control coordinates the assignment of action values based on the representations of superordinate goals, objectives, and strategies.

Figure 2 illustrates the complementary contributions that decision neuroscience and cognitive control research can make to the understanding of action selection.

Models of decision making emphasize sequential stages in the action-selection cycle, and thus provide organization along a temporal dimension. Cognitive control models contribute an anatomical dimension, consistent with hierarchical control of action selection: abstract representations engage rostral IPFC, while more concrete action representations engage caudal IPFC. Thus, representations residing at characteristic

levels of abstraction (e.g. goals and strategies, rules and plans, and possible motor acts) are able to influence hierarchically lower and anatomically more caudal action representations throughout the stages leading from preparation to action execution. Valuation, a hallmark of decision neuroscience, plays a central role in the comparison and selection of competing representations at each level of abstraction. Value, reward, and outcome signals, derived from regions such as the ventromedial and orbital PFC as well as the anterior cingulate cortex and striatum, are integrated via functional interactions with the IPFC, where this information can be used to guide action selection (Daw et al., 2006; Diekhof & Gruber, 2010; Hare et al., 2009; Savine & Braver, 2010). Importantly, the functional neuroanatomy of these interactions should specifically reflect the abstractness of the valued representation, be it a broad goal or strategy or a particular motor act.

With future adoption of rostral-caudal models, decision neuroscience has much to contribute at its interface with cognitive control. Decision neuroscience's experimental repertoire includes a range of advanced quantitative models of choice behavior and valuation (Behrens, Hunt, Woolrich, & Rushworth, 2008; Glascher, Daw, Dayan, & O'Doherty, 2010; Kable & Glimcher, 2007). These techniques can deepen our understanding of the computational roles played by brain regions and networks—particularly when used in conjunction with analyses of functional connectivity (Friston, Harrison, & Penny, 2003; Roebroek, Formisano, & Goebel, 2005). Additionally, the

emphasis within decision neuroscience on modeling both within-subject choices and between-subject individual differences provides a complementary approach to the process-isolation common in cognitive control experiments. Modeling these sources of experimental variability and correlating them with phenomenon of interest should expand the explanatory power of control models, and foster the development of richer theories of flexible behavior. These advances in turn should allow researchers studying cognitive control and decision making to together establish a more rigorous theory of the prefrontal control of thought and action.

1.7 Open questions

Recently, cognitive control researchers have taken the initiative in exploring links with decision neuroscience. Emboldened by the successes of the rostral-caudal axis model of control, researchers are extending it to address processes typically associated with decision making. Koechlin and colleagues, for example, have described interactions between their cascade model hierarchy and a parallel hierarchy of medial incentive-based motivation (Charron & Koechlin, 2010; Kouneiher, Charron, & Koechlin, 2009a). Likewise, Badre, Kayser, and D'Esposito demonstrated the role of their policy abstraction hierarchy in supporting abstract rule acquisition during an open-ended reinforcement learning task (Badre, Kayser, & D'Esposito, 2010). Despite their advantages, these models have only just begun to attract the attention of decision neuroscience researchers. One example is a report comparing distinct decision-making

and cognitive-control tasks which demonstrated a medial prefrontal topography engaged by increasingly abstract response, decision, and strategy control (Venkatraman, Rosati, Taren, & Huettel, 2009). Measures of resting-state functional connectivity have revealed hierarchically organized connections between this medial topography and the IPFC rostro-caudal axis (Taren, Venkatraman, & Huettel, 2011), solidifying this model's utility for understanding the prefrontal mechanism underlying control of goal-directed action.

This emerging integration of cognitive control and decision neuroscience models offers novel approaches and raises new and exciting questions regarding the mechanisms by which behavioral control succeeds or fails. Incorporating a hierarchical model of control may help explain individual differences in traits critical for effective regulation of behavior and decision making, including risk-taking, self-control, and impulsiveness. A relevant theory of behavioral change describes self-regulation as operating at nested levels, from concrete response inhibition in the face of temptation to abstract strategic avoidance of tempting situations, mirroring the proposed organization of prefrontal control systems (Magen & Gross, 2010). Similarly, an influential model of decision making proposes multiple interacting (and sometimes conflicting) valuation systems, from concrete stimulus-response-reward associations to abstract goal value derived from approaching a desired future state (Rangel et al., 2008). Drawing from these models, an interesting possibility is that imbalances in activation of hierarchical

sub-regions of medial and lateral PFC (reflecting imbalanced control at different levels of abstraction) leave individuals vulnerable to particular forms of self-control failure. Shortsighted behavior, for instance, could result from impoverished caudal prefrontal control over stimulus-response-reward associations in the face of temptation, but could be counterbalanced by robust rostral prefrontal control over goals, plans, and strategies. Conversely, inefficient abstract control implemented by rostral PFC might reinforce a present-oriented perspective, but be counterbalanced by momentary willpower reflected in robust caudal PFC activation. State influences such as fatigue, distraction, or emotional arousal might perturb the hierarchical balance of control processing in predictable ways, resulting in particular temporary failures of control. By contrast, chronically inefficient activation at some level of the control hierarchy (or globally throughout the hierarchy) might manifest as individual differences in control-related personality traits.

Links between prefrontal models and trait measures of control are of particular interest for the personality construct of impulsiveness, which is commonly organized into subtypes reflecting concrete failure to control momentary urges, inability to sustain executive control over short time periods, and inability to engage in abstract future planning (Patton, Stanford, & Barratt, 1995; Whiteside & Lynam, 2001). A previous study conducted by our research group provided preliminary evidence linking caudal medial PFC (mPFC) brain activation during a Stroop task to individual differences in

motor impulsiveness (Venkatraman, Rosati, et al., 2009). This study also showed an inverse relationship between rostro-medial PFC activation during strategic control and preferences for simple vs. complex thought, which are closely related to a lack of premeditation or non-planning impulsiveness (Epstein, Pacini, Denes-Raj, & Heier, 1996; Patton et al., 1995). Another study linked under-activation of a lateral contextual control region (central within the LPFC hierarchy) during uncertain decision making to attentional impulsiveness (Huettel et al., 2006a). Finally, these and a follow-up study (Taren et al., 2011) demonstrated that decision making tasks engage a medial rostro-caudal hierarchy which is functionally and anatomically interconnected with the lateral PFC hierarchy described by Koechlin, Badre, D'Esposito, and colleagues (Badre & D'Esposito, 2007, 2009b; Koechlin et al., 2003a). Together, these studies provide suggestive evidence linking PFC hierarchical control theories, decision making, and impulsiveness. These prior studies were not, however, designed to investigate individual differences in impulsive subtraits and their specific relationships with brain activation and behavior at increasingly abstract levels of control. Thus, important questions remain unaddressed: Is there sufficient evidence to organize impulsive personality sub-traits according to a principle of abstraction? Do relationships between trait, behavioral, and brain measures of impulsiveness support parallel medial and lateral prefrontal organization according to a principle of abstraction? And finally, does this model of hierarchically controlled personality and behavior advance our understanding

of impatient choice, risk-taking problem drinking, and similar failures of decision making?

To address these questions, I present four studies conducted by myself and my colleagues focused on understanding the distinct but interacting mechanisms of decision control and impulsive personality. These studies investigated relationships between impulsive personality, behavior, and brain activation during tests of cognitive control and decision making. In study 1 (Chapter 2), we used exploratory factor analysis in a large sample to define a novel measure of three subtypes of impulsiveness reflecting distinct failures of behavioral control. In study 2 (Chapter 3), we formally confirmed these measures of attentional, motor, and non-planning impulsiveness, and demonstrated their validity for measuring different facets of impulse control. Study 3 (Chapter 4) integrates this work on impulsive personality into a functional MRI study featuring behavioral and neurobiological measures of concrete control over motor responses and abstract control over decisions. Finally, study 4 (Chapter 5) used repetitive transcranial magnetic stimulation (rTMS) to investigate the causal role of a fronto-parietal impulse control network in risk-taking decisions. As a whole, this dissertation attempts to integrate techniques and evidence from the domains of personality psychology, cognitive control, and decision neuroscience in order to further our understanding of the mechanisms supporting flexible human behavior and decision making.

2. Exploring the structure of impulsive personality[†]

Chapter 2 examines core varieties of trait impulse-control failure identified using the influential Barratt Impulsiveness Scale 11. By critically examining – and ultimately improving upon – this measure of impulsiveness, we shed light on the organization of impulse-control traits, and set the stage for further research linking differences in these traits to specific behavioral and brain measures (Chapters 3-5).

2.1 Introduction

Impulsiveness is a personality trait characterized by the urge to act spontaneously, without reflecting on an action and its consequences. Trait impulsiveness influences a number of important psychological processes and behaviors, including self-regulation (Baumeister, 2002; Neal & Carey, 2005), risk-taking (Kahn, Kaplowitz, Goodman, & Emans, 2002; Stanford, Greve, Boudreaux, Mathias, & L Brumelow, 1996), and decision-making (Ainslie, 1975; Bechara, Damasio, & Damasio, 2000; Huettel, Stowe, Gordon, Warner, & Platt, 2006b). Impulsiveness is also an important component of a number of clinical conditions (American Psychiatric Association, 2000) including ADHD (Malloy-Diniz, Fuentes, Leite, Correa, & Bechara,

[†] This chapter is adapted from material to be published as “Coutlee, C. G., Politzer, C. S., Hoyle, R. H., & Huettel, S. A. (2014). An abbreviated impulsiveness scale constructed through confirmatory factor analysis of the barratt impulsiveness scale version 11. *Archives of Scientific Psychology*, 2(000).”

2007; Moeller, Barratt, Dougherty, Schmitz, & Swann, 2001), borderline personality disorder (Critchfield, Levy, & Clarkin, 2004; Ferraz et al., 2009), alcohol and drug abuse (Kollins, 2003; Perry & Carroll, 2008), and impulse control disorders such as pathological gambling (Petry, 2001; Steel & Blaszczynski, 1998).

Impulsiveness is typically measured using self-report scales, which provide a relatively inobtrusive means of assessment across a variety of clinical and research contexts. The most widely administered instrument for this purpose over the last two decades is likely the Barratt Impulsiveness Scale version 11 (BIS-11, Patton et al., 1995), cited by over 2300 sources since its formulation (Google Scholar, 2013). Consisting of 30 questions, the BIS-11 is thought to measure six related yet distinct impulsiveness factors which have been combined to form three more general subtraits: attentional impulsiveness (“inability to concentrate”), non-planning impulsiveness (“lack of premeditation”) and motor impulsiveness (“action without thought”).

This canonical three-factor structure of impulsiveness is based on a long tradition of work by Barratt and colleagues recognizing the multidimensional structure of impulsiveness while also seeking to distinguish impulsive traits from comorbid constructs, including anxiety, sensation seeking, and risk-taking (Barratt, 1965; Barratt & Patton, 1983). Beginning with the BIS-10, Barratt and colleagues formalized their multidimensional hypothesis by developing a set of items to reflect three underlying impulsiveness constructs: motor, non-planning, and cognitive (rapid decision)

impulsiveness (Barratt, 1985). Subsequent studies supported the scale's multidimensional nature, but led to the re-conceptualization of cognitive impulsiveness as attentional impulsiveness (Luengo, Carrillo-De-La-Pena, & Otero, 1991; Patton et al., 1995). Prior evidence thus consistently supports the multidimensional nature of BIS-11 impulsiveness, yet significant questions remain regarding the number and nature of influences underlying scale responses.

While the BIS-11 continues to see frequent use in both experimental and clinical contexts, attempts to replicate its canonical three-subtrait structure have generated inconsistent results. Studies examining BIS-11 items using both exploratory (Haden & Shiva, 2008; Von Diemen, Szobot, Kessler, & Pechansky, 2007) and confirmatory (Ireland & Archer, 2008; Ruiz, Skeem, Poythress, Douglas, & Lilienfeld, 2010; Someya et al., 2001) factor analysis raise important questions regarding the adequacy of the canonical BIS-11 factor structure. Some factors have proven unreliable, such as those reflecting cognitive instability (e.g., "I have racing thoughts") and perseverance (e.g., "I change residences") (Fossati, Barratt, Acquarini, & Ceglie, 2002; Fossati, Di Ceglie, Acquarini, & Barratt, 2001). Others, such as cognitive complexity (i.e., a preference for complex thought) seem to measure personality constructs distinct from core impulsiveness (Cacioppo & Petty, 1982). These inconsistencies may derive in part from analytical choices during the formulation of the BIS-11. In particular, the use of principal components analysis (Gorsuch, 1990), the failure to account for the ordinal nature of scale responses (Muthén,

1983; Wirth & Edwards, 2007), and the reliance on exploratory analysis without subsequent confirmatory replication (MacCallum, Roznowski, Mar, & Reith, 1994) represent substantial drawbacks to the original analytic approach. Finally, it is unclear which BIS-11 scales provide the most psychometrically sound measures of impulsiveness: the six-factor first order scales, the canonical three-factor second-order scales, or the commonly (mis)used single-factor total score (Fossati et al., 2002; Stanford et al., 2009).

We sought to address these concerns by conducting a methodologically rigorous examination of the factor structure underlying the BIS-11, with the goal of producing an efficient and generalizable instrument for measuring impulsiveness. Attempts have been made to produce abbreviated scales using BIS-11 items – in part because a shorter scale would be valuable in clinical contexts and for survey research – but these studies either failed to test the adequacy of the underlying BIS-11 factor structure (Spinella, 2004) or sought only a unidimensional “total-score” impulsiveness measure (Steinberg, Sharp, Stanford, & Tharp, 2013). Additionally, these studies failed to confirm data-driven models in separate replication samples, leaving their scale models vulnerable to capitalization on chance variation (MacCallum, Roznowski, & Necowitz, 1992).

In the present study, we applied exploratory and confirmatory factor analysis (EFA and CFA) to re-examine the structure of impulsiveness as measured by the BIS-11 and to produce an alternative scale, the Abbreviated Impulsiveness Scale (ABIS). Our

analysis proceeded in three broad phases. In our first study (Chapter 3), we applied EFA to BIS-11 responses from a large, diverse sample in order to identify an underlying factor structure and eliminate invalid and unreliable factors and items. The resulting ABIS factor model confirmed the attentional, non-planning, and motor impulsiveness subtraits proposed by Patton and colleagues (1995) for the BIS-11. In our second study (described in Chapter 4), we applied CFA to test the replicability and generalizability of our ABIS factor model in two separate replication samples. The ABIS model proved more generalizable than the canonical BIS-11 model. Finally, we validated the ABIS scales through comparison to the BIS-11 as well as independent behavioral and personality measures related to impulsiveness (Chapter 4). The ABIS provides an efficient, internally consistent, and generalizable alternative to the BIS-11 for measuring impulsiveness.

2.2 Methods

Analysis Procedure

Our study was designed to examine the associations between answers to personality survey questions (items) about impulsiveness, and to improve upon an existing measure of impulsive personality based on these items (i.e., the BIS-11). We used the factor analytic techniques EFA and CFA to identify latent impulsive personality traits influencing people's answers to these items. Our study proceeded in eight stages, illustrated in **Figure 3**. In Stage 1, we used CFA to test the ability of the canonical BIS-11

model to describe the patterns of item responses. This canonical model failed, leading us to Stage 2, wherein we used exploratory, data-driven techniques (parallel analysis and EFA) to construct an initial seven-factor model of impulsive personality. Next, in Stage 3, we identified and took steps to eliminate three problematic factors which were unrelated to core impulsiveness. In Stage 4, we targeted individual questions for removal, eliminating idiosyncratic items that remained poorly explained after accounting for the influence of identified factors. In Stage 5, we eliminated additional factors that were poorly measured by the remaining set of items. In Stage 6, we finalized our factor model, and simplified the structure of the exploratory model to fit the format of a confirmatory factor model, leading to the formulation of the ABIS scale. Finally, we conducted analysis stages seven and eight as part of a separate study (detailed in Chapter 3) in which we confirmed and validated the ABIS scales as measures of attentional, motor, and non-planning impulsiveness. In Stage 7, we confirmed our final model in two additional independent samples. In Stage 8, we validated the abbreviated scales derived from our model by relating them to personality and behavioral outcome variables reflecting impulsiveness.

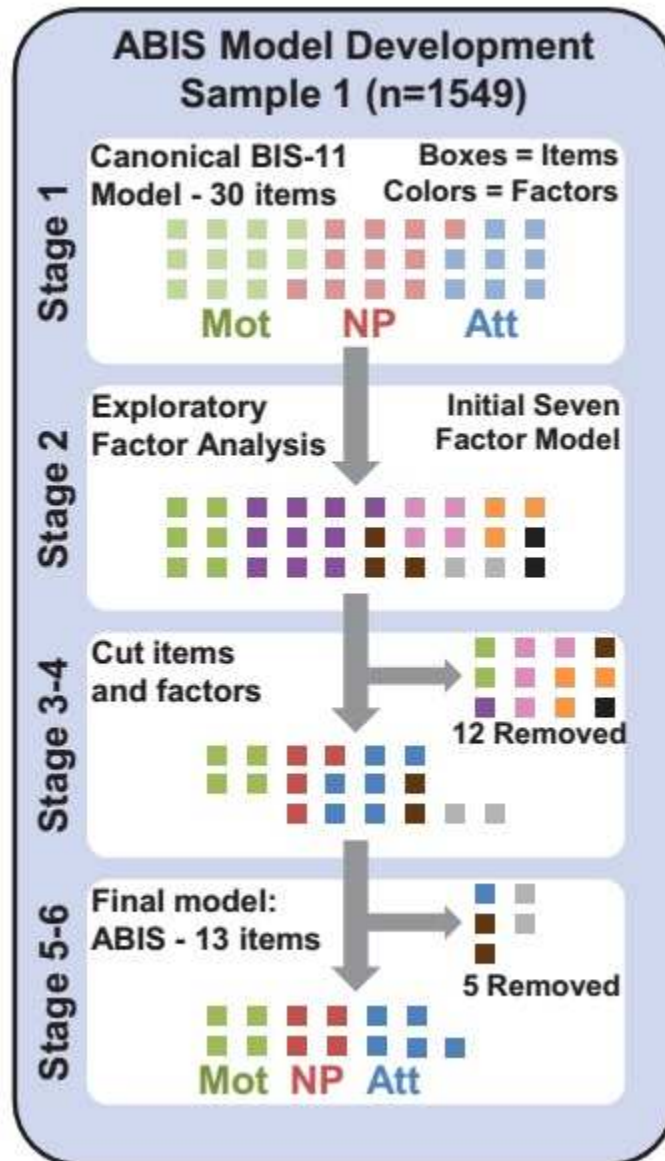


Figure 3: Flowchart of Study Analysis Procedure. Small boxes represent individual scale items, with color representing separate factors. The ABIS model was developed through Stages I–VI using EFA and CFA (Sample 1), resulting in a three-factor, 13-item scale. The ABIS was replicated in Stage VII (Samples 2 and 3) and validated in Stage VIII (Samples 1 and 4). Mot = motor impulsiveness; NP = nonplanning impulsiveness; Att =*attentive impulsiveness.

Participants

Our primary sample comprised 1549 adults from Durham, North Carolina, and surrounding communities (Sample 1). Participants were recruited via advertisements in community locations. All participants provided informed consent under protocols approved by either the Duke University or Duke University Medical Center Institutional Review Boards.

Primary Study Measures

BIS-11: Responses to these 30 items measuring attentional, motor, and non-planning impulsiveness (Patton et al., 1995) were our main measures of interest. Responses were indicated on a computer using a four-point scale: *Rarely/Never, Occasionally, Often, Almost Always/Always*. Subjects from all four of our samples completed the BIS-11. Items from this scale were used to formulate the ABIS. The BIS-11 items are publicly available at <http://www.impulsivity.org/measurement/bis11>.

Additional Personality Measures: As a part of our revision process, we compared responses on the BIS-11 scale to the Need for Cognition and Faith in Intuition scales (Epstein et al., 1996).

EFA and CFA

Model fit was evaluated using the comparative fit index (CFI, Bentler, 1990) and the root mean square error of approximation (RMSEA, Steiger, 1990). These indices have been found to perform well with categorical data under our study conditions, including

relatively large samples, 4-item response scales, and categorical model estimation techniques (DiStefano, 2002; Edwards, Wirth, Houts, & Xi, 2012; Green, Akey, Fleming, Hershberger, & Marquis, 1997; Hutchinson & Olmos, 1998). We used CFI values of .95 and RMSEA values of .06 as cutoffs for good model fit (Hu & Bentler, 1999). RMSEA cutoffs of .08 and .10 indicated acceptable and marginal fit, respectively (MacCallum, Browne, & Sugawara, 1996). See the accompanying JARS (Cooper, 2008) and JARS_SEM (Hoyle & Isherwood, 2013) questionnaires for methodological details regarding our factor analyses.

2.3 Results

2.3.1 Stage 1: Attempting to confirm the canonical BIS-11 factor structure of impulsive personality

We first attempted to confirm the BIS-11 factor structure proposed by Patton et al. (1995). These authors identified six latent factors underlying responses to the 30 BIS-11 scale items. Theoretical motivations led them to aggregate the six factors into three second-order factors. We used CFA to test the suitability of these six-factor and three-factor solutions, as well as a single-factor (unidimensional/total-score) solution. Each item was specified to load on a single factor based on its assignment to the BIS-11 subscales (Patton et al., 1995). The magnitude of these loadings as well as the factor covariances were freely estimated from the data (corresponding to congeneric

indicators, an oblique factor rotation, and strict simple structure). Model fit results appear in **Table 1**.

None of the models based on the canonical BIS-11 structure provided an acceptable explanation of the relationships between item responses. CFI values were especially poor for these models. Substantial exploratory modification was required to achieve conventionally acceptable model fit. Based on these results, we concluded that the item-factor relationships specified by the canonical BIS-11 model could not explain the patterns of responses in our sample.

2.3.2 Stage 2: Exploring an alternative factor structure of impulsive personality using EFA

Given our failure to explain our data using CFA based on the canonical BIS-11 structure, we turned to EFA to derive an alternative, data-driven model of the factor structure underlying BIS-11 responses.

Parallel analysis (Horn, 1965) using either permuted data or random normal data (Buja & Eyuboglu, 1992) indicated seven factors underlying our BIS-11 responses. EFA using the unrestricted factor model (Hoyle & Duvall, 2004; Jöreskog, Sörbom, Magidson, & Cooley, 1979) corroborated this estimate, demonstrating that a seven-factor solution was the simplest that achieved good fit (RMSEA = .05, CFI = .95). The model fit results of this initial EFA appear in **Table 1**, and served as the basis for constructing the abbreviated scale.

Our initial seven-factor EFA revealed a number of constructs that roughly correspond to subtraits identified in the original BIS-11 six-factor model, including self-control/planning, motor, perseverance, cognitive complexity, and cognitive instability factors. These initial EFA results also suggested a number of avenues by which the scale could be abbreviated without sacrificing inferential validity. Our revision proceeded as detailed below, with the EFA re-estimated at each stage after the removal of items.

Table 1: Factor analysis results and fit statistics.

Stage	Type	Model description	χ^2	<i>df</i>	RMSEA	RMSEA 90% CI	CFI	<i>N</i>
I	CFA	Patton et al. (1995) one factor (total score)	7,466.59	405	0.106	0.104 0.108	0.639	1,549
I	CFA	Patton et al. (1995) three factor (canonical model)	6,249.95	402	0.097	0.095 0.099	0.701	1,549
I	CFA	Patton et al. (1995) six factor (first order factors)	5,622.44	390	0.093	0.092 0.098	0.732	1,549
II	EFA	Seven factors, 30 items	1,145.29	246	0.049	0.046 0.051	0.954	1,549
III	EFA	Five factors, 25 items	984.49	185	0.053	0.050 0.056	0.949	1,549
IV	EFA	Five factors, 18 items	498.36	73	0.061	0.056 0.066	0.967	1,549
V	EFA	Three factors, 14 items	570.84	52	0.080	0.074 0.086	0.955	1,549
VI	CFA	Three factors, 14 items, simple structure	884.75	74	0.084	0.079 0.089	0.930	1,549
VI	CFA	Three factors, 13 items, simple structure	753.77	62	0.085	0.080 0.090	0.938	1,549
VI	CFA	Final model, three factors, 13 items, three error covariances	371.90	59	0.059	0.053 0.064	0.972	1,549
VII	CFA	Sample 2, replication of final model	262.44	59	0.072	0.064 0.081	0.968	657
VII	CFA	Sample 2, Patton et al. (1995) three factors (canonical model)	2,863.76	402	0.096	0.093 0.100	0.743	657
VII	CFA	Sample 3, replication of final model	166.04	59	0.080	0.066 0.094	0.971	285
VII	CFA	Sample 3, Patton et al. (1995) three factors (canonical model)	1,659.31	402	0.105	0.100 0.110	0.779	285

2.3.3 Stage 3: Eliminating factors unrelated to core impulsiveness

Our initial EFA revealed a factor similar to BIS-11 “cognitive complexity” and anchored by items 15, 18, and 29, which refer to a preference for complex thought. These items appeared to measure “need for cognition,” a personality construct that is distinct from impulsiveness and that reflects an individual’s desire for effortful cognitive activity (Cacioppo & Petty, 1982). We examined the correlation between responses on items from the cognitive complexity factor (with higher scores reflecting a stronger preference for complex thought) with responses on the Need for Cognition scale (Epstein et al., 1996), collected from a subset of 379 subjects. Items 15 ($r = .68$, 95% CI [.62, .73]), 18 ($r = .51$, 95% CI [.43, .58]) and 29 ($r = .42$, 95% CI [.33, .50]) exhibited substantial correlation with the need for cognition total score, while the weaker-loading items 12 ($r = .34$, 95% CI [.25, .43]) and 20 ($r = .26$, 95% CI [.16, .35]) showed moderate correlation. We chose to remove items 15, 18 and 29 on the basis of their strong relationship to need for cognition.

Our initial EFA also revealed a doublet factor consisting of items 11 and 28. These items, which refer to either “squirming” (11) or “restlessness” (28) at plays, the theater, or lectures, are redundant in concept and wording. This suggests that the “factor” they form may instead reflect a method effect unrelated to the underlying structure of impulsive personality (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Consistent with this assessment, the polychoric (i.e., ordinal) correlation between items 11 and 28 ($r = .73$, 95% CI [.71, .75]) was among the largest between BIS-11 items. To

eliminate this method factor, we chose to remove one of these two items on the basis of item R^2 values. These values, which express the proportion of variance for each item explained by the modeled factors, can be taken as an estimate of item reliability (Brown, 2006). Item 11 was removed, as it proved less reliable than item 28 upon removal and re-estimation ($R^2 = .22$ for 11 vs. $.34$ for 28).

We also identified a financial factor consisting of items 10, 22, and 25, each of which refers to impulsiveness in the context of spending or saving decisions. Financial factors have been identified in previous EFAs of BIS-11 responses (Fossati et al., 2001). Although this factor was stable and meaningful, it reflects shared variance related to impulsiveness within the particular domain of financial behavior, as opposed to a broader trait relevant across domains. Supporting this interpretation, two of the three financial items also had substantial cross-loadings on the more domain-general planning (item 10, $.37$) and motor (item 22, $.39$) factors. We chose to eliminate this domain-specific financial factor by removing item 25, which possessed the highest loading on the financial factor ($.77$) and had no substantial loadings on other factors. Items 10 and 22 were retained at this stage.

In summary, our first round of item elimination evaluated three questionable factors from our initial seven-factor EFA solution, which led to the elimination of five items: three (15, 18, 29) reflecting need for cognition, one redundant item (11) from a restlessness doublet, and one item (25) anchoring a domain-specific financial factor.

We re-estimated our EFA using the 25 remaining indicators and found a five-factor solution to be most interpretable, as summarized in **Table 1**. This model revealed factors similar to the original BIS-11 first-order factors, save for the eliminated factor of “cognitive complexity.”

2.3.4 Stage 4: Eliminating unreliable items

To identify additional items for removal, we examined the item reliability, as indexed by R^2 values. Items with low reliability fell into one of three categories: items with a pejorative interpretation (e.g., “I can only think about one thing at a time;” 23, 27, 3), items with an unusual or narrow relevance (e.g., “I change hobbies;” 4, 24), or items with residual variance due to eliminated financial factor (10, 22). When all remaining BIS-11 items were sorted in descending order by their R^2 values, we found a clear gap separating the low-reliability items mentioned above (R^2 s from .02-.26) from the remaining items (R^2 s from .32-.74). We chose to eliminate all seven of these low-reliability items. Stepwise elimination starting with the lowest reliability item did not substantively change the ordering of items by reliability. The elimination of these seven items left 18 items. We re-estimated our EFA using the 18 remaining items, and found a five-factor solution to be most interpretable, as summarized in **Table 1**.

2.3.5 Stage 5: Eliminating poorly measured doublet factors

Two of the factors in our five-factor, 18-item model were doublets, featuring strong loadings of only two items. These doublet factors reflected perseverance (items 16

and 21, “I change jobs” and “I change residences”) and cognitive instability (items 6 and 26, “I have ‘racing’ thoughts” and “I often have extraneous thoughts when thinking”). The cognitive instability doublet factor also possessed moderate loadings (.32-.35) on three items (5, 9, 28), but each of these items had stronger loadings on an attention factor. To address the “local dependence” (Yen, 1993) reflected by these item pairs, we first attempted to eliminate single items from each factor. Removing either item 16 or 21 from the perseverance factor or item 6 or 26 from the cognitive instability factor left the remaining doublet item with low reliability ($< .27$), so we excluded all four items. Removing the perseverance and cognitive instability doublet factors left a 14-item scale.

We re-estimated our EFA using the 14 remaining items, and found a three-factor solution to be most interpretable, as summarized in **Table 1**. These three factors reflected constructs similar to motor, non-planning, and attentional impulsiveness, as conceptualized by Patton et al. (1995).

2.3.6 Stage 6: Confirming the final model using CFA

We translated the results of our three-factor, 14 item EFA into a model reflecting simple structure, such that each item loaded on only one factor, while still allowing the factors themselves to covary. These results were promising, indicating marginal fit, as summarized in **Table 1**. Translation to simple structure resulted in one attention item with a low R^2 value (28, $R^2 = .20$) which we removed, leaving a final set of 13 items (**Table 1**).

After examining the model covariance matrix and modification indices (which quantify the expected change in model fit due to freeing individual fixed model parameters), three error covariances were introduced between model uniqueness terms to account for residual dependence between scale indicators. First, the error terms for items 17 and 19 were allowed to covary, as their similar wording and proximity on the scale may have introduced additional methodological correlation. Similarly, error terms for items 12 and 20 were allowed to covary on the basis of their similar wordings. Finally, error terms for 13 and 30 were allowed to covary. These two items share conceptual variation related to long-term planning, and often emerged as a doublet separate from items 1 and 7 (which reflect more near-term planning) with higher-order EFA extractions. We believe that there is sufficient evidence to justify a planning factor including all four items, but we allowed for the error covariance between 13 and 30 to account for the additional dependence between these items. Freeing these three parameters accounted for residual covariance without altering the general pattern and magnitude of item loadings, which remained large (.55-.82) and highly significant ($p < .001$) in all cases.

Results for our final model, including the three correlated uniqueness terms specified above, are represented in **Figure 4**. Model fit (**Table 1**) was good. The final model features five items measuring attentional impulsiveness (5, 8, 9, 12, and 20), four items measuring non-planning impulsiveness (1, 7, 13, and 30) and four items measuring motor impulsiveness (2, 14, 17, and 19), for a total of 13 items, less than half of the length of the canonical BIS-11 scale. This reduction was achieved by eliminating non-relevant factors, doublet factors, and unreliable items.

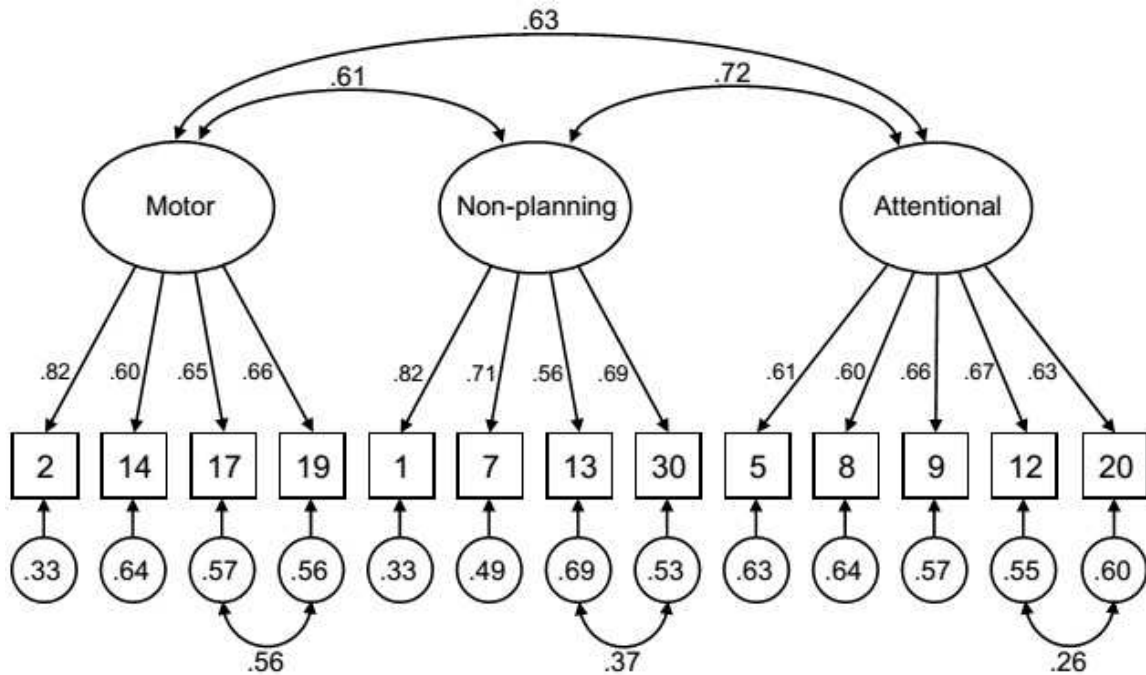


Figure 4: Path diagram illustrating the final ABIS model estimates from Sample 1. The 13 items of the ABIS (boxes, BIS-11 item numbering) measure correlated attentional (5 items), motor (4 items) and non-planning (4 items) latent factors (ellipses). Item error/uniquenesses are shown as circles; three error covariances (curved arrows between errors) were specified. Parameter estimates are standardized using the variances of the continuous latent variables as well as the variances of the outcome (i.e., Mplus StdYX) All parameters are significant at $p < .001$.

2.4 Discussion

Based on our model of BIS-11 responses refined through analysis Stages 1-6, we present the ABIS, a 13-item scale measuring attentional (5 items), non-planning (4 items), and motor (4 items) impulsiveness (**Table 2**). Scores on each subscale are computed by averaging responses on all relevant subscale items, after accounting for reverse-scored items (see Appendix A for scale administration and scoring forms).

Table 2: ABIS scale items.

ABIS scale	Item number	Item text
Attention	5	I don't "pay attention."
	8	I am self-controlled.
	9	I concentrate easily.
	12	I am a careful thinker.
	20	I am a steady thinker.
Motor	2	I do things without thinking.
	14	I say things without thinking.
	17	I act "on impulse."
	19	I act on the spur of the moment.
Nonplanning	1	I plan tasks carefully.
	7	I plan trips well ahead of time.
	13	I plan for job security.
	30	I am future oriented.

We initially set out to re-evaluate the factor structure of the BIS-11 using large samples, modern factor analytic methods (exploratory and confirmatory), and replication in independent samples. Despite demonstrating poor model fit for the BIS-11's particular factor structure, our final model corroborates its general structure, in that

our attentional, motor, and non-planning scales resemble the core impulsiveness subtraits identified by Patton et al. (1995). We argue, however, that our systematic removal of extraneous factors and unreliable items allows the ABIS to measure these preserved core subtraits with enhanced efficiency and clarity.

Our results indicate that the ABIS scales are best considered measures of separate but correlated components of impulsiveness. The scales show moderate intercorrelation (r s from .40-.50, 95% CIs \pm .04). Each scale taken alone is acceptably unidimensional after accounting for the specified correlated uniquenesses. By contrast, a single-factor model, reflecting a total score computed by summing across all items, showed unacceptable fit, reflecting a lack of unidimensionality across all items. Despite cautions from the scale authors (International Society for Research on Impulsivity, 2013), the BIS-11 subscales are commonly summed to produce a total scale, a practice which ours and others results fail to support (Ireland & Archer, 2008; Steinberg et al., 2013). We hope to avoid this misunderstanding with the ABIS scales, and emphasize that ignoring the multidimensional nature of the ABIS or BIS-11 items undermines the validity of inferences made using those items. Inappropriate use of summary scores in such cases introduces additional measurement error (Fava & Velicer, 1996; Wood, Tataryn, & Gorsuch, 1996) and can distort the nature of the measured construct (Cattell, 1958). This can lead to problems identifying true relationships between impulsiveness traits and other constructs, particularly in cases where those relationships differ between motor,

attentional, and non-planning impulsiveness. We reiterate that it is psychometrically inappropriate to combine the ABIS scales, and that they should not be summed or averaged to calculate a total score. (Note that, according to our analyses, this admonition holds equally for the original BIS-11 subscales, as well).

Although evidence from our study clearly supports the multidimensionality of impulsiveness measured via BIS-11 items, we remain agnostic regarding the potential existence or nature of a “general impulsiveness” construct underlying attentional, motor, and non-planning impulsiveness. The correlated-factors model we describe does not specifically address this question, as this model is statistically equivalent to a first-order factor model with a single general (second-order) impulsiveness factor. Bi-factor models (Holzinger & Swineford, 1937), in which items simultaneously load on both a general and uncorrelated specific factors (e.g., attention, motor, non-planning), suggest an alternative possible higher order structure (Yung, Thissen, & McLeod, 1999). Our own findings and those of others (Steinberg et al., 2013) indicate that bi-factor solutions based on the canonical BIS-11 model and items provide a poor fit overall, although including a general factor did improve models based on the full 30-item set. Applied specifically to the ABIS items, we found that a bi-factor model produced fit somewhat inferior to our final three-factor model, with moderate-to-strong loadings on the general factor across all items (covariance terms were dropped to allow model estimation). Practical attempts to investigate specific impulsiveness traits in isolation should control

for correlated impulsiveness constructs using standard methods (CFA/SEM, multiple and hierarchical regression), as opposed to more speculative bi-factor models. More generally, however, questions regarding the higher-order structure of impulsiveness require further investigation, and are likely to be informed by emerging bi-factor modeling techniques, including exploratory bi-factor analysis (Jennrich & Bentler, 2011; Muthén & Muthén, 2012).

Our final model supports the general structure of impulsiveness types as measured by the BIS-11 items, identifying core attentional, motor, and non-planning subtypes. The ABIS model can be used directly to guide and constrain future factor analytic and structural equation modeling approaches to measuring impulsive subtraits using the BIS-11 items. Use of such covariance modeling approaches in conjunction with our model to identify these three latent impulsiveness traits is ideal as such an approach formally models measurement error, which typically attenuates estimates of relationships between variables (Hurley et al., 1997). Given that many investigators interested in measuring impulsiveness are unfamiliar with covariance modelling approaches, however, we also present an ABIS scale which approximates impulsiveness factor scores through equally-weighted averaging of items (Appendix A). This procedure is simple, well-established, and produces interpretable measures. Given our efforts to enhance the internal consistency of the scale items, such an approach also produces reliable and conceptually coherent measures (Osborne & Costello, 2004). The

resulting ABIS scales represent efficient, internally consistent, and generalizable measures of attentional, motor, and non-planning impulsiveness. The ABIS can be used as a brief alternative to the BIS-11 or as a model for reanalyzing previously collected BIS-11 questionnaire responses.

3. Confirmation and validation of a novel model of impulsive personality[†]

3.1 Introduction

Factor analysis and principal components analysis have long been mainstay techniques for the development of personality scales (Floyd & Widaman, 1995; Worthington & Whittaker, 2006). These techniques are, however, fundamentally exploratory and data-driven: They identify patterns capable of summarizing or explaining data, with few constraints from prior knowledge or theory (Brown, 2012; Hurley et al., 1997). While these techniques are powerful and useful, they are also vulnerable to identifying patterns and relationships which reflect chance variation in a particular sample, rather than true relationships in the population (MacCallum et al., 1992; Osborne & Costello, 2004). Addressing this “overfitting problem,” which is a known weakness of exploratory analysis techniques, is essential for the formulation and presentation of both replicable results and reliable psychometric measures.

There has been a recent resurgence of interest in techniques for improving the reproducibility of results within the psychological sciences (Makel, Plucker, & Hegarty, 2012; Roediger III, 2013). Although empirical science is by nature self-correcting in that unreliable results will over time be discredited, such results can in the meantime be

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damaging, misleading the public as well as other scientists, and contributing to inefficiencies and wasted research resources (Ioannidis, 2012; Pashler & Wagenmakers, 2012).

Given these known challenges, psychological scientists should seek to hold themselves to a high standard when it comes to the reliability of the results they report. One of the most fundamental and effective checks on the reliability of results is the replication and refinement of findings using an independent sample prior to reporting the results in the research literature (Brown, 2006; MacCallum et al., 1994). Self-replication is particularly important when the results of an investigation are intended for broad application, as with the development of a personality scale. In such cases, if it is at all technically and financially feasible to do so, a responsible psychological scientist should report the results from an out-of-sample replication (particularly of scales based on exploratory factor analytic techniques) to support the reliability and reproducibility of a proposed measure.

We previously reported the formulation of the ABIS, a revised and abbreviated self-report scale which measures attentional, motor, and non-planning impulsiveness. The ABIS was formulated using exploratory factor analysis, meaning that the assignment of items to factors, which underlies the scale scores, was vulnerable to capitalization on chance or overfitting problems. Related problems have constrained the usefulness of the original BIS-11 scale, as its structure has been inconsistently replicated

across a number of investigations (Haden & Shiva, 2008; Ireland & Archer, 2008; Ruiz et al., 2010). The large initial sample used to formulate the ABIS only partially addresses this concern (MacCallum et al., 1996).

Additionally, although the sample used to formulate the ABIS included adult community members in addition to university students, evidence from independent samples with different demographic characteristics is desirable to support the generalizability of the ABIS. Recent work has shown internet to provide a useful check on the generalizability of psychological findings (which typically rely on convenience samples of undergraduate students) (Buhrmester, Kwang, & Gosling, 2011; Gosling, Vazire, Srivastava, & John, 2004).

To address these concerns, we replicated the ABIS model in two independent samples: a sample of 657 adults with similar demographic composition to support the replicability of our findings, and an internet sample of 285 adults to support their generalizability. Finally, we sought to validate the ABIS scales as measures of attentional, motor, and non-planning impulsiveness. To do so, we related ABIS scale scores to their corresponding BIS-11 scale scores, as well as to a variety of personality measures relevant to impulsiveness. Finally, we demonstrated the utility of the ABIS scales by measuring a relationship between the ABIS motor impulsiveness and self-reported alcohol consumption in a sample of 49 healthy adults. Our methodologically rigorous approach reinforces the generalizability and future replicability of the ABIS,

and supports its widespread use as an efficient measure of attentional, motor, and non-planning impulsiveness.

3.2 Methods

Analysis Procedure

In Stages 1-6 of our first study (described in Chapter 2) we used the factor analytic techniques EFA and CFA to develop an abbreviated scale model from the BIS-11 items, which led to our Abbreviated Impulsiveness Scale, the ABIS. In our second study described here, we sought to replicate our scale model, and validate the ABIS measurements of motor, attentional, and non-planning impulsiveness, as depicted by **Figure 5**. In Stage 7 we confirmed our final model in two additional independent samples. Finally, in Stage 8, we validated the abbreviated scales derived from our model by relating them to personality and behavioral outcome variables reflecting impulsiveness.

Participants

Two replication samples comprised 657 adults from the Duke University community (Sample 2) and 285 adults recruited online (Sample 3) through Amazon's Mechanical Turk (www.MTurk.com). A final validation sample comprised 49 adults from the Durham and surrounding communities (Sample 4) recruited for a functional neuroimaging experiment examining impulsive decision making. We also report findings from Sample 1 (N = 1549; described in Chapter 2). All participants provided

informed consent under protocols approved by either the Duke University or Duke University Medical Center Institutional Review Boards.

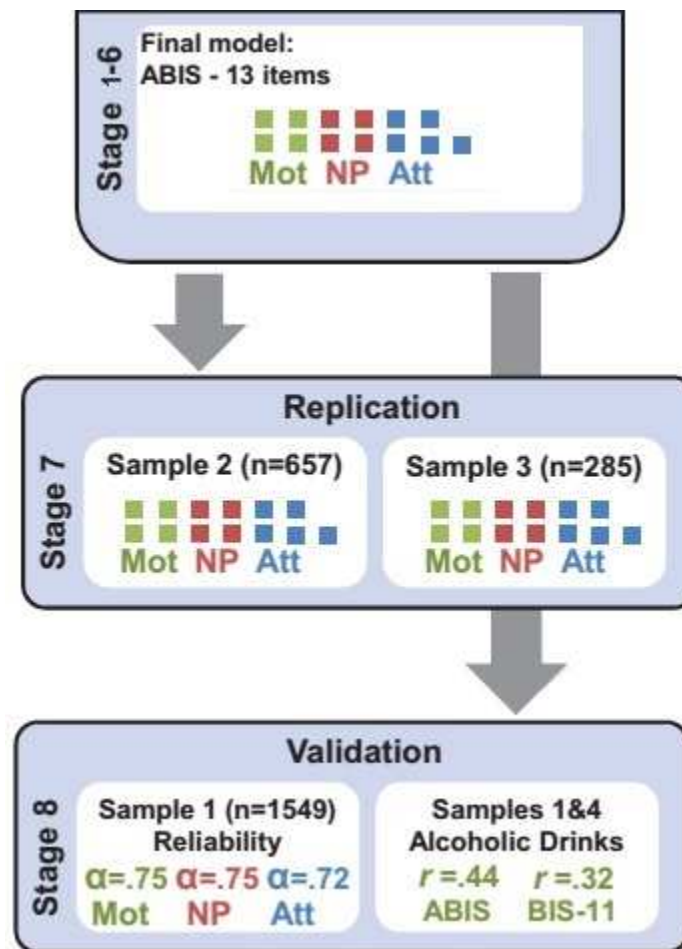


Figure 5: Flowchart of study analysis procedure for replication and validation. Small boxes represent individual scale items, with color representing separate factors. The ABIS model was developed through Stages I–VI using EFA and CFA (Sample 1), resulting in a three-factor, 13-item scale. The ABIS was replicated in Stage VII (Samples 2 and 3) and validated in Stage VIII (Samples 1 and 4). Mot = motor impulsiveness; NP = nonplanning impulsiveness; Att = attentional impulsiveness.

Primary Study Measures

Our primary measures of interest included the following.

BIS-11: Responses to these 30 items measuring attentional, motor, and non-planning impulsiveness (Patton et al., 1995) were our main measures of interest.

Responses were indicated on a computer using a four-point (five-point in Sample 3) scale: *Rarely/Never, Occasionally, Often, Almost Always/Always*. Subjects from all four of our samples completed the BIS-11. Items from this scale were used to formulate the ABIS. The BIS-11 is available at <http://www.impulsivity.org/measurement/bis11>.

Alcohol Use Questionnaire: Impulsiveness plays a key role in the initiation and maintenance of substance use and dependence (Dick et al., 2010). To examine alcohol use, we asked participants from Sample 4 to self-report the number of alcoholic beverages consumed on a typical day on which they drank, as well as the average number of days per week alcohol was consumed. From the product of these quantities, we derived a measure of average number of alcoholic drinks consumed per week.

Additional Personality Measures: We included additional measures in order to validate the ABIS. These included the Decision Making Styles Inventory Analytical and Intuitive scales (Nygren & White, 2002), the Need for Cognition and Faith in Intuition scales (Epstein et al., 1996), the BIS/BAS (Carver & White, 1994), the UPPS impulsiveness scale (Whiteside, Lynam, Miller, & Reynolds, 2005), the Brief Sensation Seeking Scale

(Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002), and the Impulsive Sensation Seeking Scale (Zuckerman, 2002).

Delay Discounting - Proportion Impatient Choice: Delay discounting, or the tendency to devalue (discount) delayed rewards, is a common behavioral measure of impulsive decision making (Bickel, Odum, & Madden, 1999; Reynolds, Richards, Horn, & Karraker, 2004; Wittmann & Paulus, 2008). Participants from Sample 4 completed an experiment examining delay discounting in which they made 100 choices between two different options: a small monetary amount which could be received immediately, and a larger amount (\$5-\$50) which could be received after a delay (1-8 weeks). We used the proportion of choices for which the participant chose the impatient (smaller but immediate reward) option as an individual difference measure of impulsive decision making.

Confirmatory Factor Analysis

Model fit was evaluated using the comparative fit index (CFI, Bentler, 1990) and the root mean square error of approximation (RMSEA, Steiger, 1990). These indices have been found to perform well with categorical data under our study conditions, including relatively large samples, 4-item response scales, and categorical model estimation techniques (DiStefano, 2002; Edwards et al., 2012; Green et al., 1997; Hutchinson & Olmos, 1998). We used CFI values of .95 and RMSEA values of .06 as cutoffs for good model fit (Hu & Bentler, 1999). RMSEA cutoffs of .08 and .10 indicated acceptable and

marginal fit, respectively (MacCallum et al., 1996). See the accompanying JARS (Cooper, 2008) and JARS_SEM (Hoyle & Isherwood, 2013) questionnaires for methodological details regarding our factor analyses.

3.3 Results

3.3.1 Stage 7: Confirming model generalizability through replication using CFA

We next sought to confirm the structural validity of our abbreviated scale using CFA in two additional samples.

We replicated the model structure in an additional survey-based sample of 657 adults (Sample 2). CFA was performed on responses to relevant BIS-11 items, specifying the final model from Stage 6. All estimated model parameters, including the three error covariance terms specified, were highly significant ($p < .001$). Overall model fit in the replication sample was acceptable to good (**Table 1**). Model fit for the canonical three-factor Patton model was marginal to unacceptable in this sample (*Table 1*). Modification indices did not suggest any conceptually relevant alterations. The results of this analysis confirm the factor structure of our abbreviated scale, which produced acceptable replication fit values in an independent sample.

To reinforce the generalizability of our abbreviated scale model, we implemented a stringent test by using CFA to replicate the model structure in a diverse Internet sample of 285 individuals (Sample 3), who completed the BIS-11 using a five-point response scale. Analysis procedures were identical to those used previously. CFA was

performed on BIS-11 item responses, specifying the final model from Stage 6 (including error covariances). Again, all estimated model parameters were highly significant ($p < .001$). Overall, model fit in this replication sample was acceptable/marginal to good (**Table 1**); the CFI value indicated good fit, while the RMSEA value, at .08, was equal to the cutoff value separating acceptable and marginal fit for this index. Model fit for the canonical BIS-11 three-factor structure was unacceptable in this sample (**Table 1**).

Modification indices did not suggest any conceptually relevant alterations. The results of this analysis confirm the factor structure of our abbreviated scale, which produced acceptable replication fit values in a moderately sized Internet sample. The Internet sample we collected is quite diverse in terms of age, occupation, race, and geography, more so than most samples studied within personality psychology (Buhrmester et al., 2011; Gosling et al., 2004). Additionally, the model results generalized well to a five-point response scale (although we recommend the continued use of a four-point scale for the sake of continuity with previous research).

Replication of the abbreviated scale model in both a local community and a broad Internet sample indicates the enhanced generalizability of the abbreviated measure. This is particularly clear in comparison to the performance of the canonical BIS-11 model, which showed inadequate fit in every sample we examined.

3.3.2 Stage 8: Validating the abbreviated scale using measures of personality and behavior

Properties of the ABIS scale scores in our factor analysis samples are shown in **Table 3**. In particular, the internal consistency of the abbreviated scales, as indexed by coefficient alpha, is greater than that for the canonical BIS-11 subscales in all of our samples (BIS-11 α : attention = .71; motor = .64; non-planning = .69). The ABIS values are also similar to or greater than those published for the BIS-11 subscales in another large sample (Stanford et al., 2009). Coefficient alpha is positively related to the number of scale items, (Churchill Jr & Peter, 1984; Voss, Stem Jr, & Fotopoulos, 2000), leading us to expect that abbreviated scale scores would exhibit lower reliability by this measure. The fact that alpha was actually greater for the shortened ABIS scale scores supports our contention that the ABIS more reliably measures the impulsive subtraits latent in the BIS-11 item set.

Table 3: Descriptive statistics for ABIS scales in factor analysis samples. Sample 3 items were measured from 1 to 5, rendering comparisons to Samples 1 and 2 uninformative. Summary statistics are shown for scale scores, which reflect the average of relevant items. Two individuals from Sample 2 reported no gender. *Gender difference $p < .05$.

Sample	Total				Females				Males			
	<i>M</i>	<i>SD</i>	α	<i>N</i>	<i>M</i>	<i>SD</i>	α	<i>N</i>	<i>M</i>	<i>SD</i>	α	<i>N</i>
Sample 1												
ABIS attention	2.05	0.47	0.72	1,549	2.07	0.47	0.74	939	2.04	0.46	0.68	608
ABIS motor	2.06	0.51	0.75	1,549	2.03*	0.50	0.75	939	2.10*	0.52	0.75	608
ABIS nonplanning	2.11	0.62	0.75	1,549	2.06*	0.61	0.75	939	2.19*	0.62	0.75	608
Sample 2												
ABIS attention	2.08	0.53	0.77	657	2.08	0.55	0.80	377	2.08	0.51	0.74	278
ABIS motor	1.94	0.56	0.81	657	1.89*	0.55	0.82	377	2.00*	0.56	0.80	278
ABIS nonplanning	2.14	0.63	0.71	657	2.06*	0.62	0.71	377	2.25*	0.63	0.71	278
Sample 3												
ABIS attention	2.25	0.70	0.77	285	2.15*	0.62	0.73	145	2.35*	0.76	0.79	140
ABIS motor	2.38	0.99	0.88	285	2.36	1.04	0.90	145	2.40	0.94	0.86	140
ABIS nonplanning	2.35	0.77	0.70	285	2.27	0.76	0.72	145	2.44	0.78	0.66	140

We next investigated the relationships between the ABIS scales, BIS-11 subscales, and relevant measures of personality and behavior. **Table 4** depicts correlations between the ABIS and BIS-11 scales. The ABIS attention, motor, and non-planning scales were strongly correlated with their corresponding BIS-11 subscales (r s from .71-.77, 95% CIs $\pm .02$). We also sought to validate the ABIS scales by relating them to a range of self-report and behavioral individual difference measures relevant to impulsiveness. These associations are depicted in **Table 5**. Despite the brevity of the ABIS scales, they produced correlations similar to those of the corresponding BIS-11 scales across a variety of personality measures. Consistent with their enhanced internal consistency, there was a general tendency towards stronger correlation estimates using the ABIS scales. Exceptions tended to have clear explanations, such as the drop in correlation between ABIS non-planning and need for cognition after the intentional removal of “cognitive complexity” items in stage three of our analysis. The similar pattern of associations observed with the ABIS and BIS-11 scales supports the inferential validity of the ABIS scales when measuring motor, attentional, and non-planning impulsiveness.

Previous research has suggested that impulsiveness is positively related to alcohol consumption in both teenagers (Fossati et al., 2002) and adults (Granö, Virtanen, Vahtera, Elovainio, & Kivimäki, 2004), with small-to-moderate effect size (r around .30 using the BIS-11). We found that self-reported alcohol consumption in adults was related to both ABIS motor impulsiveness ($r = .44, p < .05$,

Table 4: Correlation of ABIS and BIS-11 scales in Sample 1. B11 Tot = BIS-11 total score; att = attention; mot = motor; sc = self control; cc = cognitive complexity; per = perseverance; ci = cognitive instability; NP = nonplanning; fin = finance; nfc = need for cognition. BIS-11 first-order scales are abbreviated in lowercase whereas second-order scales are abbreviated in upper case. All correlations significant at $p < .01$ (excepting BIS-11 cognitive complexity with cognitive instability).

	B11 Tot	att	Mot	sc	cc	Per	ci	ATT	MOT	NP	ABIS Att	ABIS Mot	ABIS NP	fin	nfc
BIS11-Total Score	—														
BIS11-attention	0.72	—													
BIS11-motor	0.71	0.31	—												
BIS11-self control	0.79	0.48	0.45	—											
BIS11-cognitive complexity	0.59	0.35	0.25	0.37	—										
BIS11-perseverance	0.55	0.22	0.30	0.37	0.23	—									
BIS11-cognitive instability	0.48	0.37	0.28	0.22	0.04	0.20	—								
BIS11-ATTENTION	0.75	0.90	0.36	0.45	0.28	0.25	0.73	—							
BIS11-MOTOR	0.79	0.34	0.91	0.52	0.29	0.68	0.31	0.39	—						
BIS11-NONPLANNING	0.84	0.51	0.44	0.87	0.78	0.37	0.17	0.45	0.50	—					
ABIS attention	0.76	0.78	0.35	0.72	0.43	0.28	0.28	0.71	0.39	0.71	—				
ABIS motor	0.71	0.38	0.79	0.59	0.21	0.30	0.32	0.43	0.75	0.51	0.43	—			
ABIS nonplanning	0.67	0.34	0.37	0.87	0.34	0.43	0.15	0.31	0.47	0.77	0.50	0.40	—		
Finance (removed)	0.59	0.27	0.61	0.40	0.45	0.26	0.21	0.29	0.59	0.51	0.35	0.33	0.36	—	
Need for cognition (removed)	0.50	0.38	0.15	0.23	0.78	0.13	0.30	0.42	0.18	0.57	0.39	0.19	0.15	0.17	—

Table 5: External validity of ABIS scales. ^a Scale difference (ABIS vs. BIS-11, 2-tailed) $p < .05$. * $p < .05$.

Measure	Attention		Motor		Nonplanning		N
	ABIS	BIS-11	ABIS	BIS-11	ABIS	BIS-11	
Decision-Making Styles Inventory—Analytical	-0.46 ^{*a}	-0.26 [*]	-0.44 [*]	-0.39 [*]	-0.51 [*]	-0.52 [*]	379
Decision-Making Styles Inventory—Intuitive	0.11 [*]	0.07	0.33 [*]	0.37 [*]	0.16 [*]	0.20 [*]	379
Need for Cognition	-0.35 ^{*a}	-0.26 [*]	-0.12 [*]	-0.12 [*]	-.10 ^a	-0.45 [*]	379
Faith in Intuition	-0.02	0.05	0.18 [*]	0.16 [*]	-0.01	-0.01	379
Behavioral Approach System—Drive	-.02 ^a	0.05	0.17 [*]	0.16 [*]	-0.11 ^{*a}	-0.06	1,167
Behavioral Approach System—Fun-Seeking	0.23 [*]	0.23 [*]	0.50 ^{†*}	0.43 [*]	0.28 ^{*a}	0.23 [*]	1,167
Behavioral Approach System—Reward Responsiveness	-.04 ^a	0.04	0.07 [*]	0.05	-0.12 ^{*a}	-0.07 [*]	1,167
Behavioral Inhibition System	0.11 [*]	0.13 [*]	-0.08 [*]	-0.12 [*]	-0.13 ^{*a}	0.01	1,167
UPPS—Premeditation	-0.38 [*]	-0.18	-0.49 [*]	-0.42 [*]	-0.59 [*]	-0.57 [*]	49
UPPS—Urgency	0.21	0.27	0.42 [*]	0.25	0.09	0.17	49
UPPS—Perseverance	-0.53 [*]	-0.51 [*]	-0.32 [*]	-0.44 [*]	-0.55 [*]	-0.40 [*]	49
UPPS—Sensation-Seeking	0.05	0.12	0.15	0.06	0.03	-0.16	49
Brief Sensation-Seeking Scale	0.15	0.17	0.30 [*]	0.21	0.33 [*]	0.21	49
Impulsive Sensation-Seeking	0.27	0.27	0.37 [*]	0.33 [*]	0.50 ^{*a}	0.28	49
Average number of alcoholic drinks per week	0.06	0.10	0.44 [*]	0.32 [*]	0.20	0.31 [*]	48
Delay Discounting—Proportion Impatient Choice	0.04	0.03	0.28	0.14	0.23	0.28	49

95% CI [.17, .64]) and BIS-11 motor impulsiveness ($r = .32, p < .05, 95\% \text{ CI } [.04, .55]$). The difference between these correlations was non-significant ($p = .21$), although this comparison was likely underpowered (Sample 4, $N = 48$). Definitive conclusions regarding the relative size of these effects across scales will require further analysis in larger samples, although the results for motor impulsiveness and alcohol consumption are consistent with the overall trend towards strengthened relationships when using the ABIS scales. There were no significant relationships with ABIS attentional or non-planning impulsiveness in this sample ($r = .06, 95\% \text{ CI } [-.23, .34]$ and $r = .20, 95\% \text{ CI } [-.10, .45]$).

We also examined the relationship between the ABIS scales and delay discounting, a laboratory-based measure of impulsive decision making. Decisions reflecting delay discounting (willingness to accept a smaller reward that can be obtained sooner) are commonly described in terms of self-control and impulsiveness (Coutlee & Huettel, 2012; Madden & Bickel, 2010), although studies have not found a consistent relationship between delay-discounting behavior and self-reported impulsiveness (Reynolds, Ortengren, Richards, & de Wit, 2006; Stanford et al., 2009). Consistent with these latter findings, we failed to identify any significant relationship between impulsiveness (measured with either the ABIS or BIS-11) and individual differences in impatient decision making in a delay discounting task ($r = .04$ to $.28, 95\% \text{ CIs from } -.24$ to $.52$), although ABIS motor and BIS-11 non-planning impulsiveness showed trend-level

relationships ($p < .10$). Because statistical power was relatively low for this sample ($N = 49$), the extent of any relationship between impulsiveness and delay discounting remains unclear.

3.4 Discussion

We describe the replication and validation of the ABIS, a brief scale that measures attentional, motor, and non-planning impulsiveness with better than twice the efficiency of the BIS-11, while maintaining similar, if not better, score reliability. Critically, we demonstrated through CFA in two independent replication samples that, in contrast with the BIS-11, the model underlying the ABIS generalizes to independent samples drawn from separate respondent populations. Finally, we show evidence linking impulsiveness measured by the ABIS to other relevant personality measures and alcohol consumption. These findings support the use of the ABIS in basic, clinical, and applied research as either a brief alternative to the BIS-11 or a model for reanalyzing previously collected BIS-11 questionnaire responses.

The ABIS motor impulsiveness scale, anchored by items 2 and 19, “I do things without thinking,” and “I act on the spur of the moment,” reflects spontaneous, reactive, and uninhibited action. ABIS motor impulsiveness relates strongly to BIS-11 first- and second-order motor impulsiveness, and moderately to UPPS Urgent impulsiveness (tendency for uninhibited emotional acts), intuitive decision making style, BAS Fun Seeking, and sensation seeking. ABIS motor impulsiveness also showed a significant

association with alcohol consumption – and that association was at least as large as that from the full BIS-11, using far fewer items.

The ABIS non-planning impulsiveness scale, anchored by items 1 and 7, “I plan tasks carefully” and “I plan trips well ahead of time,” (both reverse scored), reflects a tendency to forego premeditation, forethought, and preparation. It encompasses lack of planning for shorter-term, concrete aims, such as tasks and trips, as well as longer-term and more abstract aims, such as job security and the future more generally. It is strongly related to the BIS-11 second-order non-planning and first-order self-control subscales, as well as the UPPS premeditation scale. It also shows moderate relationships with an analytical decision making style and sensation seeking.

The ABIS attentional impulsiveness scale, anchored by items 12 and 9, “I am a careful thinker” and “I concentrate easily,” (both reverse scored), reflects inconsistency in controlling thought and focusing attention. ABIS attentional impulsiveness relates strongly to the BIS-11 first-order attention and self-control subscales, as well as to UPPS perseverant impulsiveness (lack of focus and self-discipline). ABIS attention also showed moderate negative relationships with analytical decision making style and need for cognition.

To the best of our knowledge, our study reflects the first attempt to independently re-examine and abbreviate the BIS-11 using both EFA and CFA methods in replication samples. The ABIS scales, which are the result of this analysis, are

supported by findings from two previous studies that sought to produce reduced scales based on BIS-11 items. Spinella (2004) produced a 15-item scale with three subscales by selecting the five items with the highest loadings on each factor from a three-factor orthogonal principal components analysis of BIS-11 data. This method, while straightforward to implement and useful for eliminating some of the weaker-loading and unreliable BIS-11 items, fails to identify the strong minor factors present in the data, such as the restlessness doublet removed in stage three of our analysis. Unextracted minor or methodological factors can distort the nature of major factors and the patterns of item loadings (Wood et al., 1996) . This may be the case for the Spinella attentional impulsiveness factor, which is dominated by the restlessness doublet. Aside from the attention scale, however, the Spinella results show consistency with the ABIS scales, although our model tends to show modestly better fit values and replicability (**Table 6**).

Another study (Steinberg et al., 2013) used unidimensional item response theory models to produce an eight-item scale intended to replace the problematic BIS-11 total score measure. The authors initially applied a bi-factor item response model based on the BIS-11 canonical three-factor model. As in our own analyses using EFA/CFA (**Table 1**) and a bi-factor model (**Table 6**), they found that many of the BIS-11 items failed to load on the general impulsiveness factor, and that many items were characterized by high correlations with only one or two other items,

Table 6: Alternative model analysis results and fit statistics

Model description	χ^2	<i>df</i>	RMSEA	RMSEA 90% CI	CFI	<i>N</i>	
Sample 1, ABIS attention unidimensional model	19.63	4	0.050	0.029	0.073	0.994	1,549
Sample 1, ABIS motor unidimensional model	7.01	1	0.062	0.025	0.109	0.999	1,549
Sample 1, ABIS nonplanning unidimensional model	0.50	1	0.000	0.000	0.059	1.000	1,549
ABIS unidimensional model (12 × 20; 13 × 30; 17 × 19 covariances)	1,170.53	62	0.107	0.102	0.113	0.901	1,549
Steinberg et al. (2013) eight-item unidimensional model (5 × 9 covariance)	424.46	19	0.117	0.108	0.127	0.900	1,549
Spinella (2004) 15-item three-factor model	1,614.48	87	0.106	0.102	0.111	0.871	1,549
Sample 1, Patton et al. (1995) three-factor bifactor model	3,798.43	375	0.077	0.075	0.079	0.825	1,549
Sample 1, ABIS three-factor bifactor model (no covariances)	515.25	52	0.076	0.070	0.082	0.958	1,549

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reflecting doublets or other minor factors (often due to methodological factors such as similarity of item wording). The authors subsequently switched to fitting unidimensional models with the goal of producing a revised BIS total score scale by eliminating items not clearly related to the general impulsiveness factor (resulted in an eight-item scale). Although the primary goal and factor analysis technique used in this study are distinct from our own, their results, which revealed problematic doublet factors and items poorly related to impulsiveness, are consistent with our own findings. Additionally, the items they selected for their alternative BIS total-score scale represent a subset of the items which we independently selected for the three scales of the ABIS. Given this convergence of findings, we decided to test the unidimensionality of the Steinberg et al. scale items in our data. In contrast to their findings, but consistent with our own results based on the BIS-11 and ABIS models, we found that a unidimensional CFA model failed to acceptably fit the data (**Table 6**). In the case of both the Steinberg et al. scale and the ABIS items, the patterns of covariation between scale items indicate the need for a more complex explanation of the data (e.g., multiple latent factors). Some form of general impulsiveness may, in fact, underlie responses to BIS-11 items. However, neither our own findings nor the findings of Steinberg et al., Spinella, or Patton et al. provide sufficient evidence to justify measuring such a general impulsiveness factor using a total-score scale. Instead, the evidence supports the use of

scales designed to measure separate impulsiveness subtraits, as with the ABIS attentional, motor, and non-planning scales.

A limitation of our analyses and the resulting ABIS scales is that they measure a relatively focused set of impulsive traits. This results from our decisions to restrict our study to the thirty BIS-11 items and produce an abbreviated scale representing only the core factors reflected by those items. The ABIS is thus less comprehensive than measures drawn from a broader set of items, such as the UPPS impulsiveness scale (Whiteside et al., 2005). Our analyses led us to discard a number of peripheral factors reflecting financial impulsiveness, restlessness, and cognitive instability, amongst others.

Although these constructs are poorly measured by the available set of BIS-11 items, they represent potentially interesting aspects of impulsive personality and behavior.

Impulsiveness in financial domains (e.g., “I buy things on impulse”), for instance, predicted impatient economic decisions in a delay discounting task ($r = .35, p < .05, 95\%$ CI [.08, .57]). Such minor factors hold promise as a possible basis for expanded or alternative scales measuring the broader set of impulsive traits reflected by the BIS-11 items.

We are optimistic that our findings will inform such a broader discussion and contribute to future attempts to revise the BIS scale. In the present, however, we argue that the ABIS scale scores provide the most efficient and reliable measures of core attentional, motor, and non-planning impulsiveness currently available. The ABIS

generalizes well to independent samples, especially compared to the BIS-11. An important direction for future research, however, will be to examine the properties of the ABIS in high-impulsiveness populations such as substance abusers, ADHD patients, and prison inmates.

4. Differential modulation of response and decision control networks by motor and non-planning impulsiveness

4.1 Introduction

To effectively select actions consistent with their goals and desires, decision makers must resolve conflicts and dilemmas at a variety of levels of abstraction. Plans or strategies, rules, context, and possible actions represent potential sources of conflict, especially when goals and actions of very different types (e.g., long-term health goals and immediate hunger urges) compete for control of action (Rangel et al., 2008). Effective decision making under circumstances requiring flexibility and discernment relies on neural systems supporting cognitive control (Miller & Cohen, 2001). Cognitive control systems allow us to translate our plans and goals into consistent action, particularly when the most rewarding course of action is unclear or there is competition between immediate desires and long-term goals (Coutlee & Huettel, 2012).

Research examining the organization of cognitive control within the prefrontal cortex (PFC) suggests that control may be anatomically organized as a hierarchical network according to a principle of abstraction (Badre, 2008; Koechlin & Summerfield, 2007b). Evidence from neuroimaging and lesion studies indicates that as control becomes more temporally or conditionally abstract, increasingly more rostral regions of lateral PFC are engaged to mediate control of behavior, with the influences of these

regions exerted in a hierarchical fashion (Azuar et al., 2014; Badre et al., 2009; Koechlin et al., 2003a). Research incorporating motivational information and rewards has shown that the medial PFC (mPFC) follows a parallel hierarchical organization (Taren et al., 2011), with mPFC signals reflecting reward contingencies influencing lateral action-selection hierarchical processing (Charron & Koechlin, 2010; Kouneiher, Charron, & Koechlin, 2009b). Consistent with this evidence, our work has previously shown that conflicts between motor responses, decision options, and choice strategies engage progressively more rostral regions of mPFC (Venkatraman, Rosati, et al., 2009).

If control over decisions and actions is organized along a principle of abstraction, then failures of control possess a corresponding structure. Impulsiveness, a trait which reflects an inability to control immediate urges and insensitivity to future consequences, is typically conceptualized as a set of linked subtraits reflecting immediate failures to control urges, contextual failures to focus attention over the short-term, and long-term failures to plan and organize action sequences (Patton et al., 1995; Whiteside & Lynam, 2001). We recently reexamined the widely applied Barratt Impulsiveness Scale 11 (BIS-11) and developed an improved measure of impulsiveness which measures more focused impulsive traits. Despite substantial alterations to the original BIS-11 scale, this study confirmed this core organization of motor, attentional, and non-planning impulsive subtypes. These definitions parallel the hierarchical organization of action processing in the PFC from short term and concrete to long term and abstract (Badre &

D'Esposito, 2009a). Though they derive from distinct methodologies, the structural similarity between models of impulsiveness cognitive control suggest an intriguing possibility: the organization of control functions in the brain may define patterns of impulsive action and decision which manifest over time as trait motor, attentional, and non-planning impulsiveness. Previous studies provide evidence linking hierarchical control regions with impulsive traits and behaviors. Motor impulsiveness is linked to response control (Gorlyn, Keilp, Tryon, & Mann, 2005; Logan, Schachar, & Tannock, 1997) and has been shown to correlate with caudal mPFC activation during Stroop and go/nogo tasks (Horn, Dolan, Elliott, Deakin, & Woodruff, 2003; Venkatraman, Rosati, et al., 2009). More abstract attentional and non-planning impulsiveness, by contrast, have been associated with disrupted performance in planning and delay-discounting tasks (de Wit, Flory, Acheson, McCloskey, & Manuck, 2007; Mitchell, Fields, D'Esposito, & Boettiger, 2005; Mobini, Grant, Kass, & Yeomans, 2007), and modulation of rostral PFC regions supporting contextual and strategic control during economic decision making (Huettel et al., 2006b; Venkatraman, Rosati, et al., 2009). Together, these findings implicate brain regions along a caudal-to-rostral axis in increasingly complex and abstract varieties of impulsive behavior and decision making. Yet, no neuroimaging studies have been conducted to investigate the relationship between impulsiveness, cognitive control, and decision making.

Given the evidence suggesting a parallel organization of cognitive and impulse control, we hypothesized that impulsive trait subtypes might be reflected in control exercised at predictable levels of the hierarchy, and that these influences should be identifiable as differential brain activation, particularly within mPFC regions previously associated with concrete and abstract decision control (Kouneiher et al., 2009b; Venkatraman, Rosati, et al., 2009). We tested these hypotheses by measuring brain activation and behavior during tasks requiring control over either competing motor responses (a Stroop task) or decision options (a delay-discounting task). Behavior and brain activation during these tasks were correlated with multiple individual difference measures of trait motor, attentional, and non-planning impulsiveness. We hypothesized that concrete, short-term motor impulsiveness would be positively correlated with brain activation and response times during response control, while increasingly abstract attentional and non-planning impulsiveness would influence activation of more rostral PFC regions supporting foresight during decision making. The results of this study speak to the fundamental organization of control over behavior and decisions, and the links that exist between this organization and self-report measures of trait impulsiveness.

4.2 Experimental design and methods

Participants

Forty-nine adults (mean age 24.04, range 20-34, 26 female) recruited from the Durham, North Carolina and Duke University communities participated in the functional magnetic resonance imaging (fMRI) experiment. Participants had normal or corrected to normal vision, reported no history of psychiatric or neurological disorders, and were screened for MRI safety and pregnancy (where appropriate) prior to the fMRI session. Participants were compensated \$20 per hour for the study (\$30-\$35 total), but earned additional immediate or delayed bonus payments during the task (details below). The study procedures were approved by the Duke University Medical Center Institutional Review Board.

Study Procedure

Participants completed a single study session which consisted of one-hour of fMRI imaging followed by a half-hour of completing self-report questionnaires. Total study length was about two hours. Prior to undergoing fMRI, participants provided informed consent, were screened, familiarized with the study equipment and procedure, and trained on the task. Participants then completed a practice run of the counting Stroop and delay-discounting decision making tasks prior to the fMRI scan. Participants completed a high resolution anatomical MRI scan followed by three 11-minute fMRI scan runs: one for the counting Stroop task, and two of the delay discounting task. After the imaging was completed, participants responded to a number of self-report

questionnaires focused on impulsiveness (scales detailed below). Participants were then debriefed and paid for their participation.

Counting Stroop Task

We implemented a counting Stroop task (**Figure 6a**) to reveal neural activation reflecting cognitive control over competing motor responses. We programmed the task using the Psychophysics Toolbox version 2.54 (Brainard, 1997) for MATLAB (MathWorks, 2011). Following the procedures of Bush et al. (Bush et al., 1998) and Venkatraman et al. (Venkatraman, Rosati, et al., 2009), participants responded to alternating twenty-second blocks of neutral and incongruent trials. For each trial, participants were presented with between one and four identical, vertically listed words, and were asked to push a button on a four-button handheld controller indicating the number of words appearing on the screen. Participants were encouraged to respond as quickly as possible while still maintaining high accuracy, and had 1.5 seconds to enter their response. For neutral trials, the displayed words (which differed from trial to trial) were common animal names (e.g., dog, cow). For the incongruent trials, the displayed words were numbers between one and four (i.e., one, two, three or four), and there was always a mismatch between number of words appearing on the screen and the meaning of those words (e.g. “one” repeated four times, requiring the response “four” from the participant). Each participant completed 18 neutral blocks and 18 incongruent blocks, with eight trials per block, for a total of 288 counting Stroop trials per participant.



Figure 6: Experimental tasks. a) Counting Stroop Task. Twenty-second blocks of neutral trials (“cat”) alternated with equal-lengthed blocks of incongruent trials (“two”). In both cases, participants pressed a button to indicate the number of words appearing on the screen. b) Delay Discounting Task. Participants viewed a two-second cue indicating the type of response required (choose “Want” or “Don’t Want”), followed by a five-second response period in which they chose between a larger delayed and smaller immediate option.

Delay Discounting Task

We implemented a delay-discounting task (DD, **Figure 6b**) to reveal neural activation reflecting strategic and decision-level control of responses during economic decision making. We programmed the task using the Psychophysics Toolbox version 2.54 (Brainard, 1997) for MATLAB (MathWorks, 2011). Participants were each presented with 104 unique decision trials with real financial consequences presenting a choice between a larger amount of money to be received at a later time (e.g., \$20 in 4 weeks) and a smaller amount of money available immediately (e.g. \$19.24 NOW). Larger later reward magnitudes were \$5, \$10, \$20, or \$50, and delays were 1, 4, 6, or 8 weeks.

Immediate reward magnitudes were set to cover a range of discounts to the larger later values (from 17% lower to 1% lower) in order to manipulate the degree to which the immediate option was tempting. Four trials in which the immediate and later option magnitudes were equal were also included.

On a typical delay DDT trial, a cue reading “Want?” would appear for two seconds, indicating a trial in which the participant was instructed to select their preferred decision option. Next, one immediate and one delayed option would appear, with one option on the left side of the screen and the other on the right (with side counterbalanced). Participants had up to five seconds to review the options and enter their choice by pressing either the left or right button (corresponding to the left or right option) on a handheld controller. In order to dissociate motor control from preferences, half of the trials were preceded by a “Don’t Want?” cue, which instructed subjects to indicate with their button press the option they did not prefer and were rejecting (thereby accepting the alternative). Participants completed 52 “want” and 52 “Don’t want” trials, divided across two eleven-minute fMRI runs.

To motivate participants to choose in a realistic way consistent with their subjective preferences, we employed a mechanism to provide participants an incentive for truthful choice. At the end of the experiment, we randomly selected one decision trial from the DD task, revealed the participant’s choice for that trial, and then paid them according to their chosen option. Bonus payments were made in the form of electronic

Amazon.com credits for the exact amount chosen by the option, and, depending on the participants' choice, were either deposited immediately (e.g. \$17.78 "NOW") or after the chosen delay (e.g., \$20, 4 weeks after the experiment). Since each decision trial had an equal probability of being chosen for real payment, participants were incentivized to choose realistically for each trial (the nature of these bonus payments were explained in detail prior to the start of the experiment). The average bonus payment was \$20.21 with a range from \$4.58 to \$50.

Self-Report Measures

Participants completed a number of pen-and-paper self-report questionnaires, primarily measures related to impulsiveness:

Barratt Impulsiveness Scale Versions 11 (BIS-11): Responses to these 30 items were used to derive measures of attentional, motor, and non-planning impulsiveness subtraits via methods developed as a part of the ABbreviated Impulsiveness Scale, or ABIS (Coutlee, Politzer, Hoyle, & Huettel, 2014). We also applied the original BIS-11 scoring methods to derive the six first order factors (attention, motor, self-control, cognitive complexity, perseverance, and cognitive instability), the three second-order factors (attentional, motor, and non-planning impulsiveness) and the BIS-11 total score (Patton et al., 1995).

Urgency, Premeditation, Perseverance, and Sensation-Seeking Scale (UPPS): The UPPS is a 45-item scale designed to distinguish and measure four facets of personality which

results in impulsive behaviors (Whiteside & Lynam, 2001). These facets are considered separate processes which lead to impulsive-like behavior.

Alcohol Use Questionnaire: We asked participants to self-report the number of alcoholic beverages consumed on a typical day on which they drank, and also the average number of days per week they consumed alcohol. We used these values to calculate the average number of alcoholic drinks consumed per week.

Additional Impulsiveness and Sensation Seeking Measures: We included two additional secondary measures of impulse-related traits: the Brief Sensation Seeking Scale (Hoyle et al., 2002), and the Impulsive Sensation Seeking Scale (Zuckerman, 2002).

Behavioral Data Analysis

“Delay premium index” predictor: We used an index reflecting the relative value of the larger-later reward (adjusting for the delay time) as a predictor in our behavioral and imaging analyses. This value was calculated for each decision trial using the hyperbolic delay-discounting function previously found to characterize delay discounting behavior (McKerchar et al., 2009; Rachlin, Raineri, & Cross, 1991). The delay premium is equal to $((LL/SS)-1)/\text{Delay}$, where “LL” and “SS” are the delayed and immediate reward magnitudes in dollars, and “Delay” is the delay time in weeks (Mazur, 1987). It is minimized at zero when the later option is equal to the immediate option, thus providing no incentive to accept the delayed option. As the difference between the later

magnitude and immediate magnitude gets smaller OR the delay time gets shorter, the delay premium index increases.

Subject-by-subject delay preference estimation: We used the delay premium index for each trial and participant's choices of immediate or delayed options to estimate a hypothetical value for the delay premium at which each participant would be indifferent between the immediate and delayed options (assuming a hyperbolic discounting function). Using MATLAB, we first calculated the delay premium index for each trial, and ordered them from lowest to highest delay premium. Assuming hyperbolic discounting and invariant preferences, a point should exist for each participant along the vector of delay premiums at which the value of the delay premium overcomes the temptation to receive immediate rewards, leading to a switch from immediate to delayed choices. In reality, these transitions are often noisy for a given participant, but a point estimate of each participants' preference value was obtained by calculating the delay premium value which maximized classification accuracy for the separation of immediate and delayed choices (for cases in which two adjacent sampled delay premium values showed equal classification performance, we assigned the median of those two values as the participant's delay preference).

We used each individual's delay preference to estimate the subjective value of the delayed option for each participant on every trial. This value was used in our imaging models to derive both the value of the chosen option and a measure of decision

conflict. Decision conflict reflects the difficulty of a choice, and is largest when the subjective values of two options are equal, and small when one option is clearly more valuable than the other. For each participant, we estimated a hyperbolic discounting parameter which best predicted that individual's choices across all delay discounting task trials (maximized classification accuracy). This value was then applied to each delay trial to adjust the subjective value of the delayed option based on their personal distaste for delay, using the hyperbolic discounting formula, where present value of a delayed reward is equal to the value of the delayed reward divided by $1 + k*d$, where k is the hyperbolic discounting value and d is the delay time in weeks. The difference between the subjective values of the chosen and unchosen options gave a continuous measure of decision clarity, with the inverse of this contrast reflecting decision conflict, which increased as the value difference of the options approached zero, regardless of choice.

Repeated Measures and Multilevel Modeling: For our analysis of behavioral responses and choices in the counting Stroop and delay discounting tasks, we implemented multilevel mixed-effects models for repeated measures (Snijders, 2011). This approach allowed us to properly account for the nested levels of sampling in our design (sampling of participants, followed by sampling of trials within each participant), in order to make valid inferences to decisions in the broader population. A key justification for implementing a mixed models approach was the non-normal nature of the dependent variables (RT's were lognormally distributed, and choices/errors are

binary), as standard fixed-effects repeated measures ANOVA/regression cannot be used to correctly infer population effects of predictors in the case of non-normal outcome measures. Individual trials were treated as the “subject level” observations, while participants were treated as the “group level” observations. This modelling approach allowed us to control for the sources of dependency in our data, account for variance in outcomes at both the trial and participant levels, and make valid inferences regarding the expected size of experimental effect in the broader population. We examined random intercept-only models for each dependent variable order to estimate the intraclass correlation (participant-level variance/participant + trial level variance). The intraclass correlation is the proportion of total variance accounted for by clustering of responses by participant. These values were large for each of our dependent variables, demonstrating substantial participant-level variation and justifying the mixed-models for repeated measures approach.

We fit generalize linear mixed models using SAS 9.3 Proc GLIMMIX (Sas Institute, 2011). We used residual pseudo-likelihood estimation with subject-specific Taylor series expansion (Breslow & Clayton, 1993). F test and denominator degrees of freedom were corrected using the modified Satterthwaite approximation described by Kenward and Roger (Kenward & Roger, 1997, 2009). We examined fixed effects by testing whether the omnibus test for the effect (Type III sum of squares *F*-test) was significant (with statistical significance set at the 5% level for all effects).

Counting Stroop Task: Our primary outcome measure for the counting Stroop task was response time (RT) for each trial. Response times in the counting Stroop task were poorly characterized by a normal distribution, but fit a lognormal distribution well. We thus employed multilevel generalized linear regression with a lognormal distribution and an identity link function to examine the effects of predictor variables on RT. Parameter estimates were back-transformed to dollars by raising the constant e to the power of the parameter estimate (i.e., the exponential, or inverse natural log function, e^{Estimate}). As a secondary consideration, we examined errors in the Stroop task (using multilevel logistic regression with a logit link function and binary distribution) to confirm expected increases in error rates for the incongruent condition (overall error rates are quite low for this variant of the Stroop task). Independent variables of primary interest included the trial condition (incongruent or neutral trial), and the ABIS measures of impulsiveness. Factors and covariates of no theoretical interest included categorical factors controlling for the number of words presented on each trial and for atypical behavior on the initial trial of the experiment (exceptionally slow responses).

Delay Discounting Task: Primary outcomes of interest were the chosen option (immediate or delayed) and choice response time (from the time the options appeared until response) for each trial. We again employed a multilevel logistic regression to examine choice and a multilevel generalized linear model with lognormal distribution to examine RT. Independent variables of interest included the response condition (“Want”

or “Don’t Want” trial), magnitude of the immediate reward, the delay time for the later option, the trial’s “Delay premium index” (see *Behavioral Data Analysis* above for details), and the ABIS measures of impulsiveness. Covariates of no theoretical interest (but controlled for in the analysis) included practice effects on response times (indexed by the number of decisions previously completed).

MRI Image Acquisition

Functional MRI images reflecting blood-oxygenation-level-dependent (BOLD) contrast were acquired on a 3.0 Tesla General Electric scanner with an 8-channel receiver/head coil. We used an inverse-spiral pulse sequence for each of the three functional runs (330 volumes, TR = 2 s; TE = 27 ms; voxel dimensions 3.75 x 3.75 x 3.8 mm; 34 axial AC-PC aligned slices; 64 x 64 matrix; 60° flip angle). We also acquired a full-brain high resolution anatomical MRI scan (T₁ weighted ASSET 3D SPGR; TR = 7.48 s; TE = 2.98 ms; voxel dimensions 1 x 1 x 1 mm; 34 axial AC-PC aligned slices; 256 x 256 matrix; 12° flip angle) for normalizing and co-registering participants’ fMRI image data.

fMRI Data Preprocessing

Preprocessing was conducted using FSL version 4.1.5 (Smith et al., 2004). Nonbrain voxels were removed using BET (Brain extraction tool). In-scanner head motion was corrected using MCFLIRT (Motion Correction using FMRIB’s Linear Registration Tool), with images realigned to the middle volume of the time series. We corrected for variations in slice-time acquisition and implemented a high-pass filter to

remove low-frequency drift in the MRI signal. Signal values were spatially smoothed across voxels using a Gaussian kernel function with a full-width at half maximum value of 8mm. Functional volumes were registered to high-resolution anatomical images and transformed into standard space (MNI stereotaxic coordinates) using FLIRT (FMRIB Linear Registration Tool). The first five volumes of each scan were discarded to account for stabilization of the magnetic field.

fMRI Data Analysis

Imaging data analysis was conducted via a multilevel mixed general linear model procedure using FSL FEAT (fMRI Expert Analysis Tool) and FLAME (FMRIB's Local Analysis of Mixed Effects) Stage 1, both a part of the FSL analysis package. For each image voxel, the dependent measure was BOLD contrast activation measured at each timepoint (0.5 Hz sampling rate), after correcting for local autocorrelation of the time-course. Independent variable regressors included to predict timecourse-level signal changes are detailed below for each task. In all cases, regressors were constructed by convolving a double-gamma hemodynamic response function with either boxcar-function time blocks (a block-design, used for the counting Stroop task) or unit impulse functions specified at the start time of the event (an event-related design, used for the delay discounting task). For the delay discounting task, the two fMRI image acquisition runs were treated as a fixed effect. The mixed-effects analysis group level characterized variation in BOLD activation grouped by participants, with inferences made to a

broader population of possible research participants. Predictors of interest investigated at this higher level included participant-level individual differences (e.g. economic preferences, trait impulsiveness). Statistical images were thresholded at a cluster-wise threshold of $z > 2.3$ and a whole-brain cluster-corrected significance threshold of $p < .05$. MRIcron and MRIcroGL were used for visualization of 2D and 3D brain images and statistical overlays (Rorden & Brett, 2000), and all coordinates are reported in MNI standard space.

Stroop Imaging Models: The first level (trial timecourse level) model for the counting Stroop task included eighteen blocks (lasting 18 seconds each) defining the time periods during which incongruent trials were presented. Interleaved were eighteen blocks (also 18 seconds each) containing neutral stimuli which were not explicitly modelled with a regressor, so that the intercept (mean or baseline) term reflected activation during the neutral Stroop condition. Two contrasts of interest were defined for the incongruent Stroop predictor: +1, reflecting the neural effects of incongruent (relative to congruent) trials, and -1, the neural effects of congruent (relative to incongruent) trials. Mean-centered impulsivity covariates were included as between-subjects regressor. We first tested a model including all three ABIS scales, then proceeded to models with each covariate tested using a separate higher-level model.

Delay Discounting Imaging Models: The first level (trial timecourse level) model for the delay discounting task included five primary regressors: The first two defined a

main effect of task separately for the cue and response periods, and were 1 for all timepoints during which the task was active, and -1 for all other timepoints. The second regressor defined a contrast between trials for with “Want” instructions (1) and those with “Don’t want” instructions (-1). The third regressor represented the subjective value of the chosen option (see *Subject-by-subject delay preference estimation* above for estimation details). The fourth regressor reflected “decision clarity,” and was calculated as the difference between the subjective values of the two options on each trial, and applied over the decision period. All regressors were mean centered. We defined contrasts reflecting each effect and its inverse: the inverse contrast of the decision clarity regressor reflected decision conflict present on each trial. Mean-centered impulsivity covariates were included as a between-subjects regressor. We first tested a model including all three ABIS scales, then proceeded to models with each covariate tested using a separate higher-level model.

4.3 Results

4.3.1 Response conflict, caudal mPFC, and motor impulsiveness

We first examined behavior in the counting Stroop task to test the prediction from previous studies linking motor impulsiveness to individual differences in caudal mPFC activation. During incongruent Stroop trials, response times were slower (24ms, $t_{14038} = 13.26, p < 0.0001$) and errors were more frequent (odds ratio = 1.99, $t_{14098} = 6.26, p < 0.0001$), reflecting increased response conflict and control demands compared to the neutral condition. Errors were rare in this variant of the Stroop (3.2% overall), so we focused on modelling effects on RT (Bush et al., 1998). We found no main effects of impulsiveness on RT (measured using the ABIS scales) but did identify an interaction between the ABIS motor scale and trial type (incongruent or neutral), after controlling for corresponding effects of the attentional and non-planning scales. Increased motor impulsiveness slowed response times to a significantly greater degree during

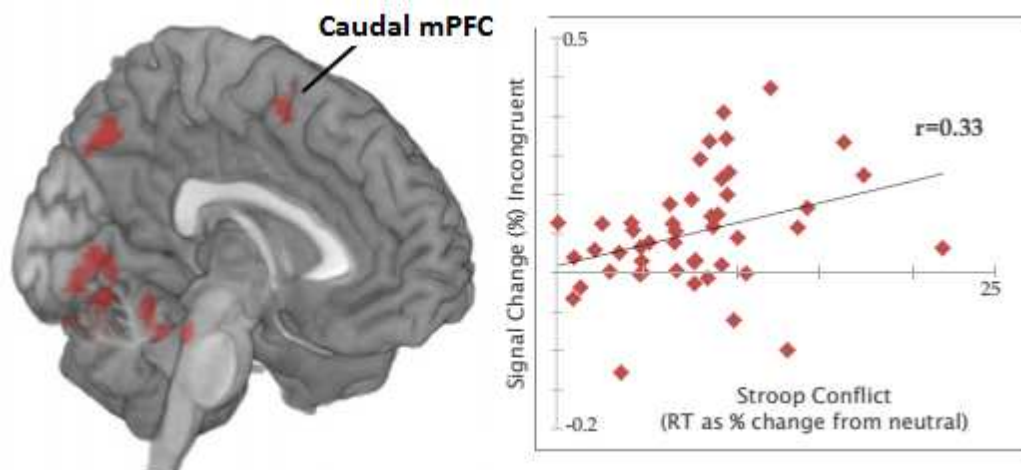


Figure 7: Caudal mPFC activation reflecting response conflict. Activation within the rostral mPFC (6mm radius region of interest centered at $x = -4, y = 10, z = 50$) was correlated with the behavioral Stroop effect on response times ($r = 0.33, p < .05$).

incongruent trials, relative to neutral trials (11ms slope difference, $t_{14049} = 2.79$, $p < .01$).

The ABIS attentional and motor scales showed neither a main effect nor an interaction with Stroop trial type (all p 's $>.09$), and models using the corresponding BIS-11 (2nd order motor, attention, and non-planning) or UPPS scales (urgency, perseverance, and premeditation) failed to identify any significant relationships. The effect of motor impulsiveness on slowing responses was thus significantly greater under conditions of high response conflict.

We next examined brain-behavior relationships during the counting Stroop task, and sought to connect variability in the neural Stroop effect to individual differences in trait motor impulsiveness. Consistent with prior metaanalytic findings, BOLD activation showed a main effect of trial type (incongruent – neutral contrast) within the mPFC/ACC (Venkatraman, Rosati, et al., 2009). Additionally, individual differences in the behavioral Stroop effect predicted activation within an unbiased caudal mPFC ROI (**Figure 7**; $r = .33$, $p < 0.05$), replicating our previous findings linking this area to interindividual variability in response conflict (Venkatraman, Rosati, et al., 2009). This prior study also found that activation in this region was significantly related to BIS-11 motor impulsiveness, but we found no evidence to support this claim using the ABIS, BIS-11, or UPPS scales.

To identify alternative brain regions showing a relationship between the neural Stroop effect and impulsiveness, we conducted separate exploratory whole-brain

analyses with individual motor impulsiveness scales as covariates. We found reliable results with only one scale: the UPPS urgent impulsiveness scale, which reflects a tendency to experience strong, and often emotionally negative, impulses and urges (Whiteside & Lynam, 2001). Greater urgent impulsiveness predicted an increased neural Stroop effect in the precuneus and posterior cingulate cortex (**Figure 8**). The related ABIS and BIS 11 motor scales showed sub-threshold activation patterns in these same regions. Decoding of the urgency map using quantitative meta-analytic reverse inference (Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011) showed that the regions associated with urgent impulsiveness were positively correlated with introspective cognitive networks (memory and resting state) and negatively correlated with motor cortex networks.

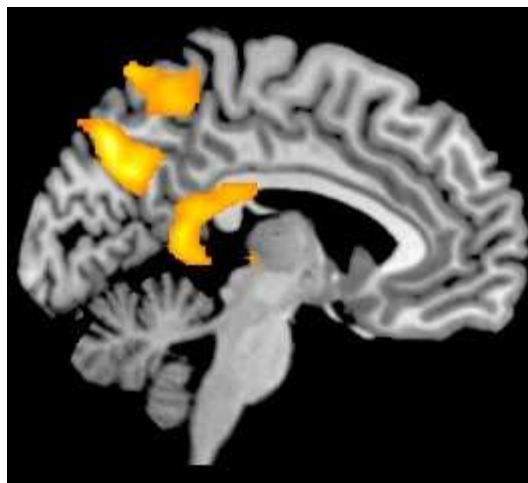


Figure 8: UPPS urgency scores predicting neural Stroop conflict. Effects were present in parietal regions associated with the default mode and internally oriented attention. Precuneus: $x = -4, y = -72, z = 40, z\text{-stat} = 3.83$. Posterior cingulate: $x = 2, y = -38, z = 18, z\text{-stat} = 3.81$.

Our task design also incorporated a manipulation of response-related control during the delay discounting task, as participants were asked to select the option they preferred NOT to receive on half the trials (“Don’t Want” trials). Cognitive control required to overcome the overlearned, prepotent urge to select the option you desire is similar to control demanded by incongruent Stroop stimuli. Response times for “Don’t Want” trials were significantly slower than for “want” trials (123ms, $t_{5032} = 8.82$, $p < 0.0001$), reflecting these control demands, although unlike in the Stroop task, we did not find evidence supporting an interaction with ABIS motor impulsiveness or the other ABIS scales (all p 's $> .57$). To investigate regions associated with the initiation of this control distinct from decision making processes, we modelled preparatory control during the cue period (Don’t Want – Want contrast). “Don’t Want” cues resulted in greater activation in a caudal mPFC region overlapping the response-conflict related activation observed for the Stroop task ($x = -2$, $y = 15$, $z = 34$, $z\text{-stat} = 4.51$). We tested a model including the ABIS scales as individual differences, and found no modulation of Don’t-Want vs. Want activity in the mPFC (some activations occurred for motor impulsiveness, but were clustered within and around non-brain voxels, and may therefore reflect task-correlated motion artifacts associated with motor impulsiveness).

4.3.2 Decision conflict, rostral mPFC, and non-planning impulsiveness

We next examined decisions in the delay-discounting task, with the expectation that decisions in a task requiring integration of more abstract context, preferences, and choice strategies would be sensitive to variability in attentional and non-planning impulsiveness. Choices during the delay discounting task were sensitive to our manipulations of value and delay, with smaller delay premiums ($t_{21.94} = -5.1, p < .0001$) and longer waiting times ($t_{39.19} = 2.77, p < .01$) increasing impatient choices. After controlling for the influence of the gamble structure (and individual differences in responses to these manipulations), we found no independent effects of the “Don’t Want” manipulation or ABIS motor, attentional, or non-planning impulsiveness on choice (all p 's $> .14$). Decision RT's did show a main effect of non-planning impulsiveness, such that greater ABIS non-planning impulsiveness was associated with slower decisions ($t_{45.5} = 2.08, p < .05$), reinforcing the counterintuitive relationship observed between motor impulsiveness and slower responses during the Stroop task.

To examine abstract control signals reflecting the interaction of the current decision context with subjective preferences, we calculated a measure of decision conflict for each trial. Decision conflict reflects the difficulty of a choice, and is largest when the subjective values of two options are equal, and small when one option is clearly more valuable than the other. The difference between the subjective values of the

chosen and unchosen options gave a continuous measure of decision clarity, with the inverse of this contrast reflecting decision conflict, which increased as the value difference of the options approached zero, regardless of choice. As a manipulation check on the validity of the subjective value model used to derive decision conflict, we examined the effects of a continuous regressor reflecting the subjective expected value of each chosen option. Consistent with our expectations, this effect showed reward and choice-related activation in the bilateral ventral striatum and dorsolateral prefrontal cortex (**Figure 9**).

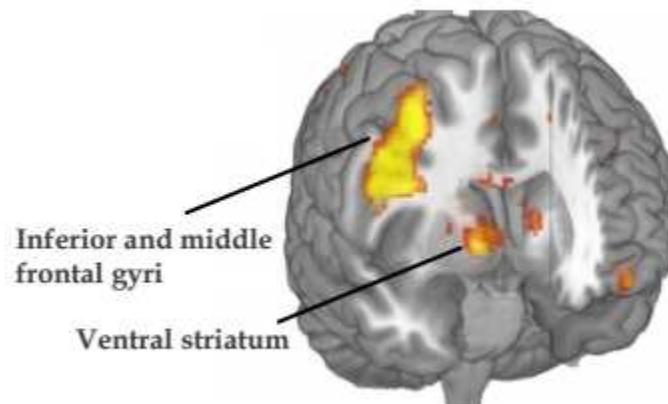


Figure 9: Value-related choice regions correlated with subjective value.

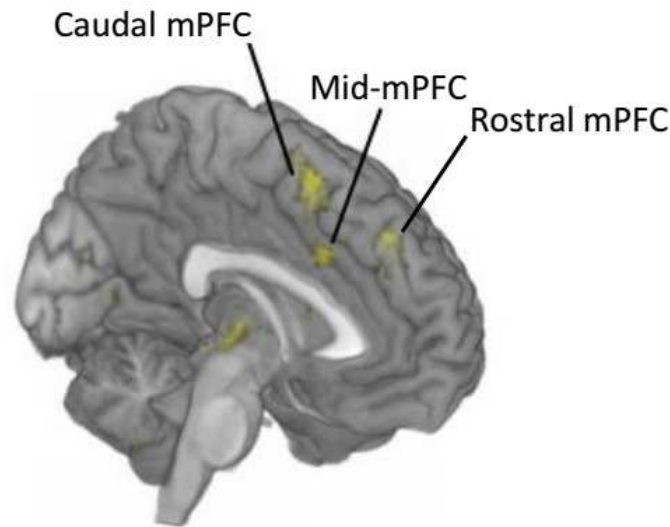


Figure 10: Activation reflecting decision conflict in the mPFC. Activation reflecting conflict between similarly valued options appeared in rostral, mid, and caudal clusters within the mPFC. Caudal mPFC: $x = -3, y = 15, z = 57, z\text{-stat} = 3.67$. Mid-mPFC: $x = -3, y = 19, z = 34, z\text{-stat} = 3.34$. Rostral mPFC: $x = -4, y = 49, z = 34, z\text{-stat} = 3.63$.

Having supported our measure of subjective value, we examined decision conflict while controlling for the subjective value of the chosen option. Decision conflict was associated with mid-mPFC activation, with clusters in the anterior cingulate and BA 8 (Figure 10). Activation reflecting decision conflict was widespread, with a caudal cluster overlapping the response-conflict cluster observed for the Stroop/Don't Want contrasts, and a more anterior cluster extending into BA9/32, regions previously associated with abstract alternative choice strategies (Venkatraman, Rosati, et al., 2009).

Finally, we examined relationships between decision conflict and individual differences in impulsiveness. No relationships were found between decision conflict signals and any of the ABIS scales, which led us to conduct an exploratory analysis

including alternative measures of impulsiveness. Amongst these, we identified a relationship between decision conflict and BIS-11 non-planning impulsiveness in the right lateral PFC within the inferior frontal sulcus (**Figure 11**, warm colors). ABIS non-planning showed maximum (subthreshold) activation within the same cluster. Activation within the inferior frontal sulcus was also influenced by individual differences in decision preferences, with increased impatient choice preferences predicting an enhanced decision conflict effect (**Figure 11**, cool colors). These effects did not appear to interact, however, as shown by whole-brain tests of the interaction between choice preferences and BIS-11 non-planning impulsiveness.

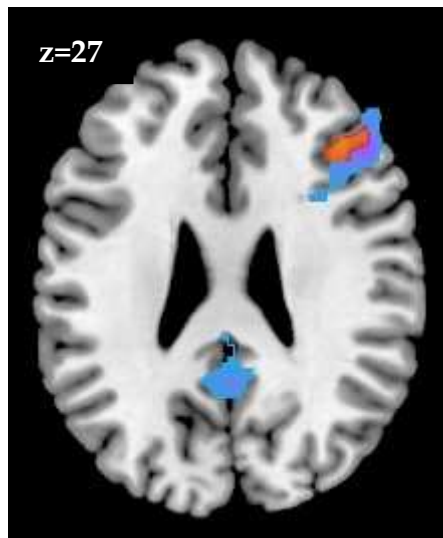


Figure 11: BIS-11 non-planning (warm) and impatient choice preferences (cool) were correlated with activation reflecting decision conflict in the right inferior frontal sulcus. BIS-11: $x = 40, y = 32, z = 28, z\text{-stat} = 3.4$. Preferences: $x = 48, y = 30, z = 26, z\text{-stat} = 3.9$.

4.4 Discussion

Motivated by evidence supporting a medial PFC hierarchy of increasingly abstract control processing guiding cognitive control and decision making (Venkatraman, Rosati, et al., 2009), we sought to test potential relationships between such control signals and more concrete and abstract varieties of trait impulsiveness, utilizing a large neuroimaging sample and multiple measures of trait impulsiveness. Our results are consistent with prior findings implicating the caudal mPFC in concrete control over competing motor responses, and more rostral mPFC in abstract control over competing decision options and preferences (Bush et al., 1998; Pochon, Riis, Sanfey, Nystrom, & Cohen, 2008). Furthermore, we demonstrate that behavior and brain activation during response control is sensitive to individual differences in motor impulsiveness, while decision-related signals and behavior are influenced by trait non-planning impulsiveness. We did not, however, replicate findings which suggested that control-related signals within the mPFC might reflect individual differences in motor, attentional, or non-planning impulsiveness (Venkatraman, Rosati, et al., 2009). Our results therefore provide evidence supporting the relevance of trait impulsiveness measures to the control of behavior during laboratory tasks of response control and patience during decision making, and address questions regarding the mechanisms by which impulsive traits operate to influence behavior.

Activation of the mPFC has been consistently associated with signaling control demands, during both cognitive and decision making tasks (Botvinick, 2007). Although we reproduce findings demonstrating caudal response-related control and more rostral decision-related control, it was lateral-frontal and parietal brain regions associated with implementing controlled behavior (Badre & D'Esposito, 2007) or an explicit absence of control (Fox et al., 2005) that showed control-related activity that covaried with impulsiveness. mPFC is most implicated in the signaling of control demands (Botvinick et al., 2001; MacDonald, Cohen, Stenger, & Carter, 2000), with executive fronto-parietal networks thought to implement ongoing control of behavior in proportion to the signaled demand (Kerns et al., 2004; Vincent, Kahn, Snyder, Raichle, & Buckner, 2008). Our results, though preliminary, suggest that trait motor and non-planning impulsiveness may represent failures of control implementation, as opposed to failures to detect and signal the need for cognitive control to resolve conflict. Our inferences about possible processing loci underlying impulsiveness are qualified, however, by the inconsistent nature of our trait findings, which involved relationships with the ABIS motor and non-planning (behavior), UPPS urgency (response conflict), and BIS-11 non-planning (decision conflict) scales. Consistency of individual difference findings within a study may be unrealistic at such moderate sample sizes, emphasizing the need for independent replication of these effects. An excellent confirmatory test of our predictions, however, would be to inhibit control-implementation using

neurostimulatory manipulation methods, and observe the impacts on behavior and decision making in individuals high and low in impulsive traits (Chapter 5 of this dissertation describes our study reporting such a manipulation of an inferior frontal sulcus region linked to both attentional impulsiveness and risk taking during economic decision making).

At the most concrete level of control examined here, our results provide evidence linking behavioral performance, brain activation, and self-reported motor impulsiveness during a Stroop task requiring participants to overcome response conflict. Responses to incongruent Stroop trials were slowed to a greater extent as ABIS motor impulsiveness increased, possibly due to greater difficulty in overcoming urges to initiate the tempting but incorrect conflicting response (Logan et al., 1997). These results run counter to the expectation that impulsiveness might tend to speed responses, but are consistent with the effect of motor impulsiveness in other experimental tasks of cognitive control and response inhibition (Enticott, Ogloff, & Bradshaw, 2006; Keilp, Sackeim, & Mann, 2005). These results support an interpretation of motor impulsiveness as primarily reflecting difficulty in controlling unwanted urges (Whiteside & Lynam, 2001) as opposed to a general hyperactivity of motor responses (Aron, 2011; Nigg, 2001).

Our fMRI findings confirm the relevance of motor impulsiveness for control of behavior during the Stroop task, albeit not, as hypothesized, within the caudal mPFC. Consistent with prior findings, Stroop conflict led to widespread activation within the

medial cingulate cortex, including the caudal mPFC, where activation was associated with individual differences in the behavioral Stroop effect on response times (Bush et al., 1998). Our previous results (Venkatraman, Rosati, et al., 2009) found activation within this caudal mPFC cluster to be positively correlated with BIS-11 motor impulsiveness, a finding we failed to confirm here, with a substantially larger sample size and alternative measures of motor impulsiveness (ABIS motor and UPPS Urgency). We did, however, identify a significant correlation between Stroop activation and UPPS Urgency (with ABIS and BIS-11 motor showing similar sub-threshold results) in a set of brain associated with internally generated attention, the resting state, and explicitly not with sensory-motor regions (Fransson & Marrelec, 2008; Raichle et al., 2001). Previous studies have shown that the balance of activation between task-positive external and task-negative internal orientation networks can predict lapses in attention and performance on experimental test of cognitive control (Weissman, Roberts, Visscher, & Woldorff, 2006). Here, the increased resting activity during incongruent trials experienced by individuals high in urgent impulsivity may reflect their difficulty or delay in mobilizing the executive resources necessary to respond correctly in the face of a more natural (but incorrect) response. Efficiency in transitioning between task positive and task negative networks has previously been linked to individual differences in response times in tests of cognitive control using the flanker task (Kelly, Uddin, Biswal, Castellanos, & Milham,

2008). Our results extend this finding by suggesting further links between individual differences in network activation states and self-reported behavioral traits.

We also included a manipulation intended to dissociate motor impulsiveness from attentional and non-planning impulsiveness during the delay discounting task. By requiring participants to select a “Don’t Want” option, we sought to prevent uninhibited approach of rewards to obscure impulsive decision making processes. Consistent with prior results, however, we found no effect of the “Don’t Want” manipulation on choices, although response times were slower in this condition (Mitchell et al., 2005). Consistent with our interpretation of this manipulation as requiring the activation of response control resources, we found greater caudal mPFC activation during the cue phase for “Don’t Want” trials in a region which overlapped the region associated with Stroop conflict. We did not observe any activation differences in the response phase of the task, nor did the cue, response, or behavioral RT effects correlate with any ABIS scale. Since impulsive responses are influenced by time pressure (Keilp et al., 2005), providing the opportunity to engage proactive control during the cue phase may have dampened potential effects of individual differences in motor impulsiveness on responses during “Don’t Want” trials (Braver, 2012).

We hypothesized that decision making during delay discounting, a procedure commonly employed as a laboratory measure of impulsive decision making, would show influences of trait attentional and non-planning impulsiveness (de Wit et al., 2007;

Mitchell et al., 2005). Intertemporal choice, which requires integrating contextual information with preferences in order to evaluate and select between competing options, requires contingent control over action selection incorporating multiple abstract levels (Badre & D'Esposito, 2007). We found no evidence for relationships between choice behavior and attentional impulsiveness, but did identify effects of non-planning impulsiveness on decision speed and right lateral prefrontal activation due to decision conflict. Signals reflecting competition between options of similar value produced widespread activation in mid-to-rostral mPFC (**Figure 10**), but showed no evidence of modulation by trait impulsiveness.

Across these findings, we find support for our conceptualization of impulsiveness subtypes as relevant to behavior at particular and distinct levels of complexity and abstraction: concrete motor impulsiveness influenced response control, while abstract non-planning impulsiveness influenced patient decision making. Previous studies designed to relate self-reported impulsiveness to similar laboratory tasks have shown inconsistent results (Reynolds et al., 2006). We suspect that impulsive traits tend to influence behavior most prominently when effortful cognitive control is only weakly engaged, posing challenges for its investigation using laboratory tasks with clear control demands. Consistent with this possibility, our tasks elicited choices that were not influenced by impulsive traits, although response time measures were sensitive enough to detect slower decisions and responses from more impulsive individuals

under demanding conditions. Manipulations which limit control resources, such as substantial time pressure (Keilp et al., 2005), invoking more powerful pre-potent urges (Logan et al., 1997), or requiring divided attention through dual-tasking (Hinson, Jameson, & Whitney, 2003) are likely to induce more robust effects of impulsiveness on behavior. On the decision making front, our incentive design may have presented an obstacle to observing relationships with impulsiveness, as about one third of our sample was at or near the limit for patient preferences, while another third of participants were at or near the limit of sampled impatient preferences. This censoring limited the accuracy with which we could represent subjective preferences for delayed options, and decreased the behavioral variability available for explanation by trait impulsiveness. This may have outweighed a distinct benefit of our task, which was that participants received real bonus payments based on their decisions. Adaptive decision tasks which personalize gambles to match the subjective preferences of the participant provide a way to overcome these limitations, enhancing both the power of the investigation and the potential influence of impulsiveness by maximizing decision conflict (Kable & Glimcher, 2007; Peters & Büchel, 2009).

Overall, our findings provide evidence linking impulsive traits with response and decision control, and qualify prior hypotheses regarding relationships between impulsiveness and mPFC activation. Instead, lateral prefrontal regions associated with the ongoing implementation of control or transitions between task-positive and task-

negative activation states may be important neural correlates of trait impulsiveness. Further investigation should seek to confirm these findings and extend our understanding of the mechanisms by which impulsive traits express as problematic behaviors.

5. Safe but sorry: Reduced calculated risk-taking following disruption of the intraparietal sulcus

As with decision making for delayed rewards (examined in Chapter 4), individuals tend to discount rewards which are uncertain, meaning that there is only a chance they will be received. Such risk-aversion can be costly, as most individuals avoid riskier options, even when those options offer greater overall (or long-term) benefits (Christopoulos, Tobler, Bossaerts, Dolan, & Schultz, 2009; Holt & Laury, 2002). Using fMRI, our laboratory previously found that individual differences in willingness to overcome risk aversion and accept lucrative but uncertain options predicted activation in lateral parietal and prefrontal regions associated with cognitive control (Brass & von Cramon, 2004; Huettel et al., 2006b). Activation within lateral PFC also showed a preliminary association with attentional impulsiveness. Furthermore, this activation overlapped the lateral PFC decision conflict activation associated with non-planning impulsiveness identified in Chapter 4. Drawing from these suggestive findings, in this chapter, we apply causal confirmatory methods to investigate the role of a fronto-parietal control network in irrational risk-aversion during uncertain decision making. Our use of neurostimulatory methods to test predictions from a prior fMRI study reinforces the exploratory-confirmatory methodology highlighted throughout this dissertation (Pascual-Leone, Walsh, & Rothwell, 2000; Schutter, Van Honk, & Panksepp,

2004). Our experiment reveals clear neurobiological control mechanisms supporting beneficial long-term decision making in the face of tempting safe alternatives.

5.1 Introduction

Decision making is often characterized by the need to make difficult tradeoffs between uncertain risks and rewards. Although excessive risk-seeking can be problematic (Yates, 1992), investors and economists have long recognized that obtaining greater rewards typically requires accepting greater risk (Markowitz, 1952). An overabundance of caution can actually threaten the achievement of long-term financial goals such as retirement and homeownership (Bajtelsmit & VanDerhei, 1997), and excessive aversion to uncertainty can lead to missed opportunities like turning down a job that requires moving to a new city. Success, in both business and life, often depends on our willingness to take a “calculated risk”: to weigh potential risks against possible rewards, and subsequently select a risky course of action with an expectation of greater future gain. Here, we investigated the dependence of calculated-risk taking on two regions previously implicated in decision making under uncertainty: the intraparietal sulcus (IPS) and the inferior frontal junction (IFJ). Evidence from functional neuroimaging studies has shown that the IPS and IFJ are both activated by uncertainty, and that preferences for economic risk (“known unknowns,” e.g., a 50% chance of \$5) and ambiguity (“unknown unknowns,” i.e., an unknown chance of \$5) are dissociably related to activation of the IPS and IFJ, respectively (Bach, Hulme, Penny, & Dolan, 2011;

Huettel et al., 2006b). Whether processing in these regions influences calculated-risk taking for individual decisions, however, remains unknown.

5.2 Results and discussion

To address this question, fifteen participants each received three fifteen-minute sessions of MRI-guided 1Hz inhibitory (Chen et al., 1997) repetitive transcranial magnetic stimulation (rTMS) over the IPS, IFJ, and a vertex control site (**Figure 12a**). After each rTMS treatment, we examined participants' risk-taking behavior across a series of decision trials with real financial consequences, each pitting a small, certain reward (\$3-\$7) against a larger but uncertain reward (\$5-\$100) (**Figure 12b**). Uncertainty was either "risky" (25%, 50%, or 75% chance of reward) or "ambiguous" (unknown chance of reward). We analyzed the effects of rTMS location on choices and response times for these decisions using a multilevel mixed-models approach for repeated measures with 165 unique decision trials paired across rTMS runs and nested within participants, treating both decisions and participants as random (as opposed to fixed) effects, and correcting statistical tests and degrees of freedom (Kenward & Roger, 2009). Our design thus allowed us to draw causal inferences regarding the role of IPS and IFJ in calculated-risk taking under both risk and ambiguity.

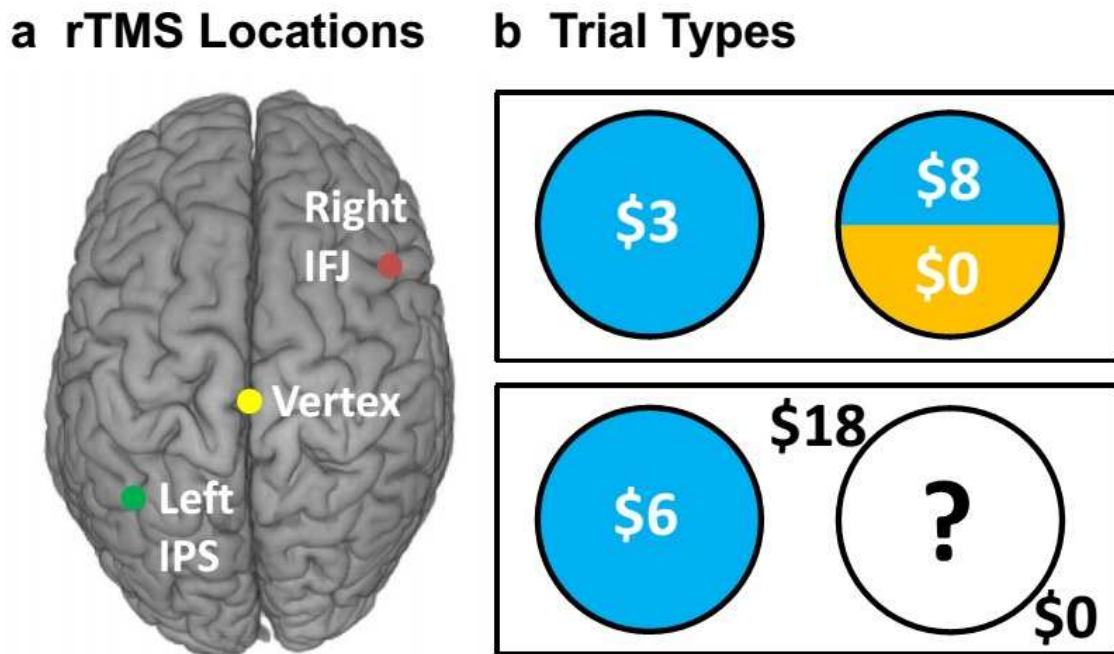


Figure 12: Experimental design. (a) For each participant, rTMS stimulation was applied to three targets: the left IPS (-36, -57, 50), right IFJ (39, 16, 33), and between the cerebral hemispheres at vertex (0, -28, 90) as an active control. Targets were based on group level fMRI contrasts from our previous investigation of risk and ambiguity preferences, and were located within each participant using their structural MRI scan from an earlier session. **(b)** Participants chose between a certain option (known outcome, left circles) and either a risky option (top right circle, known chances but unknown outcome) or an ambiguous option (bottom right circle, unknown chances and outcome). The expected value for the risky and ambiguous options exceeded that of the certain option by a variable amount. Participants completed 165 matched trials after each rTMS treatment.

We hypothesized that, compared to control rTMS, inhibition of the IPS would reduce calculated risk-taking for risky choices, while IFJ inhibition would similarly affect ambiguous choices. Our results confirmed our hypothesis for IPS stimulation, which biased choices towards superficially safer but financially detrimental certain

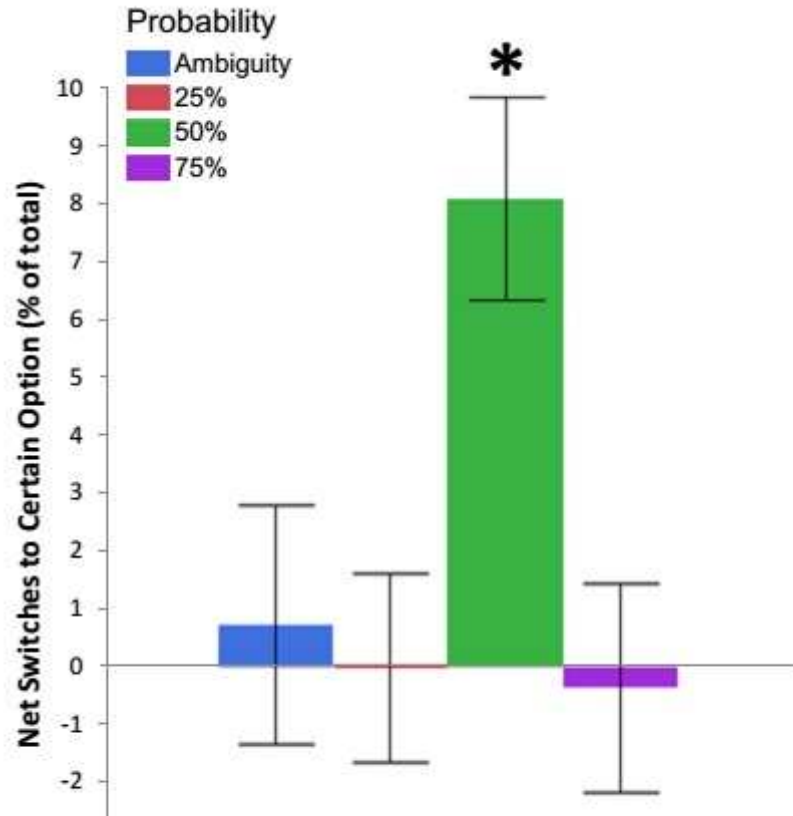


Figure 13: IPS stimulation disrupts calculated risk-taking. Inhibition of IPS using rTMS biased risky choices on 50% probability trials towards the safer but less profitable certain option, relative to matched choices in the vertex rTMS condition. Positive values indicate the extent to which the number of switches from risky options (during vertex rTMS) to safe options (during IPS rTMS) was greater than switches in the opposite direction. A null effect of rTMS on choice would thus hover close to zero. All bars indicate means \pm SE.

options within the 50% probability condition ($F_{6,6907} = 2.43, P < 0.05$; **Figure 13**). For 50% trials, IPS stimulation increased the probability of choosing the certain option by 32% (95% CI [13%, 50%], $t_{6907} = 3.43, P < 0.001$). This effect had meaningful financial consequences: the expected value of chosen options was 5% lower after IPS stimulation

($t_{4119} = -4.1, p < 0.0001$), reflecting an expected loss of \$15.30 across all 50% trials. The specificity of this effect to the 50% probability trials is consistent with previous decision making results showing maximal rTMS effects at intermediate choice probabilities (Figner et al., 2010b). IFJ stimulation, by contrast, produced no reliable effect on choices (all P s 0.10-0.52).

To gain further insight into this disruption of calculated risk-taking, we examined response times (RT), which are better suited to revealing subtle influences of rTMS on the efficiency of information processing (Luber & Lisanby, 2014). The effects of rTMS location on RT for the 25%, 50%, and 75% probabilities were similar in magnitude and direction (interaction $F_{4,5637} = 0.6, P = 0.66$), so we collapsed these trials into a single “risky decision” category. Our subsequent analysis showed a main effect of rTMS location on RT ($F_{2,4676} = 7.18, P < 0.0001$), which was qualified by a three-way interaction of rTMS location, trial type (risky or ambiguous), and chosen option (certain or uncertain; $F_{2,6895} = 3.81, P < 0.05$). IPS stimulation did not affect RTs for ambiguous trials, but the effect of IPS stimulation on risky trial RTs was moderated by the chosen outcome ($t_{6892} = 4.01, P < 0.0001$; **Figure 14**). Specifically, IPS stimulation slowed choices of the uncertain option ($\Delta RT = 52$ ms, +5.64%, 95% CI [2.11%, 9.29%], $t_{5116} = 3.16, P < 0.01$), but trended towards *facilitating* or speeding up choices of the certain option ($\Delta RT = -27$ ms, -2.88%, 95% CI [-5.76%, .09%], $t_{4421} = -1.9, P < 0.06$). No other contrasts showed evidence of decision speeds faster than their corresponding vertex control. By comparison, IFJ

stimulation resulted in a general disruption of decision processing slowing choices across all trial types (Δ RT = 52 ms, +5.59%, 95% CI [2.61%, 8.66%], $t_{5148} = 3.73$, $P < 0.001$).

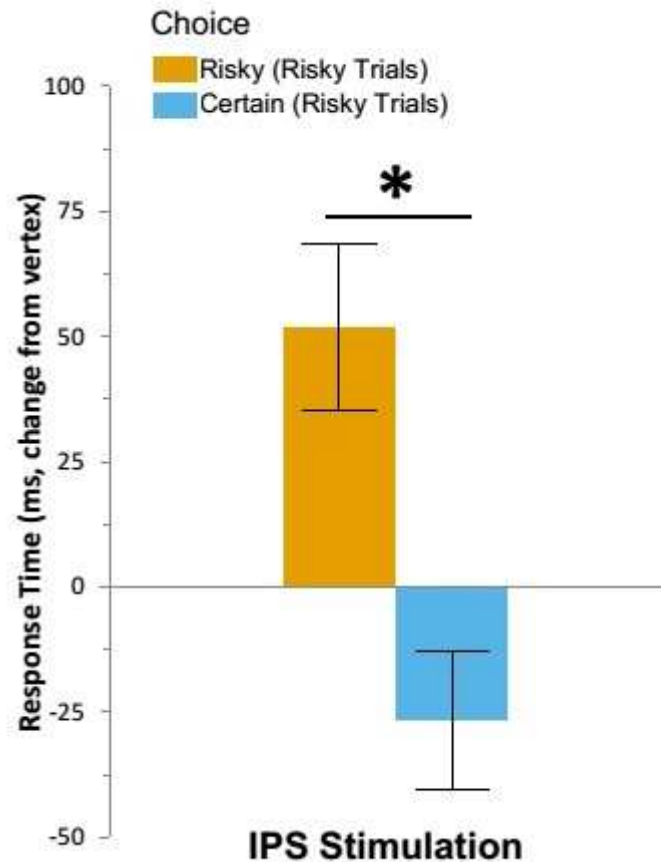


Figure 14: Inhibition of IPS biases response times for risky trials. After IPS stimulation, certain choices were speeded, while risky choices were slowed. All bars indicate means \pm SE.

Effective decision makers are capable of accepting uncertainty when it improves their chances to achieve a valued goal. Our study provides the first causal evidence differentiating parietal and frontal contributions to such calculated risk-taking.

Inhibiting IPS activity reduces risk-taking – at a cost to earnings – for decisions with known risks but uncertain outcomes. Given our previous results linking IPS activation to risk preferences (Huettel et al., 2006b), we interpret IPS inhibition as biasing risk (but not ambiguity) preferences towards certainty; this slows selection of risky options, speeds selection of certain options (**Figure 2b**) and reduces risk-taking behavior (**Figure 2a**). IPS may represent or modify the subjective probability (and thereby subjective utility) of risky options in a manner independent of utility calculations for ambiguous choices (Camerer & Weber, 1992; Dorris & Glimcher, 2004; Peters & Büchel, 2009). By contrast, despite previous evidence linking IFJ activation with ambiguity preferences (Bach et al., 2011; Huettel et al., 2006b), our RT results support a largely general role for IFJ in decision making under uncertainty. Recent findings suggest that although IFJ is engaged by the presence of ambiguity, its activity does not scale with increasing ambiguity (Bach et al., 2011). Ambiguity may be linked to IFJ through general processes of control based on contextual information (Brass & von Cramon, 2004; Koechlin, Ody, & Kouneiher, 2003b). Our results are the first to demonstrate the necessity of IPS activation for risk-taking (Helfinstein et al., 2014; Huettel, Song, & McCarthy, 2005; Peters & Büchel, 2009; Platt & Huettel, 2008b) and complement rTMS results showing *increased* risk-taking and impulsivity following inhibition of prefrontal self-control processes (Figner et al., 2010b; Knoch, Gianotti, et al., 2006; Knoch, Pascual-Leone, Meyer, Treyer, & Fehr, 2006b). The present findings suggest that engagement of IPS

during calculated risk-taking may spell the difference between bold “playing to win” and passive “playing not to lose.”

5.3 Methods

Participants

Fifteen adults (six female) recruited from the Durham, North Carolina and Duke University communities participated in the experiment, which included both anatomical magnetic resonance imaging (MRI) and repetitive transcranial magnetic stimulation (rTMS) procedures. Participants were screened for both MRI and rTMS eligibility, for the latter, following established guidelines (Rossi, Hallett, Rossini, & Pascual-Leone, 2009, 2011). All participants had normal or corrected to normal vision, and reported no history of psychiatric or neurological disorders. Participants received \$20 per hour in compensation, plus additional payments based on decision made during the task. All study procedures were approved by the Duke University Medical Center institutional review board.

Study Procedure

Each participant completed separate one-hour MRI imaging and three-hour rTMS studies. Anatomical scans from the MRI session were used for personalized neuronavigated targeting during the rTMS study. Prior to receiving rTMS, participants were screened, familiarized with the study equipment, and procedure, and trained on the task. Participants then completed a full paid practice run of the decision making task

prior to receiving any rTMS stimulation. Immediately prior to the first rTMS treatment, stimulation strength was calibrated by measuring their personal motor evoked potential threshold.

We conducted a within-subjects experiment in which each participant received two rTMS treatments: one to the right inferior frontal junction (IFJ) and one to the left intraparietal sulcus (IPS). Participants also received an active-control session of rTMS to the interhemispheric fissure at vertex, for a total of three rTMS sessions per participant (order of TMS stimulation sites was counter-balanced over participants). Each session consisted of 15 minutes of 1 Hz inhibitory (Chen et al., 1997) rTMS applied over the brain region of interest. After each session of rTMS, participants immediately completed a run (165 decision trials) of the decision making task. There was a resting period of about 10 minutes after each run of the task to minimize carryover effects.

After completing the three rTMS sessions, participants were debriefed, screened to insure intact basic cognitive function, and completed a few brief questionnaires. Participants were contacted one day after the rTMS session, and reported no discomfort or medical complications from the study.

Anatomical MRI Scan Acquisition

For the MRI session, participants completed a high-resolution anatomical MRI; these images were used for subject-specific targeting of rTMS administration in this study. A functional MRI task examining cognitive control was collected, but considered

in a separate study. Anatomical imaging was conducted on a 3.0 Tesla GE Discovery MR750 system using an eight-channel head coil. Anatomical images were acquired using a T1-weighted FSPGR scan in the axial plane with a 3D inversion recovery prepared sequence (120 slices, 1mm slice thickness, 1x1mm in-plane resolution).

Repetitive Transcranial Magnetic Stimulation (rTMS)

Each participant received three 15-minute, 900-pulse trains of 1 Hz rTMS applied at an intensity of 100% of their resting motor threshold using a Magstim Rapid² stimulator with a Magstim Double 70mm Air Film Coil (The Magstim Company Limited, Whitland, Dyfed, UK). Motor threshold was determined for each participant using electromyographic recording of the dorsal interosseus muscle of the right hand. Following standard procedures (Rossi et al., 2009; Rossini et al., 1994), motor threshold was defined as the lowest percentage of maximum stimulator output required to evoke at least 5 out of 10 motor-evoked potentials with peak-to-peak amplitude of at least 50 μ V. Stimulation was conducted with the coil positioned tangential to the skull, perpendicular to underlying gyral/sulcal brain anatomy, and with the coil head more anterior and coil handle more posterior.

Neuronavigated rTMS targeting

rTMS was applied to three anatomical locations: the left intraparietal sulcus (IPS), the right inferior frontal junction (IFJ), and the interhemispheric fissure at the brain vertex. We employed a neuronavigated rTMS approach in order to accurately

target functional loci within these brain regions previously implicated in risky and ambiguous decision making. Standardized MNI coordinates for the IPS (-36,-57,50) and IFJ (39,16,33) were based on peak group activations associated with risk and ambiguity preferences in our previous fMRI study(Huettel et al., 2006b). MNI coordinates for the vertex active control site (0,-28,90) were determined by selecting the coordinates falling most directly over the interhemispheric fissure at the peak of the standardized MNI brain.

We identified these target coordinates for each participant using their structural MRI scan and a neuronavigated rTMS procedure implemented using theBrainsight suite of tools and software (Rogue Research, Montreal, Canada). Each participant's anatomical MRI image was mapped to MNI standard space based on manual registration landmarks (anterior commissure, posterior commissure, brain size and edges), allowing rTMS targets defined in MNI coordinates to be translated to each individual's native brain anatomy. Next, we co-registered our participants' cranial features with their anatomical MRI scans, using the left and right intertragal notch, nasion, and tip of nose. This allowed us to target the IPS, IFJ, and vertex consistently within individual participants. Participants were re-registered prior to each rTMS administration to insure accurate administration.

Decision-Making Task

On each trial, participants made self-paced choices with real financial consequences between a certain option (e.g. 100% chance of \$5) and a risky (e.g., 50% chance of \$12) or ambiguous (e.g., ??% chance of \$12) option. Participants were instructed that the winning probability for ambiguous options was hidden, but could take any value from 0 to 100%. We manipulated the certain option reward amount (\$3-\$7), uncertain option reward amount (\$2-\$98) and the degree of option uncertainty (75%, 50%, 25%, or ??%) to reveal subjective preferences (or degree of aversion) for risk and ambiguity. From these variables, we constructed 165 unique gamble trials (45 each for 25%, 50% 75% risk, and 30 for ambiguity), which constituted a single run of the task. This identical set of 165 gambles was repeated for each task run, allowing repeated measures comparisons with subject, gamble, and subject-by-gamble effects controlled. The vast majority of these gambles (150 out of 165) were constructed such that the uncertain option had a higher expected value than the certain option. The ratio of the uncertain vs. the certain expected value (assuming ambiguous options to have an expected probability of .5) ranged from 0.5 to 3.6. The higher end of this range was covered by the ambiguous and 25% gambles to sufficiently reward risk taking, as participants are typically strongly risk-averse to such gambles. By contrast, the 75% gambles covered the lower end of this range, with 50% gambles intermediate to these extremes.

To provide participants an incentive to choose according to their preferences, we explained that for each run of the task (165 gamble trials) we would randomly select one trial, resolve the gamble according to their choice, and pay them the winnings from that trial. Participants completed four runs of the task (initial run followed by three rTMS treatment runs) and were thus paid for a total of four such bonus trials. The average bonus compensation per run was \$9.61, or \$38.43 per participant (actual range of total bonus received was \$8 to \$125).

Data Analysis: Primary Study Measures

The dependent variables of primary interest for our study were choice and decision time, both examined at the trial level. Choice reflects whether the certain or uncertain option was selected for a trial, while decision time measures how long it took from the time the options appeared for a choice to be entered. We used multilevel logistic regression with a logit link function and binary distribution to analyze choice, and multilevel generalized linear regression with a lognormal distribution and an identity link function to analyze decision times. We also examined the financial consequences of participants' choices by computing the expected value of the chosen option for each trial.

Independent variables of primary interest included the rTMS treatment condition (vertex, IFJ, or IPS), the difference of uncertain and certain option reward magnitudes (continuous), the uncertain option probability (25%, 50%, 75%, or

ambiguous), and the interactions of these variables. Variables included in our models but not of primary interest were a categorical variable reflecting the rTMS condition order (controlling for order effects), and in the decision time model, a continuous variable reflecting the total number of trials already completed (controlling for practice effects).

Repeated Measures and Multilevel Modeling

We implemented multilevel mixed-effects models for repeated measures (Snijders, 2011) in order to account for non-independent observations due to both our design (165 unique gambles repeated across three rTMS treatments) and subject effects (individual differences in risk/ambiguity aversion and average decision speed). The 165 unique gambles were treated as the “subject level” observations (with three observations for each), while participants were treated as the “group level” observations. This modelling approach allowed us to control for the sources of dependency in our data, account for variance in the data at both the decision trial and participant levels simultaneously, and make valid inferences regarding the expected size of the rTMS effect in the broader population. These models also allowed the simultaneous examination of trial-varying effects (such as practice effects on decision speed, which evolve through time) and participant-varying effects (such as broader preference or personality trait influences on decisions). We examined null models (random intercept, no trial-level regressors) for our dependent variables in order to estimate the intraclass

correlation (participant-level variance/participant + trial level variance). This value reflects the proportion of total variance accounted for by clustering of responses by participant. As these values were large for each of our dependent variables (indicating a violation of the independence assumption), a mixed model approach was justified.

We fit models using SAS 9.3 Proc GLIMMIX (Sas Institute, 2011), which implements generalized linear mixed models. Models were estimated using residual pseudo-likelihood estimation with subject-specific Taylor series expansion (Breslow & Clayton, 1993). The residual degrees of freedom were determined using the improved F approximation procedure described by Kenward and Roger (Kenward & Roger, 1997, 2009). To avoid unnecessary statistical comparisons between conditions, we restricted our examination of significant effects in two ways. First, we restricted our pairwise comparisons to the examination of rTMS treatment effects, always matching other model factors across comparisons (i.e., comparing choices on the 50% trials between control, IFJ, and IPS rTMS, but not comparing the 50% and 25% conditions). Secondly, we conducted such comparisons only for cases in which the omnibus test for the effect (Type III sum of squares *F*-test) was significant (with statistical significance set at the 5% level for all effects).

An advantage of a multilevel models approach to repeated measures is that missing-at-random observations are permissible. Data was missing from three runs in our study: one participant declined to complete the IFJ rTMS condition, and data from

two other runs (one IFJ, one vertex) was deemed unreliable because neuronavigated targeting failed in the midst of the rTMS administration. Observations from the successful runs with these participants are included in the analysis, while these unsuccessful runs were coded as missing observations. These missing runs slightly altered the treatment order counterbalancing. We controlled for the potential impact of this imbalance by including the order of treatment effects as a categorical variable in our analysis (“rTMS Condition Order”), and observed no substantive change in our results.

6. Conclusion

In this concluding chapter, I review the key findings and contributions presented by this dissertation, highlight some limitations of our research findings as well as our current understanding of impulse control, and suggest areas for future investigation.

6.1 Summary of contributions

Chapter 1 compares and contrasts decision neuroscience and cognitive control approaches to flexible behavior. These research domains stand to benefit from an emerging approach that integrates theory and techniques from both research domains. This chapter introduces one potential point of contact between these literatures, based on models describing a hierarchical stream of control processing within the medial and lateral prefrontal cortex. The anatomical organization of cognitive control over concrete, short term, and long-term levels of abstraction may provide an organizing principle useful for understanding a variety of processes dependent on this control, including decision making and impulse control. The integration of cognitive, personality, and decision scientific approaches to behavioral control provides the intellectual foundation for the subsequent empirical work described in Chapters 2 through 5.

Chapter 2 presents evidence from exploratory factor models supporting the organization of impulsive personality (measured using the prominent BIS-11 scale) into motor, attentional, and non-planning components. Previous models attempting to measure these factors were found to lack coherence, leading us to reevaluate, revise, and

abbreviate the original measure substantially. The resulting Abbreviated Impulsiveness Scale, or ABIS, maintains conceptual focus and internal consistency with far fewer items, provides a substantially more versatile measure, and remains true to the primary impulsiveness subtypes originally identified by Barratt, Patton, and colleagues (Patton et al., 1995). The ABIS scales thus represent a data-driven improvement upon the world's most widely employed measure of impulsiveness.

Chapter 3 extends the utility of the ABIS, demonstrating its replicability, generalizability, and validity for measuring attentional, motor, and non-planning impulsiveness. Psychological science has faced recent challenges in regards to unreliable findings, an issue which is particularly important for results intended for widespread application, such as personality scales. The ABIS, in contrast to its BIS-11 forebear, demonstrated consistent results when replicated in an independent sample. The ABIS also generalized well to a third independent internet sample collected from a substantially different population of respondents. Finally, the ABIS showed evidence of validly measuring attentional, motor, and non-planning impulsiveness subtypes, and clearly reproduced relationships between motor impulsiveness and alcohol consumption. Evidence from Chapter 3 strongly reinforces the conclusions from Chapter 2, demonstrating the superior stability and predictive utility of inference based on the ABIS.

Chapter 4 integrated behavioral, brain, and trait measures of impulse control at concrete and abstract levels, addressing the question of whether the structure of cognitive control, decision making, and trait impulsiveness each depend on a common principle of abstraction. Individual differences in motor impulsiveness were found to relate to brain activation during a Stroop task requiring inhibitory control over a pre-potent but incorrect motor response. Specifically, increased activity in a resting-state network was associated with urgent impulsiveness. By contrast, more abstract control over competing decision options in a delay-discounting task was associated with nonplanning impulsiveness, particularly in a region of right lateral PFC implicated in contextual control. These results qualify hypothesized relationships between medio-lateral control networks and impulsiveness, suggesting that motor and non-planning impulsiveness may manifest as variable activation within regions associated with the implementation of actions and control, as opposed to in medial PFC regions engaged in the detection of conflict.

Chapter 5 employs experimental neurostimulatory techniques to investigate causal contributions of contextual and impulse-control regions to calculated risk-taking. Although risk-taking behavior is often negatively construed within the psychological sciences, an ability to accept uncertainty for the chance to obtain a highly valued outcome is essential to successful decision making. The results of this study revealed a general involvement of a prefrontal contextual control region associated with attentional

impulsiveness in the processing of uncertain decisions. By contrast, an intraparietal region associated with cognitive control, numeric processing, and risk preferences showed a specific involvement in calculated risk-taking: inhibiting this parietal brain region biased choices away from uncertainty and towards safety, to the financial detriment of the decision maker. This study further reinforced the neural dissociation of risky and ambiguous decision uncertainty, and, more importantly, provided the first evidence supporting a causal role for the left intraparietal sulcus in calculated risk-taking decisions.

6.2 Present questions and future research

The research presented as a part of this thesis has considered impulse control as a phenomenon observable at neurobiological, behavioral, and trait levels of analysis. Our findings regarding the organization of trait impulsiveness anchor our empirical results by describing the development and application of the ABIS scales. These measures link our subsequent empirical investigations of alcohol use, cognitive control, decision making, and risk-taking. Impulsiveness has been typically operationalized at the trait level, and has a rich history as construct of interest in both theoretical and applied research (Dickman, 1990; Eysenck & Eysenck, 1978; Moeller et al., 2001; Petry, 2001; Whiteside & Lynam, 2009). Despite this relevance, important questions remain regarding the nature of trait impulsiveness, its subtypes, varieties, and correlates, and even its very existence as an independent personality construct.

6.2.1 Defining trait impulsiveness

Two influential but distinct approaches to impulsiveness come from Barratt and colleagues (Barratt, 1965; Barratt & Patton, 1983; Patton et al., 1995) and Whiteside, Lynam and colleagues (Lynam & Miller, 2004; Miller, Flory, Lynam, & Leukefeld, 2003; Whiteside & Lynam, 2001; Whiteside et al., 2005). Barratt's perspective on impulsiveness and his approach to measuring it have evolved over fifty years of research. His measure (currently the BIS-11), by far the most widely utilized impulsiveness scale, has an outsized influence on the way impulsiveness is studied across a variety of behavioral fields. At its core, Barratt's modern conceptualization of impulsiveness describes a set of interrelated but distinct sub-traits, distinct from related action-oriented constructs such as sensation-seeking, risk-taking, and extroversion (Stanford et al., 2009). This perspective recognizes the multi-dimensionality of impulsiveness while distinguishing the construct as a whole from behaviors and traits often thought of as closely related.

Lynam and Whiteside, by contrast, conceptualize varieties of impulsiveness not as subtypes of a common trait, but rather, as separable styles of behavior which produce a similar appearance of impulsiveness (Whiteside & Lynam, 2001). These styles emerge from distinct processes and facets of personality, linked to the broad five-factor theory of personality (McCrae & John, 1992). Thus, distinct regulatory processes (and their failure) produce convergent behavioral responses which produce the appearance of disinhibition, present-orientation, and a lack of forethought. Behavioral patterns like

sensation-seeking – as measured by their UPPS impulsiveness scale – are, in fact, the very behaviors the BIS-11 impulsiveness subtraits are thought to be distinct from. In contrast to the high intercorrelations of BIS-11 subtraits, the UPPS scale measures tend to show only low to moderate intercorrelation, consistent with Whiteside and Lynam’s conceptualization of independent impulse-related control processes and patterns of behavior emerging from distinct facets of personality.

The results presented in this thesis support a model of trait impulsiveness and which allows for an integration of these opposing perspectives. A mechanistic approach to impulse control rooted in hierarchical models from cognitive psychology and neuroscience provides the basis for integrating these perspectives. The results and research presented and reviewed by this dissertation support the core impulsive subtraits hypothesized by Barratt and colleagues, but also demonstrate specific interrelationships between these traits and the behavioral styles measured by the UPPS scales of Whiteside and Lynam. Our review of cognitive neuroscience results and models supporting a hierarchical organization of behavioral control according to a principle of abstraction provides a potential explanation: Both correlated system-level disturbances and independent disruptions of control processing may produce dependent and independent patterns of self-regulatory failure.

Our findings in Chapter 2 and Chapter 3, which detail the formulation and replication of the ABIS scales, clearly support Barratt and colleagues’ multidimensional

conceptualization of impulsiveness. Our findings are consistent with theirs in identifying correlated motor, attentional, and non-planning dimensions of impulsiveness. The ABIS scale measures, however, also show clear correspondence with measures of impulsive behavior from the UPPS (Chapter 3, **Table 5**). ABIS non-planning correlates preferentially with UPPS premeditation, and attentional impulsiveness (as well as non-planning) show clear relationships with UPPS perseverance. The relationship between motor impulsiveness and UPPS urgency is the most specific, however, and is clearly identified by the ABIS, but not the BIS-11, motor scale (Coutlee et al., 2014). Sensation seeking is the only UPPS scale without an ABIS/BIS-11 analogue (although the ABIS reveals a weak correspondence with motor impulsiveness, reinforced by positive results with the Brief and Impulsive Sensation Seeking Scales). Thus, despite their roots in opposing theoretical perspectives, our work with the ABIS reconciles Barratt et al. and Whiteside and Lynam's measures of impulsive behaviors, particularly in regards to control in the moment (motor and urgent impulsiveness) and strategic control (non-planning and (lack of) premeditation impulsiveness).

6.2.2 Varieties of impulsive behavior and hierarchical models of control

Our findings from Chapters 1, 4, and 5, which present evidence from cognitive neuroscience supporting hierarchical concrete-to-abstract organization of control behavior, provide a model for understanding the mechanism through which both interrelated and independent impulsive traits and behaviors can emerge. According to

the hierarchical control perspective, control processes at different levels of abstraction are distinct, but linked through the influence of higher, more abstract levels of control. In order to be expressed in flexible, effective behavior, these systems channel regulation to the primary motor output control levels in caudal PFC. Thus, the overall system is linked and interactive, but different forms of self-regulatory failure can result from disruptions to different components (brain regions or systems) affecting different control processes (supported by those regions and systems). This control-system perspective allows for the possibility of both global and local disruptions of impulse control, which could produce both linked subtrait-like and superficially similar but behaviorally independent manifestations of impulsive behavior.

Disruptions or inefficiencies of control exercised at particular levels of abstraction could produce mechanistically distinct, but behaviorally similar, patterns of impulsive behavior. Such patterns of distinct self-regulatory failures presenting as impulse-like patterns of behavior would be consistent with Whiteside and Lynam's perspective on impulsiveness. Individual differences in specific regulatory processes could result from imbalances in control exercised at different levels of abstraction – particularly in interaction with reward and decision making processes. For example, a large reward response to novelty (nucleus accumbens) or risk-seeking preferences (IPS activity), if unbalanced by abstract future rewards and strategic control (rostral PFC) could present as sensation-seeking behavior, venturesomeness, or motor impulsiveness

(Abler, Walter, Erk, Kammerer, & Spitzer, 2006). Likewise, difficulty in maintaining focus and resisting distraction (mid-PFC) could present as attentional impulsiveness, diminished perseverance, or urgent impulsiveness through weakness to prepotent responses (Aron, 2011). Failure to engage long-term goals and stick to plans (rostral PFC) could lead to a reliance on reactive, rather than proactive control (Braver, Paxton, Locke, & Barch, 2009), a condition which encourages shortsighted decision making and vulnerability to instant gratification (Braver, 2012; Hinson et al., 2003).

In healthy self-regulatory systems, regulation implemented at different levels of abstraction can shore up weaknesses in other areas (Magen & Gross, 2010), but persistent imbalances are likely to show through as patterns of impulsive behavior, as measured through self-report instruments like the UPPS. Investigations of the potentially hierarchical mechanisms of specific control failures suggested here would benefit from research with individuals with lesions to different areas along the PFC axis, such as frontopolar patients suffering from strategy application disorder (Azuar et al., 2014; Shallice & Burgess, 1991b) and studies deactivating these regions experimentally using TMS (Basso, Ferrari, & Palladino, 2010; Costa et al., 2011). These methods could contribute specific tests of the proposed theory that disturbances in the balance of control at multiple interacting levels produces a variety of disturbances, many of which may ultimately appear as impulsive behaviors.

6.2.3 Impulsive subtraits, global control, and general impulsiveness

A regulatory system operating at multiple interacting levels of abstraction can also suffer disturbances that act across multiple levels simultaneously. Such disturbances would produce correlated disruptions of distinct but related control behaviors, a pattern more consistent with Barratt's conception of correlated impulsive subtraits. At the global scale, for example, individual differences in the integrity or efficiency of processing through the prefrontal cortex – due to polymorphism in the COMT gene, for instance (Meyer-Lindenberg et al., 2005) – or disturbed functional connectivity between hierarchical control regions could produce correlated, trait-like differences in control measured across multiple levels of abstraction. Recent research using graph-theoretic measures of resting-state connectivity in the brain have implicated prefrontal control network abnormalities in impulsiveness (Davis et al., 2013; Li et al., 2013). System-level differences could produce global changes in self-regulatory capacity, and might therefore be particularly relevant and apparent in clinical disorders of control, such as ADHD or OCD. In such cases, the diffuse regulatory impacts of pharmacological interventions might be well matched to the global inefficiency of control processing (Konrad & Eickhoff, 2010; Robbins, Gillan, Smith, de Wit, & Ersche, 2012; Winstanley, Eagle, & Robbins, 2006).

The possibility of intercorrelated global disruptions of control leads us to an important question regarding the nature of trait impulsiveness left unresolved by our

current work: is there a “general impulsiveness” that cuts across these constructs, and if so, what is its nature? The BIS-11 subtraits are conceptualized as multi-dimensional manifestations of an impulsiveness construct, and are substantially intercorrelated. That the ABIS measures remain highly correlated after our extensive revision of the BIS-11 is interesting, since this process increased the specificity and internal consistency of the resulting ABIS scales substantially, but did not thereby eliminate relationships between the scales. Our work in Chapters 2 and 3 discourages the use of existing general total score measures of BIS-11 impulsiveness (Coutlee et al., 2014; International Society for Research on Impulsivity, 2013), and we declined to present one as a part of the ABIS, due to the clearly multi-dimensional character of impulsiveness, and the distortions of inference that can occur if multidimensionality is ignored (Cattell, 1958; Fava & Velicer, 1996). The fact remains, however, that the BIS-11 and ABIS scales are substantially intercorrelated, suggesting a possible general impulsiveness construct which might underlie the measured subtraits. So long as these intercorrelations are a component on responses to the BIS-11 self-report items, a psychometrically appropriate means for measuring and understanding that shared variation would represent a substantial and valuable contribution. Hierarchical models of control may contribute to advancing this understanding.

Hierarchical models of control suggest the possibility that an apparent general impulsiveness trait could result from the cascading nature of hierarchical control. Since

each level of control influences all lower levels of abstraction (Koechlin et al., 2003a), poor planning might tend to result in poorer attention and motor control, and poor attentional focus might produce poor motor control. As the base output level, motor impulsiveness serves as a common link. This scheme would predict that levels of control (and impulsiveness types) adjacent in level of abstraction should show stronger correlations. The patterns of factor correlations observed in our ABIS model from Chapter 2 (**Figure 4**) supports this prediction, as the correlations between non-planning and attentional impulsiveness is strongest, followed by attentional to motor, with non-planning and motor least correlated. This evidence is interesting but speculative, and future investigations designed to examine this possibility should explicitly test models which impose the proposed hierarchical constraints on the flow of control influence. Such models could be tested using mediation analysis, or more flexibly, structural equation modeling with directional relationships specified down the hierarchy of latent impulsive traits (Hoyle, 2011; Jöreskog et al., 1979). An important alternative for investigation would be a bi-factor structure of impulsiveness, whereby uncorrelated subtraits as well as a single general impulsiveness factor underlie impulsive traits and behaviors (Holzinger & Swineford, 1937; Jennrich & Bentler, 2011). Emerging modeling techniques, especially exploratory bi-factor analysis, will allow competing alternative hypotheses regarding the nature and importance of a potential general impulsiveness trait to be more thoroughly investigated.

6.3 Brains, traits, and behavior: limits and opportunities

At the heart of the research described here lies an effort to explore what measures of individual differences in personality, preferences, and cognitive abilities can tell us about how the mind and the brain solve problems of self-control. More broadly, a key question is whether examining brain circuitry informs our understanding of personal characteristics, traits, and their variability across individuals. Decision neuroscience research questions frequently address qualities that vary markedly in the population, such as risk-aversion (Christopoulos et al., 2009; Kuhnen & Knutson, 2005), self-control (Figner et al., 2010b; Hare et al., 2009; Kable & Glimcher, 2007; McClure et al., 2007), reward sensitivity (Beaver et al., 2006; Hariri et al., 2006), and subjective preferences for particular goods (Aharon et al., 2001; Clithero, Reeck, Carter, Smith, & Huettel, 2011; Huettel et al., 2006b). Neuroimaging research drawing on tools and techniques from economics and personality psychology to estimate and examine individual differences in preferences and traits often addresses compelling questions. Nevertheless, it is important to recognize the fundamental limitations constraining an individual-difference approach to cognitive neuroscience, and to consider some of the ways these obstacles might be overcome.

6.3.1 Introspection and insight as challenges for self-report

It is important to acknowledge a primary limitation characterizing all forms of individual-difference research that relies on self-report measures of traits, preferences,

and personality: These measures suffer from the known failings of an introspective approach to knowledge. Insights from introspection are often overly optimistic (Sharot, Riccardi, Raio, & Phelps, 2007; Weinstein, 1980), biased (Podsakoff & Organ, 1986; Tversky & Kahneman, 1974), and incomplete reflections of the true natural state of the world (Baumeister, Vohs, & Funder, 2007; Dunning, Heath, & Suls, 2004; Wilson & Dunn, 2004). More insidiously, differences in self-insight may be confounded with groups of interest, possibly presenting as spurious group differences in impulsiveness or other traits (Ben-Porath, 2003; Sackeim & Gur, 1979). For example, depression or anxiety could encourage pessimistic self-evaluation and present as impulsiveness, or a lack of focus necessary for self-reflection might produce noisy “trait” measures in individuals with attention-deficit disorder. A related concern affects socio-economic status: individuals forced by their circumstances to live paycheck-to-paycheck (or even handout to handout) must rationally adopt a concrete, short term perspective in which long term planning is neglected, thereby possibly presenting as impulsive nonplanners due to circumstance rather than personality (Takeuchi, Williams, & Adair, 1991). A method which partially addresses these issues is to measure traits and preferences using behavioral procedures rather than through self-report alone. Behavioral economics, and decision neuroscience by extension, often utilize this approach, employing repeated-choice procedures to reveal subjective preferences for use as individual difference measures.

Awareness of the limits of self-report measures is important to the interpretation of findings reporting individual differences in traits and behavior. Attempts to generalize findings across different populations and relate self-report measures to measures of behavior from experimental or observational studies represent important steps to guard against these limitations. In the studies reported in this dissertation, we attempt to address these limitations by relating self-report measures of impulsiveness to a variety of personality constructs to demonstrate validity for measuring impulsive traits, as well as to measures of experimental task performance (response inhibition), financially consequential decisions (delay discounting), and reported outcome variables (alcohol consumption).

6.3.2 Limits of the individual-difference approach to neuroimaging

Setting aside issues of self-report, individual-difference research based on neuroimaging faces a serious limitation due to the high costs of obtaining anything but small participant-level sample sizes for neuroimaging studies. The issue is stark: sample sizes of below around 200 are considered small in personality psychology (Comrey & Lee, 2013; Guadagnoli & Velicer, 1988), but such sample sizes are still a full order of magnitude larger than the sample size of a typical neuroimaging studies (Desmond & Glover, 2002; Friston, Holmes, & Worsley, 1999). The standard neuroimaging strategy of collecting large quantities of noisy trial-level scanning data – which is quite effective for inferences regarding within-subjects experimental manipulations – provides little

benefit when considering the effects of between-subjects variables like personality traits. This leaves most analyses incorporating individual differences woefully underpowered and vulnerable to false positives via capitalization on chance variation (Ioannidis, 2005; MacCallum et al., 1992). We observed such a failure to replicate in Chapter 4 for a relationship between motor impulsiveness and the neural Stroop conflict effect, with the correlation originally estimated as $r = .60$ in a sample size of 20 but $r = .01$ our subsequent 49 subject attempt at replication (Ioannidis, 2005; Venkatraman, Rosati, et al., 2009). Such false positives neuroimaging findings based on spurious relationships can lead to costly misallocations of limited resources by influencing experimental questions and study designs.

What are some ways to address problems associated with low sample sizes in neuroimaging studies of individual differences? An obvious, but ultimately unrealistic solution, is to collect larger participant-level sample sizes. A small number of investigators have the opportunity to attempt this approach, with some notable neuroimaging samples pushing into the range of a few hundred, and on rare and limited occasions, a few thousand subjects (Biswal et al., 2010; Nikolova, Singhi, Drabant, & Hariri, 2013; Utevsky, Smith, & Huettel, 2014). Given an operational cost of fMRI experiments in the hundreds-to-thousands of dollars per hour range, however, large subject-level sample sizes are likely to remain out of reach for most cognitive neuroscientists and research questions.

More realistic possibilities involve maximizing the value of the imaging and individual difference measures that are already being collected. Mirroring the within-subjects approach used to average noisy imaging data, within subject replicates of individual difference measurements could be taken (perhaps survey questions with slight wording changes) to increase the reliability of every precious individual measure obtained. Such close replicates are often eliminated during self-report scale design (Podsakoff et al., 2003), but repeated sampling of highly similar items should decrease measurement error for the individual differences of interest. Statistical approaches to addressing measurement error could also be quite beneficial in these cases. Error-in-variable methods, and in particular, structural equation modeling, are exceptionally useful for separating the reliable latent-variable “signals” from the error-variance “noise” (Anderson, Stone-Romero, & Tisak, 1996; Bollen, 1998). Although there are some examples of brain imaging data extracted from limited brain areas being incorporated into a structural equation model (Koechlin et al., 2003a; Lahey et al., 2012; McIntosh & B, 2012), methods for using these techniques to refine individual difference covariates have not been integrated into major neuroimaging analysis packages. While sample sizes may still represent a limiting factor, experimental and statistical approaches to minimizing measurement error in individual difference have potential for helping to address these challenges.

6.3.3 Opportunities for a convergent approach to individual differences

Finally, given these constraints, it is important to teach and maintain realistic expectations regarding what can be expected from neuroimaging approaches to individual differences. By and large, these findings should be explicitly reported as exploratory, thereby clearly acknowledging the influence of sampling variance in the estimated relationship. Given small sample sizes, unreliable trait measures, and a large number of tests, the potential for identifying spurious relationships between brain regions and individual difference measures is very high. Unless a study is strictly confirmatory and makes publicly accountable predictions ahead of time (Wagenmakers, Wetzels, Borsboom, van der Maas, & Kievit, 2012), individual difference results in neuroimaging should be interpreted as preliminary and hypothesis-generating, and not as predictive statements about the known state of relationships in the natural world (Cumming, 2014; Gelman, 2004).

These limits to the neuroimaging approach to individual differences create opportunities for convergent cognitive neuroscience techniques less limited by participant-level sample sizes. Electroencephalography (EEG) has traditionally been seen as a natural complement of neuroimaging, as it provides better temporal but poorer spatial information on cognitive processing. EEG has a substantially lower cost of acquisition per subject, and EEG waveforms have been shown to reflect individual

differences in cognitive processing and personality traits (Gale, 1973; Riding, Glass, Butler, & Pleydell-Pearce, 1997; San Martín, 2012).

An altogether different set of techniques with great promise, however, are the neurostimulation procedures TMS and transcranial direct current stimulation (tDCS). The evidence furnished by TMS and tDCS provides an ideal complement to exploratory evidence derived from neuroimaging studies. rTMS, and especially tDCS, are safe, non-invasive, relatively easy to apply, and about as expensive as behavioral or EEG studies, once the (comparably small) investment in equipment has been made. This allows for the collection of large participant-level sample sizes, especially with tDCS, where it is quite feasible to collect data from multiple participants simultaneously (Fehr, 2009; Knoch et al., 2008). Experiments employing these techniques, which subtly manipulate brain activity and then observe the consequences on behavior, are capable of providing causal evidence regarding the involvement of particular brain regions in cognition. This form of evidence is inaccessible to neuroimaging, in which behavioral states are manipulated and changes in brain activation are observed. Neuroimaging and neurostimulation are thus ideally suited for an exploratory-confirmatory approach to cognitive neuroscience, and to the study of individual differences in the brain and cognition in particular.

6.4 Summary

The research studies presented by this dissertation constitute a methodologically diverse and conceptually integrative approach to understanding impulsiveness in the context of cognitive control and decision making. Broadly, these findings address the validity of current conceptions of trait impulsiveness, relationships between those traits and brain or laboratory measures of cognitive control, and links between impulsive traits and economic decisions under conditions of delay or uncertainty. The findings presented in this thesis affirm the multidimensional nature of impulsiveness as a construct, and link individual differences in specific impulsive types to behavioral and neurobiological measures of control function. The nature of motor, attentional, and non-planning impulsive types are contextualized by reference to evidence supporting a broad theory of behavioral control based on hierarchical organization of action, ranging from concrete acts to abstract plans and strategies. We provide evidence linking concrete forms of urgent/motor impulsiveness to behavior and brain activation during response-related control, and more abstract and future-oriented premeditative/non-planning impulsiveness to decision control signals in more rostral PFC. Finally, these findings are complemented by causal evidence from a neurostimulation study linking a contextual control network to optimal behavior during risky decision making. Taken together, the results of these studies suggest that impulse control, cognitive control, and decision making may share a common organization from concrete to abstract. Our use of diverse

research techniques and confirmatory replication adds methodological rigor and provides convergent evidence linking impulsiveness to behavioral and decision control. This approach reinforces the advantages of an integrative approach across the domains of personality psychology, cognitive control, and decision making for understanding the flexible decision making and behavior.

Appendix A: ABIS (ABbreviated Impulsiveness Scale) Administration and Scoring

The Abbreviated Impulsiveness Scale (ABIS) provides an efficient, reliable, valid, and generalizable measure of attentional, motor, and non-planning impulsiveness. The ABIS can be used as a brief alternative to the BIS-11 or as a model for reanalyzing previously collected BIS-11 questionnaire responses.

DIRECTIONS: People differ in the ways they act and think in different situations. This is a test to measure some of the ways in which you act and think. Read each statement and put an X on the appropriate circle to the right. Do not spend too much time on any statement. Answer quickly and honestly.				
	①	②	③	④
	Rarely/Never	Occasionally	Often	Almost Always/Always
12	I am a careful thinker. (Reverse Scored)			
7	I plan trips well ahead of time. (Reverse Scored)			
2	I do things without thinking.			
9	I concentrate easily. (Reverse Scored)			
13	I plan for job security. (Reverse Scored)			
17	I act "on impulse."			
8	I am self controlled. (Reverse Scored)			
14	I say things without thinking.			
5	I don't "pay attention."			
19	I act on the spur of the moment.			
1	I plan tasks carefully. (Reverse Scored)			
20	I am a steady thinker. (Reverse Scored)			
30	I am future oriented. (Reverse Scored)			

ABIS item order (using BIS-11 item numbering): 12, 7, 2, 9, 13, 17, 8, 14, 5, 19, 1, 20, 30

ABIS Scales:

Attention (5 items): 12, 9, 8, 5, 20

Motor (4 items): 2, 17, 14, 19

Non-planning (4 items): 7, 13, 1, 30

Reverse-scored items (4, 3, 2, 1): 12, 7, 9, 13, 8, 1, 20, 30

Standard-scored items (1, 2, 3, 4): 2, 17, 14, 5, 19

To score each scale, take the average of the scores for each item on that scale (after reverse-scoring the specified items). Do not average across separate scales to produce combined scores.

The BIS-11 items used as the basis for the ABIS can be found at:

<http://www.impulsivity.org/>

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Biography

Christopher Gilbert Coutlee was born to Jeffrey and Joanne Coutlee on January 23rd, 1984, in Adana, Turkey. He attended Geneva High School in Geneva New York, followed by Colgate University, where he studied cellular neuroscience under the mentorship of Dr. Jun Yoshino, graduating as the Salutatorian of his class and with high honor in neuroscience in 2006. He was received an Intramural Research Training Award fellowship to train with Dr. Karen Berman at the National Institute of Mental Health from 2007-2009. He attended Duke University from 2009-20014, studying under Dr. Scott Huettel, and publishing work on “The Functional Neuroanatomy of Decision Making: Prefrontal Control of Thought and Action.” At Duke, he received his Master of Arts in Psychology and Neuroscience in 2012 and his Doctor of Philosophy in Psychology and Neuroscience in 2014. He subsequently left academic science to pursue applied opportunities as a research analyst.