FUNCTIONAL LOCALIZATION OF BRAIN ACTIVITY IN THE IOWA GAMBLING TASK USING GRAPH-THEORETICAL METHODS

BY

TAYLOR BOLT

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Approved By:

Dale Dagenbach, Ph.D., Advisor

Wayne E. Pratt, Ph.D., Chair

Paul J. Laurienti, MD, Ph.D

Christian E. Waugh, Ph.D.
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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIST OF ILLUSTRATIONS AND TABLES</td>
<td>v</td>
</tr>
<tr>
<td>LIST OF ABBREVIATIONS</td>
<td>vi</td>
</tr>
<tr>
<td>ABSTRACT</td>
<td>vii</td>
</tr>
<tr>
<td>INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>MATERIALS AND METHODS</td>
<td>22</td>
</tr>
<tr>
<td>RESULTS</td>
<td>33</td>
</tr>
<tr>
<td>DISCUSSION</td>
<td>46</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>57</td>
</tr>
<tr>
<td>APPENDICES</td>
<td>70</td>
</tr>
<tr>
<td>CURRICULUM VITA</td>
<td>79</td>
</tr>
</tbody>
</table>
LIST OF ILLUSTRATIONS AND TABLES

FIGURES

Figure 1. Modularity example....................................................................................16
Figure 2. Construction of a network...........................................................................26
Figure 3. IGT Block Performance.............................................................................33
Figure 4. Selections of sample participant.................................................................34
Figure 5. Modularity change in sample participant....................................................35
Figure 6. Subject Node-consistency image for rest..................................................36
Figure 7. Subject Node-consistent image for IGT.....................................................37
Figure 8. Subject Node-consistency image for spatial-orienting...............................38
Figure 9. Meta-consistency images for Node-Consistency method............................38
Figure 10. Subject-level SI image for rest.................................................................40
Figure 11. Subject-level SI image for IGT.................................................................41
Figure 12. Subject-level SI image for spatial-orienting.............................................41
Figure 13. Meta-consistency Images for Scaled Inclusivity Method.........................42
### LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAL</td>
<td>Automated Anatomical Labeling Atlas</td>
</tr>
<tr>
<td>ACC</td>
<td>Anterior Cingulate Cortex</td>
</tr>
<tr>
<td>ANOVA</td>
<td>Analysis of variance</td>
</tr>
<tr>
<td>BA</td>
<td>Brodmann’s area</td>
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<tr>
<td>BOLD</td>
<td>Blood-oxygen-level dependent</td>
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<td>DLPFC</td>
<td>Dorsolateral Prefrontal Cortex</td>
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<td>DM</td>
<td>Dorsomedial Prefrontal Cortex</td>
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<td>DMN</td>
<td>Default-Mode Network</td>
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<tr>
<td>EPI</td>
<td>Echo-planar imaging</td>
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<tr>
<td>fMRI</td>
<td>Functional Magnetic Resonance Imaging</td>
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<td>IGT</td>
<td>Iowa Gambling Task</td>
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<tr>
<td>JC</td>
<td>Jaccardized Czekanowski similarity index</td>
</tr>
<tr>
<td>K</td>
<td>Number of connections of a node (degree)</td>
</tr>
<tr>
<td>MNI</td>
<td>Montreal Neurological Institute</td>
</tr>
<tr>
<td>MRI</td>
<td>Magnetic Resonance Imaging</td>
</tr>
<tr>
<td>N</td>
<td>Number of nodes in the network</td>
</tr>
<tr>
<td>OFC</td>
<td>Orbitofrontal Cortex</td>
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<td>PET</td>
<td>Positron Emission Tomography</td>
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<td>PPI</td>
<td>Psychophysiological Interaction analysis</td>
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<tr>
<td>Q</td>
<td>Modularity</td>
</tr>
<tr>
<td>RJC</td>
<td>Jaccard ratio</td>
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<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
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<tr>
<td>ROI</td>
<td>Region of interest</td>
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<td>SI</td>
<td>Scaled Inclusivity</td>
</tr>
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<td>SPM</td>
<td>Statistical Parametric Mapping</td>
</tr>
<tr>
<td>vmPFC</td>
<td>Ventromedial Prefrontal Cortex</td>
</tr>
</tbody>
</table>
ABSTRACT

Functional connectivity methods, particularly graph-theory methods, are an area of growing interest for researchers interested in network-based neuroimaging approaches. This study attempted to offer another useful extension of graph-theoretical approaches to functional neuroimaging. In particular, the neuroimaging study of the Iowa Gambling Task (IGT). Several task-related brain regions have been found during IGT performance using standard subtraction-based neuroimaging paradigms. However, the identification of a proper baseline for the IGT has complicated the study of task-related activations in the IGT. In this study, two graph-theory methods are offered as an alternative method of functional localization without traditional subtraction assumptions. These methods rely on the consistency of functional groupings of brain areas across time to identify areas in the brain specialized for particular cognitive functions, without the need for a baseline comparison. They are applied to a within-subject fMRI data set consisting of 8 healthy young adults at rest, and performing the IGT and a simple spatial-orienting task. Both methods localized areas in the visual and sensorimotor cortices. Unexpectedly, the Scaled Inclusivity method localized areas of the DMN across both task states in addition to rest. However, permutation tests of the SI maps revealed significant differences in the spatial extent of DMN consistency across all three tasks. The future application of both methods for functional localization, and the functional significance of the DMN during the IGT and other task-states are discussed.
INTRODUCTION

The Iowa Gambling Task (IGT) is a popular assessment of real world decision-making often used by clinicians and researchers (Bechara, Damasio, Damasio, & Anderson, 1994). In this task, individuals are instructed to consecutively select cards from four decks (typically referred to as A, B, C, and D). Each deck is associated with varying degrees of cash rewards and punishments after each card selection. Decks A and B yield large cash rewards, but large penalties, resulting in a net loss; decks C and D yield small cash rewards, but small penalties, resulting in a net gain. Successful decision making is measured by the difference between the number of selections from “advantageous” decks (C and D) and the number of selections from “disadvantageous” decks (A and B) (Bechara et al., 1994), though there are other outcome measures as well (van den Bos, Houx, & Spruijt, 2006). The IGT was first developed by Damasio and colleagues to study decision-making deficits in populations with certain neurological conditions, particularly prefrontal and subcortical damage (Bechara, Damasio, Tranel, & Anderson, 1998; Bechara et al., 1994; Bechara, Damasio, Damasio, & Lee, 1999). Since then the IGT has been applied across a variety of populations, including substance abusers (Bolla et al., 2003), psychopaths (Ross, Benning, & Adams, 2007), pathological gamblers (Goudriaan, Oosterlaan, de Beurs, & Van den Brink, 2004), as well as schizophrenics (Sevy et al., 2007).

The identification of the areas in the brain supporting performance on the task is still controversial and an active area of research (Bechara, Tranel, & Damasio, 2000; Bolla et al., 2003; Clark, Cools, & Robbins, 2004; Lawrence, Jollant, O’Daly, Zelaya, & Phillips, 2009; Manes et al., 2002; Windmann et al., 2006). There are a variety of
methods that have been used to identify relevant brain areas and the processes supported by each. Early studies of the IGT used neuropsychological techniques, primarily lesion studies (Bechara et al., 1994, 1999; Bechara et al., 1998; Manes et al., 2002). However, a growing number of studies have emphasized functional neuroimaging techniques, particularly PET and fMRI, as a convergent methodology that allows for more precise measurements of the brain areas contributing to the task, and without the disadvantages associated with lesion studies (Bolla et al., 2003; Rogers et al., 1999; van den Bos et al., 2006; Windmann et al., 2006). This study wishes to introduce another, more recent methodology to the functional neuroimaging study of the IGT. It is proposed that functional connectivity analysis of fMRI data allows further insight into the functional interactions among the brain areas that support performance on the IGT. Functional connectivity analysis of fMRI data involves examining the temporal correlations between fluctuations of the blood-oxygen level dependent (BOLD) signal between brain regions (voxels or more broadly defined brain areas). This study uses a graph theory approach to functional connectivity, in which voxels are represented as nodes and the temporal correlations between them as edges (Bullmore & Sporns, 2009a; Guye, Bettus, Bartolomei, & Cozzone, 2010). Graph theory allows the representation and quantification of the functional relationships among brain areas as a network of nodes and edges. It is proposed that graph-theory methods may offer the possibility of an alternative method of functional localization without traditional subtraction-based methods. This method relies on the consistency of network structure across time to identify areas in the brain specialized for particular cognitive functions, without the need for a baseline comparison.
Lesion studies of the IGT

Early studies by Bechara and colleagues emphasized the ventromedial prefrontal cortex (vmPFC) as mediator of performance on the IGT (Bechara et al., 1994; Bechara et al., 1998). According to their somatic marker hypothesis, emotional experience (“somatic states”) is a necessary constituent of successful decision making. The vmPFC, they argue, is a crucial component of this process, responsible for integrating somatic markers into the decision-making process (Bechara et al., 1994). A series of experiments testing the IGT on patients with varying degrees of prefrontal damage has supported their theory (Bechara et al., 1994, 1998, 1999, 2000). Generally, these studies found that those patients with damage to ventromedial areas of the prefrontal cortex performed worse on the IGT relative to controls, while they performed similar to controls on working memory/intelligence tasks.

Manes and colleagues (2002) observed findings inconsistent with those of Bechara et al. (1994, 1998, 2000) in their study of patients with prefrontal damage. In their study, patients with prefrontal damage were categorized into 4 groups: a) patients with localized orbitofrontal (OFC) lesions, b) patients with localized dorsolateral (DL) lesions, c) patients with localized dorsomedial lesions (DM), and d) patients with diffuse lesions across the ventral and dorsal areas of the prefrontal cortex (the large lesion group). Surprisingly, the patients with OFC (corresponding to area the area labeled vmPFC above) lesions were unimpaired on the IGT relative to controls, while patients with DL, DM, and diffuse lesions across the PFC were impaired, choosing more disadvantageous cards compared to controls. The authors (Manes et al., 2002) note that the inconsistency of their findings with previous studies may be the result of more stringent selection criteria
for OFC lesions. In the Bechara et al. studies (1994, 1999, 2000) the medial OFC (or vmPFC) group was categorized by lesion overlap in the medial OFC with lesions extending outside that region, while Manes et al. (2002) study included only those with focal lesions in the OFC. Under Manes et al. (2002) criteria, Bechara and colleagues’ patients would have been classified in the large lesion group. Further, the laterality of the lesion was not taken into account by previous studies; the Bechara et al. patients had bilateral lesions in the vmPFC. Four of the five patients in the large lesion group of the Manes et al. study had right-sided lesions, while four of the five patients in the OFC group had left-sided lesions. Thus, impairments in the IGT may be associated with right-sided lesions in the ventromedial prefrontal cortex.

However, even after taking into consideration the laterality of the lesion, the findings of Manes et al. (2002) suggest that other areas of the prefrontal cortex outside of the OFC may be involved. The DL group, with focal DL lesions primarily in the right hemisphere, was also impaired on the IGT. Furthermore, the DM group showed impaired performance on the IGT as well. The dorsomedial prefrontal cortex (DM) is often associated with complex cognitive processes, including the processing of uncertainty (Eickhoff, Laird, Fox, Bzdok, & Hensel, 2014), an important factor in the IGT. These findings seem to support the conclusion that executive functions (e.g. working memory) are in fact a necessary component of advantageous decision-making. Consequently, the processes that produce advantageous decision-making may extend outside of the vmPFC (possibly just the right vmPFC) to other areas in the prefrontal cortex.
Functional neuroimaging studies of the IGT

Studies using PET and fMRI have been generally consistent with the above framework. Not surprisingly, the OFC is the most consistently activated area of the prefrontal cortex during the IGT (Bolla et al., 2003; Ernst et al., 2002; Lawrence et al., 2009; Rogers et al., 1999; Windmann et al., 2006). Also, consistent with the findings of Manes et al. (2002), neuroimaging evidence points to a widespread recruitment of the prefrontal cortex, as well as areas in the temporal and parietal lobe. In a PET study, by Ernst and colleagues (2002), the OFC, anterior cingulate cortex (ACC; anterior portion of the medial PFC), dorsolateral PFC (DLPFC), insula, and the inferior parietal cortex were found to be active in an IGT task compared to a control task. An even greater number of task-related activations were observed in a block-design fMRI study of the IGT by Li et al. (2010). Compared to a control task, significant activations were found in the DLPFC, insula, posterior cingulate cortex, OFC, dorsal striatum, and supplementary motor area (Li, Lu, D’Argembeau, Ng, & Bechara, 2010).

Given the complexity of the cognitive components in the Iowa Gambling Task, event-related fMRI methods have also been used to study each component separately. In a study by Lawrence et al. (2009), the decision-making component (i.e., card selection) of the IGT activated a cluster in the medial OFC. In addition, they found that a risky card selection versus safe card selection (risk anticipation) contrast revealed greater activation in the medial PFC (including the ACC and frontopolar cortex), lateral OFC, and insula. Consistent with these results, a previous event-related fMRI study found that risky decisions versus safe decisions activated the medial PFC, and the magnitude of activation was positively correlated with IGT performance (Fukui, Murai, Fukuyama, Hayashi, &
Hanakawa, 2005). In addition, Lawrence et al. (2009) found that during the wins/losses phase of the task, reward-related areas of the brain (e.g., ventral striatum and thalamus), parieto-occipital areas supporting visual attention, and the cerebellum were more responsive to wins; no significant activations were seen in losses relative to wins.

A slightly different design from the Lawrence et al. (2009) study was used in Lin and colleagues’ (2008) event-related fMRI study, in which they examined the neural correlates of anticipation vs. outcome and the choices from different decks in the IGT. In the anticipation phase, activation was primarily seen in the thalamus, and consistent with the results observed in the risk anticipation phase of Lawrence et al.’s (2009) study, activation was also seen in the insula. The outcome phase was associated with activation in the inferior parietal cortex, and choices from risky decks were associated with greater medial PFC activation.

**A Network-Oriented Approach to the IGT**

Lesion and neuroimaging studies have roughly identified those areas consistently activated during the IGT. Further insights can also be provided by observing the functional interactions that occur between these areas, and how they are modulated over time. This represents a more general trend in cognitive neuroscience towards an understanding of the brain as a distributed network of areas that interact to produce mental states and processes (Friston, 2011; Fuster, 2000; Rogers, Morgan, Newton, & Gore, 2007).

According to a network-oriented approach, a multitude of brain regions should be involved in any sort of cognitive process. Similarly, no one brain region is devoted to one cognitive process. A single brain region can be recruited by a variety of networks to
support a variety of cognitive processes. A recent meta-analysis of 1,469 fMRI experiments in eleven task domains (e.g., action inhibition, emotion, language, reasoning) found that on average, a cortical region is activated by nine different task domains (Anderson, 2010). Other researchers have argued for similar conclusions (Fuster, 2000; Klein, 2012; Lindquist & Barrett, 2012). For example, emotion has long been considered to consist in a series of brain regions each devoted to its own emotion faculty (e.g., amygdala and fear, insula and disgust, etc.). However, recent meta-analyses have failed to demonstrate any sort of consistent relationship between any one brain region and one emotion faculty (e.g., fear or disgust) (Lindquist, Wager, Kober, Bliss-Moreau, & Barrett, 2012). In reflection on the current evidence, Lindquist and Barrett argue that “to date, no consistent and specific one-to-one correspondences have been observed between physical measurements and anger, sadness, fear, disgust etc. Together, these findings point to a qualitatively different model of the mind” (Lindquist & Barrett, 2012).

Thus, despite the success of standard neuroimaging methods in localizing task-related activity, no explanation of a particular brain function is complete without considering connectivity between activated regions. Functional connectivity methods have already been applied successfully to decision-making tasks similar to the IGT (Cohen, Heller, & Ranganath, 2005; Hare, Camerer, & Rangel, 2009; Schoenbaum, Chiba, & Gallagher, 2000; Zeeb & Winstanley, 2013). In an event-related fMRI study of risky decision-making using seed-based functional connectivity analysis, functional connectivity between the ACC and OFC was significantly increased during high-risk decisions compared to low-risk decisions (Cohen et al., 2005). The authors speculate that this may indicate increased regulation by the ACC over reward-related regions of the
brain during decisions associated with high risk. Further, the ACC and OFC were found to have different connectivity profiles during both low and high-risk decisions (Cohen et al., 2005). The ACC was connected to a network of brain regions including the cingulate gyrus, striatum, parietal cortex (BA 39/angular gyrus), and dorsolateral PFC. The OFC also had an extensive network of functionally connected brain regions including the frontopolar PFC, dorsolateral PFC, dorsomedial PFC (including ACC), parietal cortex (BA 40/7), and temporal cortex (inferior temporal region). In a study of decision-making requiring participants to choose between food items, psychophysiological interaction (PPI) analysis identified task-related functional connectivity between the left DLPFC and inferior frontal gyrus (IFG/rostral BA 46) (Hare et al., 2009). This region is known to have anatomical connections with the OFC and a second PPI analysis identified task-related functional connectivity between this region and the OFC. The authors interpret this finding to suggest that the left DLPFC may “communicate” to the OFC through the IFG (Hare et al., 2009).

Thus, the lesion and neuroimaging studies to date suggest a more comprehensive account of neural activity, and its associated functional connectivity, during IGT performance, as opposed to limiting an account of the task exclusively to the medial OFC (or vmPFC). The data available suggests that activation in, as well as communication between, the medial OFC, ACC, and DLPFC is associated with IGT performance. All of these brain areas and their associated processes come together in the support of decision-making behavior of the kind that is necessary for advantageous performance on the IGT. An interpretation of each area’s contribution to IGT performance can be found in Krawczyk’s (2002) comprehensive review of the processes in the prefrontal cortex.
responsible for decision-making. In his review, he splits the prefrontal cortex’s contribution to decision-making into three primary functions: a) emotional and reward processing, b) deliberation among options, and c) conflict monitoring and processing, corresponding to OFC, DLPFC, and ACC/frontopolar cortex function, respectively. These functions comprise a variety of cognitive processes, and according to Krawczyk, are all necessary for the selection of an option among several alternatives. As demonstrated in the lesion studies of Behara et al., the OFC is crucially important in the generation and maintenance of reward contingencies in the environment, as well as their adjustment in response to change (Windmann et al., 2006). Therefore, any decision involving rewards and punishments will likely activate the OFC. The DLPFC, consistent with its role in working memory, is responsible for the holding of several options in short-term memory, and the comparison of those options through relational processing (Prabhakaran, Smith, Desmond, Glover, & Gabrieli, 1997). The OFC supports this process by the subjective “tagging” of certain decision options with reward-related information, available to the individual through “gut feelings” or emotional states (Bechara et al., 1994); thus, the decision between alternative options is made considerably more efficient. This conclusion is supported by observations of patients with OFC damage taking long amounts of deliberation time to decide, even for decisions of negligible importance (e.g., small purchases) (Eslinger & Damasio, 1985). In general, the ACC seems to be implicated in conflict monitoring (Botvinick, Braver, Barch, Carter, & Cohen, 2001). This area is likely to be crucial for the detection of conflict among multiple, ambiguous options, as well as the evaluation of those conflicting options (Holroyd, Nieuwenhuis, Mars, & Coles, 2004; Krawczyk, 2002).
Consider a rather simplistic description of how these processes may operate in the context of a single trial during the IGT: at the onset of a trial, the ACC operates to identify the conflicting response options available to the participant (Decks A, B, C, D) and possibly cues the prefrontal regions (the OFC and DLPFC) a decision needs to be made. The DLPFC acts to hold the four deck options in short-term memory, and evaluates them based off explicit and implicit rules (e.g., “gain as much money as possible” & “choose cards which provide the most money”). The OFC makes this process efficient by the activation of reward contingency representations, established from previous experience with other trials, that subconsciously or consciously bias decision-making towards the decks associated with advantageous decision-making (decks C & D). After a card selection is made, the amygdala and striatum generate the emotional response (positive or negative) in reaction to the monetary gain or loss. No doubt, this is a deliberately simplified account of the processes and their many interactions that make up the decision-making process. This description is intended as a general sketch of how these areas might come together to support the behavior associated with the IGT in healthy participants.

**Graph-Theoretical Analysis of the IGT**

*Problems with traditional neuroimaging methods applied to the IGT*

The lesion and neuroimaging studies of the IGT to date seem to implicate the medial OFC, ACC, and DLPFC in IGT performance. However, despite the identification of these areas across multiple studies, a comparison between any two lesion or neuroimaging studies rarely results in a consistent map of task-related activations between the two studies. In regards to neuroimaging data, this can be for several reasons.
First, there is the problem of spatial normalization as a preprocessing step in most neuroimaging studies. Group analysis requires neuroimaging data collected from each individual to be co-registered to a standard brain space for analysis. As noted in the study of language processes, spatial normalization to a standard brain space can obscure the localization of language-specific brain areas because of the often large amount of anatomic variability between participants (Fedorenko & Kanwisher, 2009). Another cause of variability in task-related localizations between any two studies is experimental design. For example, subtle changes in task instructions or the order of conditions between two studies can lead to the use of different behavioral strategies in the task, and as a result, a different activation profile between the two studies.

Another experimental design-related problem may be the choice of baseline as a comparison condition in standard neuroimaging studies. The choice of baseline is crucial because task-related activations are defined as a statistically significant increase in signal from the measured signal in the baseline condition. Therefore, differences in the baseline/comparison condition between two studies using identical tasks can result in different maps of task-related activations. This is particularly problematic for studies using complex tasks such as the IGT (Gusnard, Raichle, & Raichle, 2001). In such tasks, the identification of what aspects of the task to match in the baseline or control condition is not straightforward. For example, most attempts to create a baseline for the IGT have matched the sensorimotor aspects of the task (Ernst et al., 2002; Rogers et al., 1999). However, studies differ in what sensorimotor aspects are matched in the comparison condition. For example, in some studies the comparison condition consists of four decks equal in gains and losses (i.e. no advantageous or disadvantageous decks), and
participants are instructed to choose sequentially from the four decks in a fixed order (e.g., A-B-C-D-A-B-C-D; Bolla et al., 2003; Ernst et al., 2002). In other studies, the gain/losses associated with each deck are randomly chosen and displayed on each deck, and participants are asked to choose the card with the maximum gain or the minimum loss (Li et al., 2010). In addition, some studies do not change the gain/loss schedule associated with each deck in the task for the comparison condition, but simply instruct participants what deck to choose for each trial and then display the outcome (Tanabe et al., 2007). These subtle differences in the baseline/comparison condition between each study could explain the discrepancies in the localization of task-related activations across neuroimaging studies of the IGT. One solution to this problem would be the implementation of a standard baseline/comparison condition across studies of the IGT. However, the identification of what that sort of baseline is needed is difficult given the complexity of the task, and is bound to differ between researchers with diverse theoretical backgrounds.

Even if a standardized baseline/comparison condition could be decided upon, there is the more foundational issue concerning the conceptual justification of the methods of standard neuroimaging studies applied the IGT. The neuroimaging studies of the IGT cited above rely on a paradigm known as the *subtraction paradigm* in the identification of task-related activations in the brain. The subtraction paradigm refers to an assumption common to most fMRI and PET studies that the identification of task-related activation can be done by contrasting two conditions (typically a task condition and a baseline/comparison condition) that differ in a single separable cognitive component. The activations observed after contrasting the two conditions are then
identified with the cognitive component that differed between the two conditions (e.g., risky decision-making). The subtraction paradigm operates on the assumption of pure insertion (Friston et al., 1996). Pure insertion refers to the assumption that an isolated cognitive process produces an added activation in the brain regardless of the cognitive context in which it occurs. The subtraction paradigm requires that the addition of a new cognitive process to the operation of preexisting cognitive processes (i.e., baseline) produces no change in those processes. There is good reason to believe that while such an assumption may be true at the level of cognitive theory, it is not true in at least some cases of its physiological implementation (Friston et al., 1996; Sartori & Umiltà, 2000). This is especially true for studies of the IGT, which involves the addition of the cognitive process of “risky decision-making” to the baseline/comparison condition. Further, most attempted studies of the IGT may not attain the requirements of a valid subtraction-based study. One requirement of the subtraction paradigm is that the contrasting conditions differ in only one separable cognitive component, so that the observed activation can be identified with that added component. However, studies to date have only used a sensorimotor control condition. This fails to account for a plethora of processes that consist in the addition of a “decision-making” component to the sensorimotor control condition: judgments of probabilities, processing of rewards and punishments, and maintaining previous outcomes in working memory. Therefore, the contrast may not adequately localize the areas of the brain devoted to each or many of these processes.

Using Graph-theoretical methods as an alternative to standard subtraction methods

This study attempts to use recently developed methods in graph-theoretical modeling of functional connectivity (Steen, Hayasaka, Joyce, & Laurienti, 2011) to
overcome the limitations of a baseline comparison. The value of this new technique is
twofold: a) it localizes areas of interest without comparison to a baseline condition (i.e.
rejection of the subtraction paradigm), and b) areas of interest are defined from a
connectivity perspective, rather than from the perspective of task-related activation. It is
predicted that this graph-theoretical technique will successfully localize brain areas of
functional significance in the IGT (e.g., ACC, DLPFC, & medial OFC), and do so
without reliance on subtraction from a baseline condition.

Graph-theory applied to neuroimaging data involves representing the brain as a
complex network of interconnected components. The network is defined by a simple
structure, consisting of nodes (vertices) and links (edges) between them. More precisely,
networks are mathematical graphs representing a set of nodes linked by k connections or
edges (Guye et al., 2010). This definition, derived from graph theory approaches in
mathematics, allows for the specification of parameters that quantify the network (for a
comprehensive list of measures, see Rubinov & Sporns, 2010). Nodes can be a brain
area of any size (from a voxel to larger structures defined by a brain atlas) and edges are
the temporal correlations in the blood-oxygen-level dependent (BOLD) between those
areas.

The goal of this study is to further develop and test a new method for localizing
function in the brain using the tools of graph-theory (Steen et al., 2011). This method
takes advantage of the consistency of community (i.e., modular) structure across time. In
networks derived from real world data, it is often observed that networks can be
partitioned into groups of nodes that are more interconnected among themselves than
with nodes outside those groups (Figure 1). Groups of nodes are called “communities” or
“modules,” and a network is partitioned into communities through the operation of community-detection algorithms. There are many such algorithms, each with advantages and disadvantages (for a more detailed treatment see (Newman, 2004)). Community-detection algorithms can be applied to networks derived from functional connectivity data. The application of a community detection algorithm partitions brain areas into groups or modules that tend to be functionally connected together. The method of functional localization used in this study identifies areas of the brain that are consistent in their community or modular structure across different blocks of the same task. First, networks are created from each block of the task (i.e., IGT) and a community-detection algorithm is applied to partition each network into groups of tightly interconnected brain areas. Second, a node’s consistent community structure is assessed using two methods: Node-Consistency and Scaled Inclusivity (SI). Traditionally, SI has been used as a between-subjects metric that measures modular consistency across different subjects (Moussa, Steen, Laurienti, & Hayasaka, 2012; Moussa et al., 2014) For the purposes of this study, SI is a within-subject metric that represents the overlap of nodes in modules across networks derived from different blocks of the same task, while penalizing for any disjunction between modules (Steen et al., 2011). Node-consistency or SI is calculated for each node in the network, and the value for each node represents the consistency of that node’s community structure across iterations of the same task. Third, a node-consistency or SI map of those nodes that remained consistent across task blocks is examined to identify their location in the brain.
Figure 1. Modularity example. A module refers to a group of nodes that are more interconnected among each other compared to outside the group. In this example, three modules are identified. An effective community-detection algorithm would presumably partition these nodes into three modules.

A between-subjects SI analysis has previously been applied successfully to the IGT (Moussa et al., 2014). As already mentioned, between-subjects SI detects the consistency in modular structure across subjects for the same task. In their study, Moussa et al. (2014) examined differences in network community structure between older and younger adults while they performed three blocks of the IGT. For the first block (dubbed the “exploratory phase”), consistent modular organization was observed in the visual cortex, sensorimotor cortices, and medial PFC (including ACC) to varying degrees across both young and older adults. For the third, and final, block of the IGT consistent modular organization was observed in the same regions across younger and older adults, but consistency was generally higher in these areas relative to the first block, or exploratory phase. However, no consistent community structure was observed in the OFC across both the younger and older adults in the “exploratory” first block, and consistent community structure in the OFC was only found across the younger adults group in the final blocks. The lack of consistent community structure in the OFC across subjects in both groups may be for two reasons. First, previous research suggests that the OFC is
involved in the representation of reward contingencies associated with each deck (Windmann et al., 2006); during the exploratory trial, reward contingencies have yet to be established, and the function of the OFC is minimal or absent. Thus, it is not surprising consistent community structure was not found across subjects in the IGT for either group. Second, another possibility for the lack of consistency in the OFC is large between-subject differences in modular organization. A diverse sample of participants may have large between-subject variability in the modular organization of their networks. The within-subject approach advanced in this study assesses modular organization across iterations of the same task (e.g., IGT) for each participant, eliminating any between-subject variability.

A similar method to the within-subjects SI analysis (labeled the Node-Consistency Method) has previously been applied to a study involving a comparison between rest and a 2-back working-memory task (Dagenbach, Rzucidlo, Laurienti, & Lyday, 2014). This method identifies modular consistency at a node level by examining the change in its modular neighbors from one block to the next. A given node is classified as changing modules from block 1 to block 2 if over 50% of its co-module nodes change from block 1 to block 2. When this method was applied to within-subject comparisons across rest and a 2-back working-memory task, consistent modular structure was found in brain areas commonly implicated in the resting state (i.e., default-mode) and working memory, respectively. When applied to networks across separate 2-back tasks, consistent nodes were located predominantly in the DLPFC, an area implicated in working memory (Krawczyk, 2002), and commonly activated in working-memory tasks. When applied to networks across resting states, consistent nodes were located
predominantly in areas that form the default-mode network. Most importantly, these areas were identified without the use of the subtraction paradigm. In other words, these areas were not identified by comparing activation in a task state to a baseline task. This method functionally localizes areas of the brain by the identification of areas with consistent modular structure across task sessions, rather than a comparison to baseline.

Importantly, both methods for localizing function use graph-theory techniques to identify important task-related areas without the assumptions of the subtraction paradigm. A network approach emphasizes the connections/interactions of a brain region with other brain regions. While the activation of a region during a task may be informative, its functional interactions also play a crucial role in the cognitive process. This method assumes that those brain regions consistently connected to the same group of other brain regions across multiple trials of a task represent a functional “core” essential to the relevant cognitive process. The reasoning is as follows: across multiple iterations of the same task, non-task-related functional connections will undoubtedly shift around across those iterations, causing changes in module membership. By examining those nodes with consistent modular overlap across iterations of the same task, as measured by SI, or by examining co-module membership for each node across iterations of the same task (Dagenbach et al., 2014), nodes with consistent connectivity structure across time can be identified. It is assumed that these consistent nodes represent a functional sub-network essential to performance for that task. In other words, both methods localize important regions of functional interaction, rather than localizing activation.

It is predicted that regions of the medial OFC, ACC, and DLPFC will be identified as having the most consistent connectivity patterns across multiple blocks of
the IGT, and thus, represent an important functional “core” for decision-making behavior on the IGT. Both techniques for examining modular consistency will be applied to examine similarities and differences in their performance. It is predicted that the SI approach will more accurately localize areas of task-related functional significance as compared to the module-membership approach. The SI approach allows for a continuous measure of modular consistency (as described in Material and Methods), rather than a binary cutoff of 50%, or other possible cutoffs, to define modular change. As modules will always vary slightly from one block to the next, a continuous measure of modularity consistency is expected to capture more subtle changes in modular organization from trial to trial.

For comparison, both techniques will also be applied to multiple within-subject blocks of a resting-state with a fixation cross and a simple spatial-orienting task. These two tasks were included in the experimental design because previous literature has established that these tasks are supported by different task-related brain networks than the IGT. While differences are predicted, a certain degree of overlap in the networks associated with each task is expected as well. For example, the medial OFC is often considered to be a part of the DMN (Uddin, Kelly, Biswal, Castellanos, & Milham, 2009), as well as serving a crucial function in the IGT. In addition, the spatial-orienting task and IGT share certain task components in common. In particular, they both require the attention to external cues and sensorimotor responses. However, satisfactory performance of both methods should differentiate consistent modular organization between the three tasks. Differences in consistent modular organization between the three tasks will be tested using a recently developed permutation test for assessing group

Coherent activity in a set of brain areas known as the default-mode network (e.g. medial PFC, superior temporal gyrus, inferior parietal cortex, and precuneus) is commonly observed while participants are at rest (typically while fixating on a cross) and not performing any task (Buckner, Andrews-Hanna, & Schacter, 2008). The default-mode network (DMN) is thought to correspond to inwardly-directed thought (i.e. introspection) or self-referential thought, and is negatively correlated with tasks that require goal-directed activity. In addition to the DMN, highly coherent fluctuations of activation in in the visual and sensorimotor cortices have also been observed in the resting-state. In fact, a previous study of between-subject consistency of community structure found that nodes in the visual cortex exhibited the highest consistency of any brain area (Moussa et al., 2012). Therefore, it is predicted that consistency of modular organization will be the strongest in the DMN, visual cortex, and sensorimotor cortex during the resting-state condition.

Activation in the dorsal attention network (e.g., frontal eye fields, superior parietal cortex, and extrastriate cortex), is commonly implicated in tasks that require exogenous orienting to spatial cues, such as the spatial-orienting task used in this study (Corbetta, Kincade, & Shulman, 2002; Yeo et al., 2011). The dorsal attention network is often contrasted with the ventral attention network, another visuospatial network that is involved in detecting unexpected stimuli in the environment and triggering shifts in attention (Corbetta et al., 2002). The importance of the dorsal attention network to exogenous orienting to behaviorally relevant stimuli is demonstrated most strikingly by
its dysfunction in patients with spatial neglect, a disorder in which patients are unable to
orient and respond to one side of space (Ptak & Schnider, 2010). Therefore, it is
predicted that consistency of modular organization will be the strongest in areas of the
dorsal attention network, particularly the frontal eye fields, superior parietal cortex, and
extrastriate cortex during the spatial-orienting task. Given the divergence between the
areas implicated in each task (IGT, rest, and spatial-orienting), it is predicted that both
methods will accurately differentiate between the brain networks associated with each.
MATERIALS AND METHODS

Participants

Participants were recruited from the Wake Forest University Introductory Psychology research participant pool and the community. Participants from the research participant pool received course credit, and community members were given monetary compensation in return for their participation. Data was collected from nine young (8 Male, M\text{age} = 19.3, range: 18-21) healthy adults. Participants were provided with a Safety Screening Form and Medical History Questionnaire to complete prior to the experiment. In addition, participants were screened for corrected visual acuity, small to moderate hearing loss, and right-handedness prior to the experiment. Participants were provided with an additional Safety Screening Form upon the day of their fMRI scan. Any participants who had implants, devices, or objects that would interfere with the fMRI procedure were excluded from the experiment.

Materials

In this study, participants performed three alternating tasks in the following order: a resting-state scan, the Iowa Gambling Task, and the spatial-orienting task. The resting-state block simply consisted of the participant laying quietly in the scanner and staring at a fixation cross. Participants were instructed to stay awake and let their thoughts wander during the duration of the scan.

During the IGT task, participants start with $0 and are told that the game consists of a long series of card selections from four decks of cards (decks 1, 2, 3 & 4). After selection of each card, the participant receives a certain amount of money that varies with
each deck. Selection from decks 1 and 3 yield a reward of $150, while selection from decks 2 and 4 yield a reward of $200. After turning some cards, the subjects may incur a penalty. The penalty amount varies with each deck. Penalty amounts are higher in the high-paying decks (2 & 4), and lower in the low-paying decks (1 and 3). Because of the higher penalty cost of the higher-paying decks, the long-term yield is a net gain for the low-paying decks, and a net loss for the high-paying decks. The decks also vary in the frequency of penalties. Decks 1 and 2 have less frequent penalties, while decks 3 and 4 have more frequent penalties. Decks 2 and 4 are referred to as “disadvantageous” because they incur a net loss for the participant, and Decks 1 and 3 are referred to as “advantageous” because they incur a net gain for the participant. Because participants were in the fMRI scanner while they were performing this task, a computerized version of the IGT was used (Appendix 1). In the non-computerized task, participants select cards from the paper decks by turning over the cards they choose. In the computerized task, participants indicated their card selection (decks will be represented on the monitor) by pressing one of four buttons on a response box that indicated their answers while in the scanner. For each trial, the participant was given two seconds to select a card, and after each response, a screen appeared displaying whether the response resulted in a win or loss, the win/loss amount, and their total earnings (Appendix 1).

The spatial-orienting task consisted of a display of four potential spatial positions in place of the deck of cards (Appendix 1). Each location is labeled with a number (1-4). For each trial, a small circle appears in one of the four locations and requires a corresponding response, consisting of pressing the corresponding button on a response box (1-4). Participant were given two seconds to respond in each trial, and after each
response, a screen appeared displaying whether it was a correct or incorrect response. Responses will be recorded using Eprime 2.0 software.

Imaging Design

Scanner Experiment

Prior to the fMRI scan, participants viewed a description of the experiment on a PowerPoint slideshow. Participants were provided with fMRI compatible goggles, ear plugs, and a hand-held button response box. An anatomical brain scan was collected for each participant (5 mins) at the beginning of the scan. Subsequently, participants alternated between a resting state during which they looked at a fixation cross without moving (4 min), the IGT (4 min), and the spatial orienting task (4 min). The participants completed four resting blocks, four IGT blocks, and four spatial-orienting blocks. In addition, a perfusion sequence was collected at the end of the experimental design, during which participants rested quietly with their eyes closed for 5 minutes (this scan was not included in the analyses). The total length of time each participant was in the scanner was 58 minutes.

Behavioral Data

The IGT data will be assessed for each session in terms of the difference between total advantageous and total disadvantageous selections (Bechara et al., 1994, 1998, 1999). Total advantageous selections is defined as the total number of selections from decks 1 and 3, and total disadvantageous selections is defined as the total number of selections from decks 2 and 4. “Advantageous” performance is defined as greater selections from advantageous decks relative to disadvantageous decks.
“Disadvantageous” performance is defined as greater selections from disadvantageous decks relative to advantageous decks.

**MR Image Acquisition**

All imaging was performed on a Siemens SKYRA 3T MRI scanner using a GE eight channel neurovascular head coil. The protocol parameters for the anatomical scan were the following: phase/frequency = 256/256; 156 contiguous slices, 1.0 mm thick; in-plane resolution of 0.938 mm × 0.938 mm; TE = 4.74 ms; TR = 4.68 ms; T1 = 600 ms. Whole-brain gradient echo echo-planar imaging (EPI) was used to detect Blood-oxygen-level-dependence (BOLD) fMRI signal changes during each task. The echo planar imaging contained the following parameters: 120 volumes with 35 contiguous slices per volume; slice thickness 5.0 mm; in-plane resolution of 3.5 mm*3.5 mm; TR/TE = 2000/25 ms. The voxels of each anatomical image were identified by using the AAL (Automatic Anatomical Labeling) atlas. All anatomical and functional image processing was be done using SPM 8, Statistical Parametric Mapping (Friston et al., 1994). Further processing for network statistics were completed using scripts performed on MATLAB.

**Functional Image Pre-processing**

Functional images were corrected for head motion by realigning them to the first image volume using “rigid body” transforms. Next, the EPI image for each participant was co-registered, normalized to the standard stereotactic MNI (Montreal Neurological Institute) space, and resliced to 4.0 mm*4.0mm*4.00mm. The images were not smoothed to avoid spurious increases in local connectivity (Hayaskaka & Laurienti, 2010). The time courses were extracted for each gray matter voxel based on the Automated Anatomical Labeling atlas (ALS) and band-pass filtered to remove signals outside the
range of 0.009-0.08Hz (Tzourio-Mazoyer et al., 2002). Global values for the whole brain, white matter, and cerebrospinal fluid were regressed from the time series to remove spurious signals associated with physiological noise such as heart beat and respirations.

**Network Construction and Analysis**

Pre-processed functional data were masked such that only gray matter voxels were included. This was achieved by first summing the gray matter, white matter and cerebrospinal segment maps to generate a binary whole-brain mask. This mask was then intersected with gray matter areas specified by the AAL atlas. Then the white matter segment was subtracted (thresholded at 99%) to remove subject-specific white matter edges that may coincide with the AAL gray matter atlas. Networks are represented as graphs consisting of nodes and edges. Each voxel represents a node, and a network is constructed through a correlation matrix containing Pearson correlation coefficients between each voxel’s time series (Figure 1). The correlations matrices were thresholded using the following equation: $N = K^S$, where $S$ is the equivalent of the shortest path length in a random network, $N =$ number of nodes, and $K =$ degree. The correlation coefficient that satisfied $N = K^S$ was used as a lower bound when creating binary adjacency matrices (Hayasaka & Laurienti, 2010). This thresholding procedure ensures that the connection densities are consistent across conditions and individual subjects in the event that there is a change in the number of network nodes. Network properties were measured at various $S$ values (2.5; 3.0; 3.5) in order to determine whether those properties are independent of threshold effects. Those coefficients in the correlation matrix above the threshold received a 1 (i.e. representing an edge between those voxel pairs), and those coefficients below received a 0 (i.e no connection). A network was be
created for each block (Rest 1, IGT 1, Spatial-Orienting 1, Rest 2, IGT 2, Spatial-orienting 2, etc.), resulting in 12 networks for each participant and 108 networks overall (N=9).

Figure 2. Construction of a network. Adapted from (Telesford et al., 2011). Functional time series are correlated and thresholded to create an adjacency matrix, representing connections between every possible pair of voxels. This adjacency matrix is mapped onto a brain space for analysis.

Defining Modular Consistency across Trials

In order to calculate the consistency of modular organization across time, the networks were first partitioned into modules (i.e. communities) using the Louvain method (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). The Louvain method is a modularity optimization algorithm that operates by identifying, through an iterative process, partitions of the network with high modularity. Modularity is defined as the quality of a particular partition of the network into modules (Newman & Girvan, 2004). Computationally, modularity (often referred to as $Q$) reflects the number of links between nodes within a module minus what would be expected given a random distribution of links between all nodes regardless of modules. This value varies from 0 to 1, with a higher value reflecting stronger community structure.
**Node-Consistency Method**

To measure the consistency of modular organization across two blocks of the same task (e.g. Rest 1 vs. Rest 2), the nodes constituting each module were compared across both blocks. Modular consistency is determined for each node by considering if 50% of the nodes in its module changes between the first and the second block (Dagenbach et al., 2014). For any node $X$, the procedure is as follows: a) for the network constructed from block 1, the set of nodes sharing a module with node $X$ is identified (after application of the community-detection algorithm), labeled node set $A$; b) for the network constructed from block 2, the set of nodes sharing a module with node $X$ is identified, labeled node set $B$; and c) the node is assessed as to whether it has changed modules, such that if the node set $B$ contains over 50% of the nodes contained in set $A$, then node $X$ receives a value of 1, if not, the node receives a value of 0. This results in a comparison map of nodes in the brain that remained consistent from block 1 to block 2. For each task (i.e., rest, IGT, & spatial-orienting), this process is repeated for every possible comparison between all four blocks of the task, resulting in six comparisons for each task ($\frac{4!}{(4!(4-2)!)i} = 6$). All six comparison maps from each task were summed to form a subject-level consistency-map for each participant. The subject-level consistency maps represent the summed consistency across the six comparisons for each node in the network.

**Scaled Inclusivity Method**

Scaled Inclusivity (SI) measures the consistency of every node’s modular classification across networks (Steen et al., 2011). The SI is a similarity index function, known as the Jaccard similarity index, which measures the overlap of modules between a
reference partition (e.g., Rest 1) and another partition (e.g., Rest 2), while penalizing for disjunction of modules. The SI for any node \( X \) (denoted \( SI_X \)), is calculated as

\[
SI_X = \frac{|M_A \cap M_B|}{|M_A|} \frac{|M_A \cap M_B|}{|M_B|}
\]

where \( M_A \) and \( M_B \) denotes sets of nodes in modules A and B, respectively, and \(||\) denotes the cardinality of the set (Moussa et al., 2012; Steen et al., 2011). Thus, how well a node is classified in the reference partition is scaled based on how well its modules in the reference partition and the other partition overlap. \( SI_X \) varies between 0 and 1. Perfect overlap between two modules (*M* \( A \) & *M* \( B \)), or an identical set of nodes in both modules, results in an \( SI_X \) of 1. Any disjunction between the two modules results in an \( SI_X \) less than 1. This process is repeated for all modules in the reference partition, until all node SI’s have been calculated. This results in an SI image of overlapping nodes between the referent partition’s modules and the other partition’s modules, and their corresponding SI values. A weighted SI image is calculated from SI images between the reference partition (e.g. Rest 1) and all other partitions (e.g. Rest 2, Rest 3, & Rest 4), resulting in a task block-specific SI image. In order to avoid bias inherent to an SI image that is based on a single reference partition (e.g., Rest 1) (Steen et al., 2011), every other task block is used as a reference partition (e.g., Rest 1, Rest 2, & Rest 3) and task block-specific SI images are calculated for each block. A global SI subject-level image for each task (e.g., rest, IGT, & spatial-orienting) is calculated by averaging together the SI values from each task block-specific SI image (e.g., Rest 1, Rest 2, Rest 3, & Rest 4). The global SI image for the rest, IGT, and spatial-orienting tasks for each participant represents the similarity
in location, size and prevalence of a module across blocks of that particular task (Moussa et al., 2014).

**Permutation Test for Differences between Conditions**

In order to assess the ability for both methods to localize different brain networks associated with each task, this study uses a recently developed permutation testing framework (Simpson et al., 2013) to test for differences in the consistent modular organization between the networks constructed from the three tasks (i.e., rest, IGT, and spatial-orienting). A permutation test calculates the distribution of the test statistic under the null hypothesis “empirically” by permuting or rearranging the group labels of the observed scores. While permutation tests are not assumption free (Simpson et al., 2013), they require no knowledge of how the test statistic is distributed under the null hypothesis, an advantage when the *a priori* determination of the test statistic’s null distribution is difficult, which is the case when testing for significant differences in network organization.

**Similarity/Dissimilarity of SI Maps between Tasks**

The permutation testing framework for this study assesses the degree of similarity/dissimilarity in the consistent modular organization between two groups of subject-level SI or node-consistency images (e.g., Rest vs. IGT). The metric used to calculate the similarity between both SI images in this study is analogous to the *Jaccard similarity index* used above for the calculation of a node’s SI (Steen et al., 2011). The metric used is a distance function known as the *Jacardized Czekanowski similarity index* (Schubert & Telcs, 2013). According to the *Jacardized Czekanowski similarity index*
(denoted \(JC\)), similarity between any two subject-level SI images (A & B) is calculated as follows:

\[
JC_{A,B} = \frac{\sum_{i}^{n} \min(SI_{i}^{A}, SI_{i}^{B})}{\sum_{i}^{n} \max(SI_{i}^{A}, SI_{i}^{B})}
\]

Where \(SI_{i}^{A}\) and \(SI_{i}^{B}\) are the SI values for node \(i\) in SI image A and SI image B, respectively, and \(n\) is the total number of nodes; \(\min(SI_{i}^{A}, SI_{i}^{B})\) and \(\max(SI_{i}^{A}, SI_{i}^{B})\) refer to the minimum and maximum value between the SI values for node \(i\) in image A and image B, respectively. \(JC_{A,B}\) varies from 0 to 1, where 1 represents an identical distribution of SI values between the two SI images.

If the two groups of subject-level SI or node-consistency images are sufficiently different in the spatial localization of its consistent modular structure, it is expected that the calculated \(JC\) will be, on average, smaller between the groups of images, compared to the calculated \(JC\) within the same group of images. The test statistic used for this study, known as the Jaccard ratio (\(R_{JC}\)) tests for the significance of this difference (Simpson et al., 2013):

\[
R_{JC} = \frac{M_{JC}(Within)}{M_{JC}(Between)}
\]

where \(M_{JC}\) denotes the mean \(JC\). An \(R_{JC} > 1\) indicates greater within-group similarity compared to between groups, signifying the groups differ significantly in the consistency of their modular organization. An \(R_{JC} \approx 1\) indicates that there is no difference in the consistency of the modular organization between the two groups.

*Statistical Test through Permutations*
Because of the within-subject design of the study, a paired two sample permutation test was used. Thus, to construct the null distribution of no differences in consistent modular organization between two groups of SI or node-consistency images, the group labels are flipped within each participant and $R_{JC}$ is recalculated between the two groups. This process is repeated for all possible permutations and results in a distribution of $R_{JC}^{Perm}$ values, representing the null distribution of $R_{JC}$. By comparing $R_{JC}$ to this constructed distribution, the p-value for the group difference can be calculated.

**ROI Analyses**

In addition to whole-brain analyses, permutation tests were also conducted to test for differences in the consistent modular organization within a priori defined regions of interest. Based on previous work (Bechara et al., 1994; Clark, Cools, & Robbins, 2004; Cohen, Heller, & Ranganath, 2005; Fukui, Murai, Fukuyama, Hayashi, & Hanakawa, 2005; Lawrence, Jollant, O’Daly, Zelaya, & Phillips, 2009; Rogers et al., 1999; van den Bos, Houx, & Spruijt, 2006), the medial orbitofrontal cortex (medial OFC), anterior cingulate cortex (ACC), and dorsolateral prefrontal cortex (DLPFC) were areas of interest to test for more localized differences among the different task states. Masks for the medial OFC and ACC were created using the AAL atlas. The medial OFC ROI included the left and right medial orbital gyrus, and the ACC ROI included the left and right anterior cingulate gyrus. The DLPFC ROI was generated using a 10 mm sphere placed at $+/-43, 22, 34$ for the dorsolateral prefrontal cortex. The medial OFC ROI contained 150 voxels, the ACC ROI contained 349 voxels, and the DLPFC ROI contained 237 voxels.
RESULTS

Behavioral Performance

Figure 3 illustrates that, on average, participants made more selections from the good decks (1 & 3) compared to the bad decks (2 & 4) in all four blocks of the IGT (M1 ± SE = 10.33 ± 5.16, M2 ± SE = 21.44 ± 7.23, M3 ± SE = 19.67 ± 6.73, M4 ± SE = 25.56 ± 9.74). As can be seen in the standard error bars of the chart, variability in performance among the participants was high. A one-way repeated-measures ANOVA was conducted to test for differences in advantageous versus disadvantageous card selections among the four blocks of the IGT. The results indicated there were no significant difference among the four blocks of the IGT (F(3, 24) = 1.877, p = .160). When comparing advantageous versus disadvantageous card selections of the “exploratory” first phase of the experiment (IGT 1) to average selections in the later “performance” phase (IGT 2, IGT 3, IGT4), a paired-samples t-test revealed a marginally significant difference between the two phases of the experiment (M1 = 10.33; M234 = 21.15; t(8) = -2.162, p = .063). Figure 5 illustrates the time course of card selections for a sample successful participant during the exploratory first block of the IGT and the final block of the IGT. In the exploratory phase of the IGT the participant initially selects randomly from the disadvantageous and advantageous decks, but eventually switches to a preference for the advantageous decks, as can be seen the final block.
As expected, all participants were nearly perfect across all four blocks of the spatial-orienting task ($M_{\text{Accuracy}} = 99.6\%$). Response times were well below the two-second response time-limit ($M_{\text{RT} \pm \text{SD}} = 636.62 \pm 179.5$ ms).

Figure 3. **IGT block performance.** Net-positive advantageous selections across all four blocks of the IGT (error bars represent standard error).

Figure 4. **Selections of sample participant.** Deck selections across all 60 trials for Block 1 and Block 4 of the IGT for a sample participant. Initially, the participant chose randomly from all four decks, with a bias towards deck 2. By block 4, the participant’s preference is for the advantageous decks 1 and 3.
Localization of Function using Node-Consistency Method

One participant was removed from network analyses due to excessive motion, particular in the latter half of the experiment. Thus, the network analyses hereafter include 8 participants. As illustrated in Figure 5, change in modular structure was found to be widespread across two points in time, both between-task and within-task. In other words, the majority of nodes in each network shift module membership from one point in time to the next. Thus, in order to find those areas with consistent modular structure over time, node-consistency images of the three tasks (rest, IGT, and spatial-orienting) for each participant were created using the method described above (see ‘Methods and Materials’). Each image represents the consistency (based off the 50% criterion) of each node’s community structure across four iterations of that particular task. There were three subject-level images for each participant, corresponding to the three tasks. Values range from 0, representing no consistency across any of the six comparisons, to 6, representing consistency across all six comparisons of the four iterations. Node-consistency images across all three tasks ranged from 0 to 5.

Figure 5. **Modularity change in sample participant.** Change in node’s community structure (as defined by the 50% criterion) from block 1 of rest to block 1 of IGT and block 1 of rest to block 2 of rest in a sample participant (nodes that change are highlighted in red). Nearly all nodes change modules from rest to IGT, and a majority of nodes change modules across two blocks of rest.
Examination of subject-level images in the rest condition revealed highly consistent nodes scattered across the cortical surface with large clusters of consistency found in the visual and sensorimotor cortices across participant (see Figure 6 for a representative subject image in the rest condition). In order to determine consistency in modular structure across all participants for rest, subject-level maps were averaged together to form a group-level, or meta-consistency image (Figure 9). Meta-consistency images represent the average amount of consistency in community structure for each node (as defined by the 50% criterion) across all participants. It was expected that the meta-consistency image would give a slightly more precise localization of consistent modular organization, averaging out those nodes scattered across the cortical surface for each participant.

Figure 6. **Subject Node-consistency image for rest.** Subject-level node-consistency image for sample participant at rest, representing the nodes that remained consistent across four blocks of rest (values range from 0-6). Consistent nodes are scattered across the brain, but significant clusters of consistency are found in the visual and sensorimotor cortex, medial OFC, and thalamus.

Examination of the meta-consistency rest image revealed that nodes in the sensorimotor and visual cortex were, on average, the most consistent in modular structure
across four blocks of the resting condition. In addition, nodes within the insula (an area believed to be important in the modulation of activity in the DMN; Menon & Uddin, 2010) and thalamus exhibited a high average consistency. Inconsistent with predictions, low average consistency was found in areas of the DMN.

Subject-level images of the IGT showed high degree of variability in consistent modular organization across participants (see figure. 7 for sample subject image), therefore, subject-level images were averaged together to form a meta-consistency image. Examination of the IGT meta-consistency image revealed that highly consistent nodes were scattered throughout the cortex, with a significant cluster of consistency in the sensorimotor cortex (Figure 9). Inconsistent with predictions, low average consistency was found in a priori defined regions of interest, the medial OFC, ACC, and DLPFC.

Figure 7. **Subject Node-consistency image for IGT.** Subject-level node-consistency image for sample participant at rest, representing the nodes that remained consistent across four blocks of rest. Consistent nodes are scattered across the brain, but significant clusters of consistency are found in the sensorimotor cortex, visual cortex, cerebellum, and superior frontal gyrus.

Subject-level images of the spatial-orienting task also showed high degree of variability in consistent modular organization across participants (see figure. 8 for sample subject image), therefore, subject-level images were averaged together to form a meta-
consistency image. Examination of the spatial-orienting meta-consistency image revealed that highly consistent nodes were scattered throughout the cortex, with high degrees of consistency in the sensorimotor cortex, supplementary motor area, and thalamus (Figure 9). It was also observed that the spatial-orienting and IGT meta-consistency images were very similar in areas identified as having high consistency. Inconsistent with predictions, low average consistency was found in some areas predicted to be associated with exogenous attention orienting (e.g., superior parietal cortex and extrastriate cortex).

Figure 8. Subject Node-consistency image for spatial-orienting. Subject-level node-consistency image for sample participant at rest, representing the nodes that remained consistent across four blocks of rest (values range from 0-6). Consistent nodes are scattered across the brain, but significant clusters of consistency are found in the sensorimotor cortex, superior frontal gyrus, putamen, insula, and medial temporal lobe.
Figure 9. **Meta-consistency Images for Node-Consistency Method.** Group-level images for rest, IGT, and spatial-oriented derived from averaging subject-level images across participants. Note, the ring of “consistency” around the brain (red nodes surrounding image) was an edge artifact, due to the preprocessing of the images, and was ignored. The rest meta-consistency image revealed scattered consistency across the brain, but with significant clusters of consistency in the visual cortex, sensorimotor cortex, thalamus, and insula. The IGT meta-consistency image also revealed scattered consistency across the brain, with significant clusters of consistency in the sensorimotor cortex and thalamus. The spatial-orienting meta-consistency image also revealed scattered consistency across the brain, with significant clusters of consistency located predominantly in the sensorimotor cortex, supplementary motor area, and thalamus. Consistent nodes were found in the sensorimotor cortex across all three tasks.
**Functional Localization using Scaled Inclusivity Method**

In addition to the node-consistency method above, the Scaled Inclusivity (SI) method was also used to identify areas with consistent modular organization. SI images were created for each participant representing the overlap of each node’s community structure across four iterations of a particular task. There were three subject-level images for each participant, corresponding to the three tasks. SI values range from 0, representing no overlap among modules across the 4 iterations of the task, to 3, representing identical overlap among modules across the 4 iterations of the task. While an SI value of 3 is theoretically possible, most values are considerably lower than this maximum value due to disjunction of modules across iterations of the task (Moussa et al., 2012). SI images across all three tasks in this study ranged from 0 to 1.

Consistent with predictions, examination of subject-images in the resting condition revealed significant clusters of consistency in some components of the DMN for all participants (e.g., inferior parietal cortex, precuneus, & medial PFC; see figure 10 for representative subject). Due to inter-subject variability in the rest condition across SI images, meta-consistency images were created by averaging together all SI subject-images. Meta-consistency images represented the average amount of overlap of each node’s community structure across all participants. Examination of the meta-consistency image from the rest condition reveals that the SI method achieved a much more precise localization of consistent modular organization, with most consistent nodes located in large clusters of multiple nodes (Figure 13), rather than the more scattered localization observed in the node-consistency method. Consistent with predictions, the most consistent nodes across participants in the rest condition were located in the visual cortex.
Consistent nodes were also found in important components of the DMN, the precuneus, dorsal medial PFC, medial OFC, and inferior parietal cortex. Consistency was also observed in the sensorimotor cortex.

Figure 10. **Subject-level SI Image for Rest.** Subject-level SI image for sample participant at rest, representing the amount of overlap of each node’s community structure across four blocks of rest. Consistent community structure was observed mainly in DMN areas (precuneus, inferior parietal lobe, medial PFC), but consistent community structure was also observed in the middle temporal, visual, and frontopolar cortices.

Examination of the subject-images in the IGT condition revealed that consistency in the medial (sometimes lateral) OFC for all participants (see fig. 11 for representative subject). In addition, consistency was found in the DLPFC for most participants, but consistency was absent in the ACC for most participants. Unexpectedly, the meta-consistency image of the IGT revealed that consistency was found predominantly in the default mode network (DMN), including the medial OFC, dorsomedial PFC, inferior parietal cortex, and posterior cingulate/precuneus across all participants (Figure 13). Consistent with predictions, strong consistency was found in the DLPFC. Inconsistent with predictions, low average consistency was found in the ACC.
Figure 11. **Subject-level SI Image for the IGT.** Subject-level SI IGT image for sample participant, representing the overlap of each node’s community structure across four blocks of the IGT. Consistent community structure was observed in the left motor cortex, precuneus, inferior parietal cortex, medial OFC, dorsolateral prefrontal cortex, and insula.

Examination of the subject-images in the spatial-orienting condition revealed significant clusters of consistency in the superior parietal, supplemental motor area, and precuneus for most participants (Figure 12 for representative subject). Similar to the IGT, the meta-consistency images revealed significant clusters of consistency in the default mode network, including the medial OFC, the dorsomedial PFC, inferior parietal cortex, and precuneus (Figure 13). Similar to rest, strong consistency was also found in the visual cortex.

Figure 12. **Subject-level SI Image for Spatial-Orienting Task.** Subject-level SI spatial-orienting image for sample participant, representing the overlap of each node’s
community structure across four blocks of spatial-orienting. Consistent community structure was observed in the visual cortices, precuneus, inferior parietal cortex, and supplemental motor area (including frontal eye fields).

Figure 13. **Meta-consistency Images for Scaled Inclusivity Method.** Group-level SI images for rest, IGT, and spatial-oriented derived from averaging subject-level images across participants. The meta-consistency image of rest revealed a cluster of highly consistent nodes in the visual cortex, as well as areas of the DMN, such as the precuneus/posterior cingulate cortex, dorsal medial PFC, medial OFC, and inferior
parietal cortex. The meta-consistency IGT image revealed consistency in the DMN as well, including the medial OFC, dorsal medial PFC, posterior cingulate, and left inferior parietal cortex. The meta-consistency spatial-orienting image revealed consistency in the visual cortex, along with areas of the DMN, including the precuneus/posterior cingulate cortex, medial PFC, and inferior parietal cortex.

**Tests for Differences between Tasks**

The paired two-sample permutation testing framework described above (see ‘Methods and Materials’) was used to test for differences in the consistent modular organization between the three tasks. In this testing framework, each SI or node-consistency subject-image was treated as one subject, and compared across task states (e.g., Rest vs IGT). Three tests were conducted to test for differences between rest, IGT, and spatial-orienting images for both the node-consistency and scaled-inclusivity method. There were $2^8 = 256$ possible permutations for each test.

Inconsistent with predictions, the node-consistency method failed to differentiate between the three different task states (Appendix 2). The permutation tests of Rest and IGT, Rest and spatial-orienting, and IGT and spatial-orienting node-consistency images found that the three conditions were not significantly different in consistent modular organization ($R_{JC} = 1.289, p = 0.5904$; $R_{JC} = 1.262, p = 0.762$; $R_{JC} = 1.283, p = 0.5588$, respectively). In other words, for the node-consistency images, there were no significant differences in a node’s consistent community structure between each task.

Consistent with predictions, the SI method differentiated between all three task states (Appendix 3). The permutation tests of Rest and IGT, Rest and spatial-orienting, and IGT and spatial orienting SI images found that the three conditions were significantly different in consistent modular organization ($R_{JC} = 1.19, p = 0.0038$; $R_{JC} = 1.184, p = 0.0117$; $R_{JC} = 1.265, p = 1.26$, respectively). In other words, for the SI images, there
were significant differences in a node’s consistent community structure between each task.

In order to further examine differences among the SI images between the IGT and the two other tasks, permutation tests were conducted in a priori defined ROI’s: Medial OFC, ACC, and DLPFC (Appendix 4). Consistent with predictions, permutation tests of nodes within the medial OFC found significant differences in consistent modular organization between the IGT and both rest and spatial-orienting ($R_{JC} = 22.78, p = 0.004$; $R_{JC} = 20.15, p = 0.0114$, respectively). Consistent with predictions, permutations tests of nodes within the ACC found significant differences in consistent modular organization between the IGT and both rest and spatial-orienting ($R_{JC} = 16.98, p = 0.007$; $R_{JC} = 14.67, p = 0.008$). Consistent with predictions, permutation tests of nodes within the DLPFC found significant differences in consistent modular organization between the IGT and both rest and spatial-orienting ($R_{JC} = 30.92, p = 0.008$; $R_{JC} = 26.91, p = 0.0078$, respectively).
DISCUSSION

The goal of this study was to further develop and test two graph-theoretical methods for identifying within-subject consistent community structure across iterations of the same task, without a comparison to some baseline or control condition. In particular, both methods were assessed in their ability to differentiate task-related brain networks specific to three different tasks: the Iowa Gambling Task, a resting-state, and a spatial-orienting task involving shifts of attentions to an external cue.

Behavioral Performance on the IGT

Inconsistent with previous studies of the IGT (Bechara et al., 1994, 2000; Ernst et al., 2002; Hare et al., 2009; Lawrence et al., 2009), there were no significant differences in performance among the four blocks of the IGT. A marginally significant learning effect was found between the exploratory first phase of the task, compared to the later performance phases. In the first block of the IGT, participants chose, on average, a net-positive number of advantageous selections. This suggests that learning effects were already present in the first phase of the task. The number of selections in each block was large (n = 60), giving participants ample time to discover the reward contingencies before the end of the first block. In fact, previous studies indicate 30 card selections are enough trials for the reward contingencies associated with each deck to be discovered by participants (Maia & McClelland, 2004). Nonetheless, the validity of the network analyses in this study is not contingent on the observation of a learning effect across the four blocks of the IGT. The purported goal of this study is to isolate regions of the brain associated with performance on the IGT, rather than successful performance on the IGT.
Modularity Change across The Same Task And Between Tasks

Figure 6 illustrates that nodal change in community structure is widespread between two different tasks, as well as between two blocks of the same task (to a lesser extent). This observation suggests that functional groupings of brain areas are not static, but highly fluid over time, even across the same task. This underlines the importance of the newly developing field of dynamic functional connectivity that studies changes in functional connectivity over time (Honey, Kötter, Breakspear, & Sporns, 2007; Kelly, Uddin, Biswal, Castellanos, & Milham, 2008). The within-subject design of this study makes this a potentially fruitful data set for future application of dynamical functional connectivity methods, such as sliding window analysis (Kelly et al., 2008). However, the goal of this study was to assess consistency across time in community structure, and therefore, required the identification of areas that remained static in their functional groupings across time.

Node-Consistency Method for Functional Localization

The results of this study indicate that the node-consistency method, used in a previous study (Dagenbach et al., 2014) to localize areas of functional significance associated with working-memory and rest, may need further refinement as a tool for functional localization. The node-consistency images revealed scattered consistency across the cortex, and subcortical regions (Figure 9). Consistent with these observations, permutation tests revealed non-significant differences among the three tasks in consistent community structure.

However, significant clusters of nodes were found to be consistent in certain brain areas. For example, as predicted, the visual cortex was found to have a high degree of
consistency in the rest condition. This finding was common to both the node-consistency and SI images. As mentioned above, a previous study has found the visual cortex to be the most consistent area of community structure across participants during resting-state, while participant’s eyes are open (Moussa et al., 2014). One possible reason for this finding is that retinal input in the resting-state (with a fixation cross in the center of the display) is constant across the entire duration of the scan, leading to strong synchronicity of BOLD fluctuations in the visual cortex. But findings of another resting-state functional connectivity study found strong synchronicity in the visual cortex when participants were placed in complete darkness, without any retinal input (Nir, Hasson, Levy, Yeshurun, & Malach, 2006). Thus, strong synchronicity in the visual cortex may only be disrupted by stimulus-driven changes in retinal input, such as in the IGT and the spatial-orienting task.

A high-degree of consistency was also observed in the sensorimotor cortex across all three tasks (Figure 8). This is expected, given a previous study has shown this area of the brain to have one of the most consistent community structures at rest (behind the visual cortex) across a large cohort of young to middle-age individuals (Moussa et al., 2012). In fact, the motor cortex was one of the first regions observed to exhibit synchronicity in the BOLD signal between its constituent areas (Biswal, Zerrin Yetkin, Haughton, & Hyde, 1995). The results suggest that this area may also be highly consistent during task-states as well. This may be explained by the fact that both the IGT and spatial-orienting task involved sensory and motor components.

Overall, the node-consistency images were less clear and precise than expected. Though there were groups of consistent nodes localized in the areas mentioned above, a
large amount of consistent nodes were scattered across the cortex. In addition, the node-
consistency images revealed low average consistency in many areas that were predicted
to be consistent. One possible explanation for the low consistency observed in these
regions of interests, was the low average overlap in the modules across networsk, as seen
in the SI images. SI images in this study ranged from 0 to 1, out of a possible maximum
of 4, which represents a relatively low average overlap in modules across networks.
While consistency was found in regions outside of the visual and sensorimotor cortices in
the SI images, the reliance of the node-consistency method on a 50% cutoff may have not
picked up on this overlap.

The central concern in this study regarding the node-consistency method is the
binary change criterion used to identify node change across the four iterations of each
task. This may explain the ubiquitous finding of consistent nodes distributed across the
cortex and subcortical areas. The results suggest that the node-consistency method may
need refinement in its change criterion before its application as a method for functional
localization. A possible solution to this concern may be the addition of weights to each
node for each comparison that represent the weighted percentage of co-module nodes that
changed from module to module across the two networks.

**Scaled Inclusivity Method for Functional Localization**

Scaled Inclusivity (SI) was originally developed as a method for identifying
consistent modular organization across participants, rather than across time. The
between-subjects version of the method has already been applied successfully in multiple
studies (Moussa et al., 2012, 2014; Wilkins, Hodges, Laurienti, Steen, & Burdette, 2014).
This study adapted SI for a within-subjects analysis to test for consistency in community
structure across iterations of the same task within each participant. The results revealed this method was able to localize areas of consistent community structure precisely, without the scattered consistency observed in the node-consistency method. Localization of functionally significant areas was confined to a handful of regions, rather than scattered across the brain. Inconsistent with predictions, the results of this study suggest that Default Mode Network maintains functional coherence across the IGT and spatial-orienting task, in addition to rest. Despite an overall pattern of DMN connectivity across rest and task states, permutation tests revealed that DMN consistency was modulated by the differing demands of both the IGT and spatial-orienting tasks.

Consistent with the node-consistency images, the visual cortex was found to be the most consistent area in the SI meta-consistency image for rest. As noted above, this is consistent with a previous study using a between-subjects SI analysis during the resting-state (Moussa et al., 2014). In addition, areas of the DMN were found to be highly consistent across the iterations of rest. These areas included several important components of the DMN, the medial PFC, the medial OFC, the inferior parietal cortex, and precuneus.

Rather than only localizing areas predicted to be components of a “decision-making” network (e.g., medial OFC, ACC, DLPFC), areas of the DMN were found to have the most consistent community structure across four blocks of the IGT. This included the medial PFC, the medial OFC, the inferior parietal cortex, and the posterior cingulate/precuneus. While the hypothesized “decision-making” network and the DMN included the medial OFC as one of their components, further examination of the medial OFC’s co-module neighbors for each block of the IGT revealed that the medial OFC was
consistently found to be a component of a DMN module for every participant. Thus, rather than the localization of isolated areas of consistent modular organization, most localized areas were components of the same module across the IGT. In addition, consistency was found outside of the DMN in the DLPFC, one of the components of the hypothesized “decision-making” network.

These findings suggest that while the DMN is often associated with task-related deactivations, it maintains functional synchronicity between its components during the IGT. Despite the characterization of the DMN as associated with spontaneous “mind-wandering” at rest, these results suggest that the DMN is a highly coherent network of correlated fluctuations across a multitude of mental states. In fact, correlated activity in the DMN is even observed when participants are minimally conscious in a state of light sedation (Greicius et al., 2008). Further, previous studies have observed sustained functional connectivity of DMN areas across a variety of task-states (Fransson, 2006; Fransson & Marrelec, 2008; Harrison et al., 2008; Hasson, Nusbaum, & Small, 2009). In a study of the DMN across rest, a moral dilemma task, and a Stroop task, Harrison and colleagues (2008) observed sustained functional connectivity of the DMN across all three states. Sustained functional connectivity of the DMN was even observed in the Stroop task, despite task-related deactivations in these areas when contrasted with the resting state. In addition, studies have found DMN consistency during externally-oriented sensory tasks, such as a passive auditory-visual task and an auditory-oddball task (Calhoun, Kiehl, & Pearlson, 2008; Greicius & Menon, 2004) Two studies have even shown maintained functional connectivity in the DMN from rest to a 2-back verbal
working memory task (Fransson, 2006; Fransson & Marrelec, 2008), which presumably excludes spontaneous thoughts, due to the demanding nature of the task.

Inconsistent with the predicted isolation of the dorsal attention network (Corbetta et al., 2002; Yeo et al., 2011), the SI map of consistent areas in the spatial-orienting task resembled that of rest and the IGT. Consistent with the studies just cited, the default mode network was also localized in the spatial-orienting task. While all three tasks had large differences in task demands, the SI images revealed remarkably similar patterns of consistency in all three tasks. It is difficult to determine whether the consistent coupling observed between areas of the DMN is functionally associated with each task, or is rather the byproduct of normal brain function; a consistent pattern observed across all possible mental states (resting and task-states).

Support for a functional interpretation of DMN consistency comes from previous studies that have found DMN connectivity to predict task performance. For example, previous research has found that the strength of connectivity between the posterior cingulate and medial PFC is positively associated with performance on working memory tasks (Hampson, Driesen, Skudlarski, Gore, & Constable, 2006; Sambataro et al., 2010). In addition, posterior cingulate connectivity at rest has been found to predict reaction time performance in an attention task (Lin et al., 2015). Further support for a functional interpretation comes from observed task-dependent modulation of the DMN. Despite the overall DMN pattern in all three tasks, permutation tests revealed significant differences in consistent modular organization between all three tasks. Thus, the DMN seems to be significantly modulated by the demands of each task. Consistent with these results, the previous studies cited demonstrating DMN coherence across task-states (Fransson &
Marrelec, 2008; Fransson, 2006; Greicius & Menon, 2004; Harrison et al., 2008) also observed task-dependent modulation of the DMN, despite overall stable functional connectivity in the DMN. Even DMN connectivity at rest may be significantly modulated by preceding tasks. For example, in a study by Hasson, Nusbaum, and Small (2009) of DMN connectivity at rest and in a language comprehension task, connectivity patterns at rest changed as a function of the preceding language comprehension task. Thus, consistent DMN coupling across time in the IGT and spatial-orienting tasks may be functionally associated with performance, rather than a non-functional, “default” coupling of brain areas across all task-states. Further application of this method to other within-subject data sets is needed to further establish the functional significance of DMN consistency during rest and task-states.

In summary, while the SI images produced a clearer localization of brain areas as compared to the node-consistency approach, the method did not localize predicted regions of interest in the IGT or spatial-orienting task. Interestingly, areas of the DMN were found to have the strongest community structure (in addition to the visual and sensorimotor cortices) in all three tasks in the SI images. The observed consistency, despite large differences in task demands between the three conditions, suggests that the DMN may be a network that pervades all mental states (rest or task-states). In addition, the strong coupling of the DMN may be modulated by the differing task demands of the IGT and spatial-orienting task, as demonstrated by the permutation tests.

**Standard Neuroimaging Paradigms of the IGT**

The areas identified in this study were generally inconsistent with neuroimaging studies that found activation in areas of the previously described “decision-making”
network (IGT, ACC, DLPFC). In contrast to standard neuroimaging paradigms, these areas were defined using graph-theoretical functional connectivity methods without a comparison to baseline. Instead, consistent community structure across blocks of the same task was used as a measure of functional localization. This represents a departure from standard subtraction-based neuroimaging paradigms, in that consistent connectivity patterns was used as a metric of functional significance. This follows a larger trend in cognitive neuroscience towards a more network-based approach to brain function (Anderson, 2010; Bressler & Menon, 2010; Bullmore & Sporns, 2009b; Lindquist & Barrett, 2012; Moussa et al., 2012; Power et al., 2011). Given the significant departure of the actual results from earlier predictions, it’s difficult to directly compare the results of the node-consistency and SI methods to the results of standard neuroimaging paradigms. For example, while the medial OFC is a prominent area localized in both the SI results and previous activation studies of the IGT, the SI method localized the medial OFC as a component of the DMN, which leads to a different functional interpretation of the medial OFC from standard activation studies.

The relation between the graph-theoretical methods developed and tested here and standard neuroimaging methods is an area for further study. The results of this study suggest that the DMN may be a functionally significant collection of brain areas, implicated across a wide range of task demands. The medial OFC, a significant component of the DMN, is an area of significant interest in activation studies of risky decision-making. This study suggests that future activation studies of the IGT may do well to consider activation of the medial OFC in the context of its association with other areas in the DMN. In order to come to a better understanding of the relation between th
two methods, future studies with both types of methods applied to the same data set may be fruitful.

Limitations and Future Directions

The most obvious limitation of this study is the small sample size ($N = 8$; one participant was excluded due to excessive motion). However, the study was also afforded more power to detect task-related brain networks by the repeated-measures design of the study. Another concern is the definition of which nodes are consistent. In both subject- and group-level images, only the most consistent nodes in the network were interpreted as functionally significant. However, it’s not clear at what level of consistency (as measured by SI or node-consistency) a node is understood to be functionally significant. This is further complicated by the fact that different studies observe different average SI values (Moussa et al. 2012; Moussa et al. 2014). For this study, only the top consistent nodes of the network were understood to be functionally significant. While this is an intuitively reasonable criterion, a standardized definition of consistent community structure may prove useful for future studies assessing network consistency.

Conclusions

Functional connectivity methods, particularly graph-theory methods, are an area of growing interest for researchers interested in network-based neuroimaging approaches. This study attempted to offer another useful extension of graph-theoretical approaches to task-based neuroimaging. The results of this study suggest that Scaled Inclusivity, rather than the Node-consistency method, was able to adequately localize areas of functional significance. The application of Scaled Inclusivity to the IGT, rest, and a spatial-
orienting task revealed DMN consistency across all three tasks, as opposed to the hypothesized “decision-making” network and dorsal attention network predicted in the IGT and spatial-orienting task, respectively. Permutation tests revealed that the DMN was significantly modulated by the differing demands of each task. Overall, the results suggest the need for further refinement of this method as a tool for functional localization.

Further research with this method is needed to test whether DMN coherence is a feature associated with other cognitive tasks (e.g., language/speech, motor-coordination, and reasoning tasks). It is hoped that this research leads to new discoveries in the area of network-based neuroimaging, and the development of more refined tools for the localization of functionally important brain areas.
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Appendix 1: IGT and Spatial-Orienting Displays

Below are the displays for the Iowa Gambling Task and the spatial-orienting task.

IGT Card Selection Display

Example IGT Win/Loss Display

Example Spatial-Orienting Display
Appendix 2: Permutation Test Distributions for the Node-Consistency Method

Histograms displaying distributions of $R_{JC}$ constructed to assess differences in the consistent modular organization between the three tasks. The red bar indicates the location of the computed test statistic ($R_{JC}$).

Rest vs. IGT
Rest vs. Spatial-orienting

IGT vs. Spatial-orienting
Appendix 3: Permutation Test Distributions for SI Method

Histograms displaying distributions of $R_{JC}$ constructed to assess differences in the consistent modular organization between the three tasks. The red bar indicates the location of the computed test statistic ($R_{JC}$).

Rest vs. IGT
Rest v. Spatial-orienting

IGT vs. Spatial-orienting
Appendix 4: ROI Permutation Test Distributions for SI Method

Histograms displaying distributions of $R_{JC}$ constructed to assess differences in the consistent modular organization in regions of interest between the IGT and the other two tasks. The red bar indicates the location of the computed test statistic ($R_{JC}$).

Medial OFC: Rest vs IGT
Medial OFC: Spatial-orienting vs. IGT

Anterior Cingulate Cortex: Rest vs. IGT
Anterior Cingulate Cortex: Spatial-orienting vs. IGT

Dorsolateral Prefrontal Cortex: Rest vs. IGT
Dorsolateral Prefrontal Cortex: Spatial-orienting vs. IGT
Education

*Wake Forest University*, Winston-Salem, NC
M.A. in Psychology, May 2015
GPA: 3.91/4.0
Gordon Melson Outstanding Master’s Student Award

*Clemson University*, Clemson, SC
Major: Psychology (B.S.) Minor: Philosophy, May 2013
GPA: 4.0/4.0 Summa Cum Laude
Departmental Honors: Calhoun Honors College

*Tri-County Technical College*, Clemson, SC
General Arts and Science Student, December 2010
GPA: 3.82/4.0

Research Experience

*Thesis Research*
Fall 2013-Present
Currently conducting research with my advisor Dr. Dale Dagenbach on the brain networks active during decision-making processes. This research is conducted while participants perform decision-making tasks (e.g. Iowa Gambling Task) in an fMRI. Along with my current research, I have previously examined differences in distributed brain networks between cognitive (i.e. nback) and resting states.

*Research Collaboration*
Currently conducting research with Dr. Michael Furr on the possibility of network science to act as a methodological supplement to factor analysis in the study of personality inventories. This research involves comparing the output of factor analysis and typical network metrics (e.g. degree, clustering coefficient, modularity) on a range of personality questionnaires. This research will be the focus of a chapter in a forthcoming publication of a book titled: “Neuroimaging Personality, Social Cognition and Character,” to be published by Elsevier in 2015.

*Research Assistant*
Summer 2014
Assisted Dr. Eranda Jayawickreme on post traumatic growth in participants among the war-affected population of Sri Lanka. My research responsibilities included compiling and entering data from a large collection of questionnaires into spreadsheets, as well as conducting statistical analysis on the data. I also assisted with another study involving post traumatic growth in a large sample of MTurk participants. My research responsibilities included editing and distributing surveys, organizing data into spreadsheets, and payment of participants.

*Undegraduate Honors Thesis- Active Perception and the Input-Output Picture*
Spring 2012 - Fall 2012
Undergraduate honors thesis was a requirement for departmental honors. My thesis research examined the implications of more active and embodied theories of perception (Alva Noe, Susan Hurley) for computational models (e.g. Anderson’s ACT-R Theory).

**Research Intern**
**Summer 2012**
Conducted research with Dr. Robert Youmans during the summer of 2012 at George Mason University for the APA Summer Science Fellowship. Studied the psychological processes involved in creativity, specifically the subject of design fixation.

**Undergraduate Research Team**
**Fall 2011 – Spring 2012**
Participated in a Creative Inquiry research team with Dr. Ben Stephens involving research in educational and I/O psychology. Researched the learning outcomes of undergraduate electronic portfolio requirements. Also studied the effect of portfolio format for job applicant appeal.

**Teaching Experience**
**Teaching Assistant, Wake Forest University**
**PSYCH 311 (Research Methods in Psychology I)**
2013-Present
Teaching assistant for the lab course associated with PSYCH 311. Students were instructed on statistical analyses and how to perform them in SPSS.

**Book Chapter in Preparation**

**Conferences and Presentations**


Stephens, Benjamin; Birckbichler, Julie; Rinz, Alexa; Marshall, Cynthia; Mckissak; Bolt, Taylor; O Harra, Christine; Rollo, Amanda (2012). *How can we describe student eportfolio websites?*. Paper presented at The Association for Authentic, Experiential and Evidence-Based Learning Conference.

Stephens, Benjamin; Mckissak, Kathleen; McCormak, Sarah; Rinz, Alexa; Marshall, Cynthia; Bolt, Taylor; O’Hara, Christine; Rollo, Amanda (2012). *ePortfolio format can enhance
appeal of job applications. Paper presented at The Association for Authentic, Experiential and Evidence-Based Learning Conference.

Birckbichler, Julie; Stephens, Benjamin; Bolt, Taylor; Brannon, Larae; Marshall, Cynthia; O’Hara, Christine; Rinz, Alexa; Rogers, Ashley (2012). NSF/REU intern eportfolio maps correlate with program learning outcomes. Paper presented at Southeastern Psychological Association Conference.

**Honors/Achievements**
- Calhoun Honors College (Clemson University)
- Psi Chi Honors Society
- APA Summer Science Fellowship 2012
- President’s List Clemson University (January 2011- May 2013)
- LIFE Scholarship Recipient (August 2009 – May 2013)
- James Corcoran and Mary Poats Littlejohn Memorial Scholarship Recipient (2012)
- President’s List Tri-County Technical College (August 2010-December 2011)
- Dean’s List Tri-County Technical College (August 2009-May 2010)

**Activities/Affiliations**
- Honors Council Student Representative (Wake Forest University)
- Calhoun Honors College (Clemson University)
- Student member of American Psychological Association
- Student member of Association for Psychological Science
- Member of Fellowship of Christian Athletes
- Undergraduate Mentor for College of Business and Behavioral Sciences (Clemson University)

**Work Experience**
- Research Assistant for Dr. Eranda Jayawickreme, Wake Forest University (2014)
- Teaching Assistant for Dr. Christian Waugh, Dr. John Petrocelli, and Emer Masicampo, Wake Forest University (2013-2015)
- Research Intern for American Psychological Association, George Mason University (2012)