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Trait-like Resting-State Brain Oscillations Predict Subsequent Problem-Solving Strategies

A Thesis

Submitted to the Faculty

of

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by

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of

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Dedications

Dedicated to

My mother: you are the most loving, patient,
and unconditionally supportive mother anyone could have.

My Father: for teaching me to think for myself. I am proud to be your son.

My Fiancé: the light of my life.

In honor of

My grandparents Hol and Joanne: for your support and confidence in me,
and for your wisdom and example.

In memory of

My great-grandmother Edna, who for me is still in her house on the hill;

and my grandfather Al, who for me is still at the lake.

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Abstract

Trait-like Resting-State Brain Oscillations Predict
Subsequent Problem-Solving Strategies

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People use different processing strategies to solve problems. Previous research distinguishes between solving problems by *analysis*, that is, in a conscious, deliberate manner, versus by *insight*, in which the solution appears abruptly in awareness (the "Aha" phenomenon) after a period of unconscious processing. Prior work provides little evidence whether the tendency to solve problems using one or the other of these strategies constitutes a stable, trait-like cognitive style. We tested this hypothesis by assessing whether individuals evince a consistent preference for a particular solving strategy across days and types of problems and whether these cognitive styles have neural correlates. We recorded participants' resting-state electroencephalograms (EEGs) on 4 occasions, approximately once per week. At the end of the third and fourth sessions, participants attempted to solve a series of short verbal problems (compound remote associates during session 3 and anagrams during session 4). Based on participants' trial-by-trial reports of the manner in which they solved anagram problems, individuals were categorized as predominantly relying on an insight or an analytic solving strategy. The resting-state EEGs of these groups, recorded during previous sessions were compared. Participants in the analytic group showed greater EEG beta power over midline and right inferior-frontal regions compared to insightful participants; participants in the insightful group showed greater beta power over left superior parietal cortex compared to those in the analytic group. Group differences in solving strategy and resting-state EEGs assessed

with anagram problems generalized to the compound remote associates problems. Overall, these results demonstrate the behavioral and neural consistency of these cognitive styles over both time and type of problem. The finding that insightful solvers exhibited a lower ratio of frontal to parietal neural activity supports the hypothesis that insightfulness results from chronic relative frontal hypoactivation and concomitant parietal disinhibition whereas analytic solvers exhibit chronic relative frontal hyperactivation and parietal inhibition.

Chapter 1: Introduction

Two individuals confronted with the same problem may use different strategies to reach identical solutions. The term *cognitive style* refers to individual differences in the tendency to favor particular processing modes or strategies. In the domain of problem solving, at least two general cognitive styles have been identified: *analytic* solving involves conscious, deliberate thought and *insightful* solving involves unconscious processing leading up to the sudden emergence into conscious of an idea or solution (i.e. the "Aha!" phenomenon; Kounios & Beeman, 2014).

Cognitive styles may be thought of as features of personality (Nickerson, 1999; Feist, 1999). The concept of personality includes the recurrence of particular perceptual modes, thoughts, and behaviors in response to similar events or situations. Behavior and internal experience are generated by the brain. Therefore, personality traits are driven by individual differences in neural architecture or recruitment (DeYoung & Gray, 2009). For example, the traits of the "Big Five" factor model (John, Donahue, & Kentle, 1990) have well-established neural correlates including regional gray matter volume and functional architecture (DeYoung, et al., 2011; Adelstien, et al., 2011; Kumari, Williams, & Gray, 2004).

Personality traits derived from questionnaires such as the Big Five have the benefits of reliability and generality. However, because personality traits are based on self-reports about broad classes of behavior and experience, they are arguably a "blunt instrument" in that they do not isolate component mental processes. At present, the neural basis that predicts what strategy an individual will use when faced with a particular type of problem is poorly understood. The study of cognitive style addresses this issue through the development of tasks that, despite having definite solutions, leave subjects free to approach the problem through their preferred strategy.

1.2: Creative versus Analytic Cognitive Style

Creative and analytic thought are examples of two processing modes or strategies which can often be applied to the same problem with equally satisfactory results. Little is known about the neural drivers that cause individuals to favor one or the other of these cognitive styles. To begin, it is necessary to understand the relationship between creativity and analysis in problem solving.

Analytic strategies are those that rely on deliberate, conscious manipulation of problem elements, as in hypothesis testing. Many studies of problem solving in cognitive science are implicitly studies of analysis – for instance, many basic math and logic problems fit this definition (Newell, Shaw, & Simon, 1958). The construct of creativity is less constrained. Most classic creativity tasks involve complex, multistep problems susceptible to order effects and the probable inclusion of significant analytic processing. This complicates the development of a task that contrasts creative and analytic thinking.

This issue can be addressed by operationalizing creativity as the phenomenon of insight. Insight is generally understood to be a manifestation of creative cognition and has the advantage of a consensus definition (which is not the case for creativity in general). Insight is experienced as an “aha!” phenomenon in which a solution is suddenly available and seems obviously correct, without conscious awareness of intermediate steps (Kounios & Smith, 1995). Insight and analytic strategies are generally understood to be opposing constructs relying on different thought patterns (Mrazek, Smallwood, & Schooler, 2012) which may sometimes coexist in parallel.

1.2.1: The History of Insight

Insight has been a topic of interest since antiquity, but became a topic of scientific study only in the early 20th century. Behaviorists such as Edward Thorndike viewed learning and problem solving as a trial-and-error process in which response tendencies are gradually strengthened by rewards or weakened by punishments. In contrast, the Gestalt psychologists recognized that the behaviorist view is insufficient, as shown by studies that demonstrated discrete, all-or-none transformations in visual perception. Furthermore, Wolfgang Kőhler's studies of problem solving in apes demonstrated what appeared to be sudden insights in problem solving (Köhler, 1925). One of his studies involved placing a bunch of bananas behind a fence out of the reach of a chimpanzee. Two bamboo sticks were available to the chimp, but neither was long enough to reach the bananas and pull them within reach. After a period of frustration and inaction, the chimp spontaneously arrived at the solution, namely, jamming one stick into the other – bamboo shafts are hollow – to make a longer rod that could be used to reach the bananas. Importantly, the chimpanzee had not been rewarded for intermediate steps that would have brought him incrementally closer to achieving this solution, such as holding both sticks at the same time or knocking them together. The use and construction of the tool apparently came to the chimpanzee suddenly and all at once – an insight.

1.2.2: Classic Insight Problems

Gestalt psychologists went on to demonstrate similar examples of insightful problem solving in humans. Their methodology was based on a corpus of "insight problems" that typically elicit an "Aha!" experience when they are solved. A famous example is the Nine-Dot Problem, a simple puzzle that nevertheless results in nearly total failure to solve in standard laboratory studies (Kershaw & Ohlsson, 2004). A square grid of 9 dots is presented with instructions to connect all the dots using four straight contiguous lines and without retracing a line segment or lifting the pencil from the paper (Maier, 1930). Subjects typically approach this problem by testing every unique pattern of lines that satisfy the instructions before reaching a point at which no novel solutions are generated for an extended period (*impasse*; Erickson & Kounios, 2013). Impasse reflects an exhaustive exploration of the current problem space (the set of all problem states satisfying the task instructions) that nevertheless does not yield a viable solution. Impasse occurs on some problems when solvers impose implicit assumptions on the problem space, rendering the solution inaccessible. These implicit limitations often arise from past experience or gestalt perceptual phenomena. For instance, the Nine-Dot Problem hinges on perception of the dots as forming a bounded box. Reaching a solution requires recognizing and relaxing this implicit assumption, also known as *restructuring* the problem representation. Sometimes a hint can facilitate this restructuring. (The Nine-Dot Problem is apparently the origin of the phrase "think outside the box"; see Appendix A.) Restructuring is a sudden process associated with a feeling of certainty either that a now-obvious specific solution is correct or more generally that a newly discovered class of viable problem states contains a correct solution and only the details of implementation remain to be worked out.

1.2.3. Issues with the Corpus of Classic Insight Problems

Classic insight problems assume that insight is required to reach their solutions and, therefore, that all solutions to this class of problems occur through insight. The Gestalt psychologists also assumed that insight requires several steps (e.g., preparation, incubation, intimation, illumination, and verification; Wallas, 1926. However, a deeper investigation of "in-vivo" insight reveals that at least some of these assumptions are sufficient but not necessary to produce the feeling of insight. Specifically, insight can strike when no problem has been presented, or may be only tangentially related to a problem under consideration. In these scenarios the problem space is unbounded, and thus there can be no impasse. Classic insight problems may also be solved in a more stepwise "constraint relaxation" method that fails to elicit the quintessential insight "aha!" experience (Danek, Wiley, & Öllinger, 2016). Thus, the assumption that strong insight is being recruited to access a solution by problem design is insufficient. Indeed, one of the main limitations with the Gestalt psychologists' research on insight was that it relied on an informal consensus regarding which problems were to be considered insight problems and which would be considered analytic problems. Additionally, failure to solve a classic insight problem could occur for many reasons, not limited to lack of insightful processing ability.

1.2.4: Insight/Analytic Self-Report Problems

For the reasons outlined above, it is difficult to classify problems as exclusively insightful or analytic. In fact the primary objective difference between insight and analytical processing is not the structure of the problem, but the experience of a solution occurring suddenly and unexpectedly (Metcalfe & Wiebe, 1987). This logic led to the development of a more recent approach in which subjects are directly asked about their experience after solving puzzles.

Anagram problems are one example of puzzles that have been studied with this method (Vincent, Goldberg, & Titone, 2006). An anagram is a string of letters that must be rearranged to form a word. Prior to presentation of anagrams, subjects are briefed on the characteristics that define an insight solutions (sudden awareness) versus analytic solutions (hypothesis testing, trial-and-error guessing, deliberate strategy). After each solved anagram, subjects are asked to report which strategy (insightful or analytic) they experienced during the solution. Interestingly, the distribution of reported strategies varies widely across subjects with some subjects reporting almost exclusive use of insight or analysis (Erickson & Kounios, 2013).

The neural and behavioral correlates of self-reported insight and analytic strategies have been studied with anagrams and other simple word-problems for over two decades (Kounios & Smith, 1995; Bowden & Beeman, 1998; Jung-Beeman et al., 2004; Kounios et al., 2006; Kounios et al., 2008; Subramaniam, Kounios, Parrish, & Jung-Beeman, 2009; Salvi, Bricolo, Franconeri, Kounios, & Beeman, 2015), validating participant reports as reflecting behaviorally and neurologically relevant features. Anagrams can be designed to have only one solution, so that only solution strategy varies across problems. Moreover, subjects can easily tolerate completing dozens of anagrams in one session. These features make anagram problems ideal for analysis of the neural bases of insight versus analytic cognitive style.

1.3: Neural Signatures of Cognitive Style

Like all factors of personality and behavior, cognitive style is a function of neurology. Because cognitive styles are traitlike patterns of behavior, their contribution to neural activity should be present over multiple recordings. This raises multi-session resting-state (RS) brain activity as a candidate for exploration. Between 40 and 50% of the variance in RS-EEG hemispheric asymmetry is consistent over multiple recording sessions (Hagemann, Naumann, Thayer, & Bartussek, 2002; Hagemann, Hewig, Seifert, Naumann, & Bartussek, 2005), and some RS-EEG power and frequency features have been demonstrated to remain stable over a timescale of days, weeks, or longer (Meindl et al., 2010; John, Prichep, Fridman, & Easton, 1988; Salinsky, Oken, & Morehead, 1991; Gasser, Bächer, & Steinberg, 1985).

Resting state features have also been shown to correlate with other traitlike factors including the Big Five (Kunisato et al., 2011), general fluid intelligence (gF; Finn et al., 2015), and psychiatric classifications (Goodkind et al., 2015). RS activity has been directly linked to on-task recordings. fMRI classification algorithms can identify a subject's on-task recordings from an anonymous database using only a sample RS recording, demonstrating that substantial variance is shared between RS and task-related activity (Finn et al., 2015). It is even possible to transform RS fMRI into accurate predictions of task-related activity (Tavor et al., 2016). Since trait-RS activity contains a great deal of information about a subject's on-task cognition, it may be a fruitful place to look for signatures of the cognitive styles individuals will employ when faced with a problem.

1.4: The Present Study

Identification of differences in trait RS-EEG related to subjects' reliance on an insight versus analytic problem solving strategy could help to uncover the neural basis of this cognitive style, and perhaps shed light on the constituent insightful and analytic mental processes themselves. Additionally, it would validate this methodology for the detection of similar trait RS dependencies of other constituent processes of cognitive style.

Thus, the present study used an anagram task to assess subjects' insight versus analytic solving strategy preferences and link them to RS-EEG. Three sessions of RS-EEG were collected and averaged within-subject to isolate trait RS-EEG. Subjects then completed an anagram task, and their I/A ratio was used to sort them into primarily-insightful and primarily-analytical groups. These groups' RS-EEG data was submitted to statistical analysis to determine scalp regions and frequency bands in which solvers who relied on insight had significantly different trait RS-EEG activity from solvers who relied on analysis.

Importantly, because all of the RS-EEG data included in the analysis were recorded prior to presentation of anagrams, significant differences revealed by this method are predictive; that is, they show that RS-EEG predicts solvers' reliance on an insightful or analytic cognitive style on a subsequent day. In a supplementary analysis, significant scalp-frequency clusters from the main analysis were compared to solvers' reliance on insight or analysis from a related type of problem, compound remote associates (CRAs), to explore the generalizability of the revealed trait RS-EEG predictors. These analyses explore traitlike RS-EEG features of cognitive problem-solving style.

Chapter 2: Methods

2.1: Subjects

Experimental protocols were approved by the Drexel University Institutional Review Board. Participants were recruited via fliers posted on the Drexel and University of Pennsylvania campuses. Subjects were prescreened to confirm that they were native English speakers; between the ages of 18 and 33; right-handed; had no diagnosed neurological conditions or learning disabilities; had normal or corrected-to-normal vision and hearing; had no symptoms of psychiatric conditions in the previous year; had no open head wounds or implants; and additionally, on each day of testing had not used any drugs or medications affecting brain function and had not consumed excessive alcohol for at least 24 hours prior to testing; and had adequate sleep the previous night. Each subject gave informed consent and verbally confirmed these criteria on the first day of testing, and subsequent sessions for relevant questions. Fifty-one right-handed, native English-speakers (27 male, 24 female) participated in the study. They ranged in age from 18 to 29 years of age (M = 20.69, SD = 2.97). Of these, 5 were excluded for failing to follow directions during one or more of the experimental tasks, 3 were excluded for solving fewer than 20% of the problems, 2 were excluded for excessive EEG artifact, and 1 was excluded for abnormally high EEG alpha activity (i.e., more than 3 SD greater than the mean of the sample).

2.2 Experimental Design

Subjects participated in 4 sessions on 4 separate days with approximately one-week separating consecutive sessions. Each session took from 1.5 to 2.5 hours. At the beginning of each session, 10 minutes of resting-state EEG was recorded (see Resting-State EEG Collection). This was followed by administration of the PANAS mood questionnaire (Watson, Clark, & Tellegen, 1988). The remaining questionnaires and activities varied across sessions. Instructional videos were presented with Microsoft PowerPoint; surveys were completed through Google Forms; and all other tasks were designed and administered with E-Prime 2.0. All stimuli were presented on a ViewSonic Graphics Series G790 monitor. Subjects were compensated $15/hour, paid at the end of each session.

On the first day, participants first filled out three questionnaires: the Morning-Eveningness Questionnaire (MEQ; Horne & Ostberg, 1975) to determine preference for and propensity to be active at different periods of the day; the Edinburgh Handedness inventory (Oldfield, 1971); and demographics. On the second day, EEG was recorded while participants completed a computer-based attention task (see Eriksen Flanker Task). Following that, they were disconnected from the EEG equipment in order to fill out the Creativity Achievement Questionnaire (CAQ; Carson, Peterson, & Higgins, 2005) and the Abbreviated Torrance Test for Adults (ATTA; Goff, 2002). On the third day, participants' EEG was recorded while they solved compound-remote associates problems (see CRAs). On the fourth day, EEG was recorded while participants completed a set of anagrams (see Anagrams). Each EEG task was preceded by instructions to relax and avoid artifact-inducing movements and eye activity.

As our strategy for revealing trait-like RS predictors of cognitive style relied on correlating RS-EEG recorded during sessions 1-3 with the problem-solving performance on the session 4 anagram task. It was therefore important to avoid biasing subjects' brain activity during the RS-EEG recordings. Since the RS-EEG recording preceded the event-related task in each session, RS data from sessions 1-3 could not have been biased by the expectation of having to solve problems. Thus, the central results include only these first 3 RS-EEG sessions; session 4 RS data are included in some ancillary analyses.

2.3 Eriksen Flanker Task

The attention task given on Day 2 of testing was modeled after a study by Rowe, Hirsh, & Anderson (2007) in which subjects were asked to identify the center letter in a row of seven letters. Participants were told that this was a "reaction time task" and that they should identify the center letter as quickly as possible. Participants first viewed a video describing the Flanker task and procedure with the script:

"The next part of the experiment will test your reaction time. We will monitor your button press responses in addition to the brain activity associated with each response. First, we'll explain the instructions and give you some time to practice before beginning the experiment. If you have a question at any time prior to the beginning of the experiment, please ask. We want the instructions to be as clear as possible! You will only be using the mouse in this experiment. Hold it with both hands as shown here. Whenever you need to press the left button, use your left thumb. When you need to press the right button, use your right thumb. At the beginning of each trial, you will see a plus sign in the center of the screen. When you see this plus sign, keep your eyes fixed on it. Seven letters will appear. Try to pay attention only to the center letter and ignore the 6 "distractors" appearing to the left and right of the center. If the center letter is a K, press the left mouse button. If the center letter is an S, press the right mouse button. Respond as soon as you identify the center letter. Responding quickly is just as important as responding accurately. The center letter and the distractors will change from trial to trial. They might match but they might not. Remember that your button press depends ONLY on the center letter. So in this example, you would press the right button. In this one, you would press the left button. If you get an answer wrong, you will see "error" appear on the screen for a few seconds before the computer moves onto the next trial. You will only receive feedback for incorrect answers. When you answer correctly, the computer will just move onto the next trial without any message. Now you're ready to begin the practice trials! If you have any questions, you can ask now or at any time while you're practicing."

All text including stimuli was written in white font against a very dark gray background (RGB: 38, 38, 38). Participants viewed a fixation cross for 500 ms before the stimulus was displayed on the screen. Each stimulus consisted of seven letters: either S or K. Participants were instructed to press the left mouse button if the center letter was a "K" and the right mouse button if the center letter was an "S." Half of the stimuli were flanked by response-compatible letters (e.g. "K" in the middle of six other "K") and half of the stimuli were flanked by response-incompatible letters (e.g. "K" in the middle of six "S"). Additionally, half of the stimuli were closely spaced (e.g. "KKKKKKK") and half of the stimuli were distantly spaced (e.g. "K K K S K K K"). Combining these factors allowed for eight different possible stimuli, which were used for eight practice trials and randomly repeated for 480 experimental trials. If the participant answered incorrectly, "error" appeared on the screen for 500 ms. If the participant answered correctly, a blank screen was displayed for 500 ms. A fixation cross was displayed during the intertrial time, which randomly varied between 500, 600, 700, or 800 ms so that participants would answer as quickly as possible rather than falling into a rhythm. The experimental trials were broken into three blocks of 160 trials with breaks of about 60 seconds between each block. For trials in which the letters were closely-spaced, the visual angle between each letter was .06 degrees. For distantly-spaced letters, the visual angle was .5 degrees. This was for letters of about .48 degrees of height.

2.4 Compound Remote Associates

Participants first viewed a video detailing the experimental procedure for compound remote associates (CRA) problems (Bowden & Jung-Beeman, 2003) and defining insight and methodical experiences:

"This is a task that examines problem solving. Before each trial begins, you will see a fixation cross on the computer screen. You determine when each problem will be presented to you by clicking both mouse buttons at the same time. Use your left thumb for the left button and your right thumb for the right button, as shown here. Before clicking the buttons to show that you are prepared, you should focus your attention and center your eyes on the fixation point in the center of the screen. Try not to move your eyes around. This is where the problem will appear. After you press the buttons to indicate that you are prepared, a word puzzle made up of 3 problem words will appear on the screen. Try to look at all of the words at once rather than each individual word—this will prevent unnecessary eye movements. Your job is to find a solution word that makes a familiar compound word or phrase with each of the problem words. The solution word could come before or after each of the problem words. The answer is "apple," which combines with each of the problem words to form pineapple, crabapple and applesauce. Here's another example. What is the solution that can form a word or phrase with over, plant and horse? The answer is "power," which generates overpower, horsepower, and power plant. In this example, two of the words are compound words, and the last is a compound phrase. Either is acceptable, as long as you are able to form a familiar word or phrase. You will have 15 seconds to solve each word puzzle. As soon as you know the answer, simultaneously press both mouse buttons as quickly as possible. Responding quickly is as important as responding accurately. Remember to use your left thumb for the left button and your right thumb for the right button. There is no rush to verbalize your response. You must wait until you see the solution prompt on the screen, and then you may say the solution aloud. If you do not come up with the solution to a word puzzle after 15 seconds, the problem words will disappear from the screen and the fixation cross will reappear. The computer will then move onto the next trial. If you do solve the problem, we want to know how you felt when you discovered the solution. Specifically, we want to know if you solved the problem methodically or if you had a feeling of insight. An insight is an "Aha!" feeling, characterized by suddenness and obviousness. You are not completely sure how you came up with it, but you are confident that it is the answer. The feeling of insight does not have to be overwhelming, but it should be something along these lines. A methodical thought process involves more deliberate processing. This commonly involves trial-and-error guessing; for example, you might have devised the word “applesauce” and then mentally placed “apple” alongside the other two problem words to form crabapple and pineapple. If you can remember how you arrived at a solution, then you used methodical thought processing. Most people interchange between insight and methodical strategies when solving word puzzles, and can easily determine which strategy they used. Use your intuition when deciding. If you experienced an “Aha!” feeling, please press the right button when the “Methodical” vs. “Insight” prompt appears. If you used methodical thought processing, press the left button. Try to use mostly these two responses, but if for some reason you are unsure and cannot decide, simply wait a few seconds and the experiment will automatically move onto the next trial. Keep in mind that this is not a test of intelligence, and these problems are intentionally difficult to solve. Think of it as a challenge; press the button as quickly as possible when you think you know the solution, and have fun!

A fixation cross was displayed at the beginning of each trial until participants clicked to initiate a problem. Upon button press, cross hairs appeared around the fixation cross in order to prepare the participants and focus their attention. After 1000 ms, three CRA problem words replaced the fixation cross within the cross hairs. The words were displayed in yellow, Courier New, 14-point font for up to 14 seconds. Participants were instructed to try to read all the words without moving their eyes. If they found an answer, they were to indicate that a solution had been found with another bimanual button press. Then “Solution?” appeared on the screen and the participants spoke the solution aloud, and the experimenter recorded whether or not the solution was correct. Then the participants indicated whether they had solved the problem by insight or analytically. Half of the participants indicated insight with their left thumbs while the other half indicated insight with their right thumbs. In the rare cases where participants were unsure of the solution method they used, they did not press any buttons and after 4 seconds the solution method was recorded as “unsure.” Participants were told that insight problems were characterized by the “Aha!” experience. They were told that if they used trial-and-error or some kind of method, then they solved the problem analytically, and that if they could remember how they arrived at a solution, they most likely used analysis. If the participant did not solve the problem within 14 seconds, then the fixation cross preceding the next trial was displayed. Participants could relax and refocus their attention for as long as desired while the fixation cross was displayed, and the procedure would only continue with another bimanual button press. This procedure was used for 12 practice trials followed by 153 experimental trials.

2.5 Anagrams

The anagrams task (Figure 1) was modeled on previously developed experiments (Kounios et al., 2006). Participants first viewed a video detailing the experimental procedure and defining insight and methodical experiences:

“This is a task that examines problem solving. Before each trial begins, you will see “Get Ready” and then a fixation cross on the computer screen. Then you will see an anagram on the screen. For each anagram, we want you to come up with a word by rearranging the letters. For example, if you see the anagram “owlet”, you must try to rearrange the letters to make another word. The answer is “towel”. Here’s another example. If you see the anagram “omits”, you must try to rearrange the letters to form “moist”. You must use all of the letters in the original anagram. You will have 16 seconds to solve each anagram. As soon as you know the answer, simultaneously press both mouse buttons as quickly as possible. Responding quickly is as important as responding accurately. After you make your response, a fixation cross will appear on the screen. Please try to keep your eyes focused on the fixation until the “Solution” prompt appears. There is no rush to verbalize your response. You must wait until you see the solution prompt on the screen, and then you can say the solution aloud. If you do not come up with the solution to an anagram after 16 seconds, the anagram will disappear from the screen and the fixation cross will reappear. The computer will then move onto the next trial. If you do solve the problem, we want to know how you felt when you discovered the solution. Specifically, we want to know if you had a feeling of insight. An insight is an "Aha!" feeling, characterized by suddenness and obviousness. You are not completely sure how you came up with it, but you are confident that it is the answer. The feeling of insight does not have to be overwhelming, but it should be something along these lines. Alternatively, you could solve the anagram methodically. This normally involves some kind of strategy, such as systematically rearranging the letters in particular patterns. Trial-and-error guessing would also be considered methodical. Even if you’re working on a problem methodically, a solution could pop into your awareness all of a sudden as an insight that is not a product of your conscious, deliberate thought. This would be considered an insight, not a methodical solution. If you experienced the “Aha!” feeling, please press the left button when the “Methodical or Insight” prompt appears. If you solved the anagram methodically, press the right button. Try to use mostly these two responses, but if for some reason you are unsure and cannot decide, simply wait a few seconds and the computer will automatically move onto the next trial. Keep in mind that this is not a test of intelligence, and these problems are intentionally difficult to solve. Think of it as a challenge; press the buttons as quickly as possible when you think you know the solution, and have fun!

Before each trial, participants saw “Get ready” in red text against a dark grey screen for two seconds. A fixation point appeared for 500 ms before the anagram appeared. The anagram remained on the screen for 16 seconds or until the participant found a solution. If a solution was found, participants pressed both mouse buttons with their thumbs at the same time. If there were more than 500 ms between the two button presses, the participant saw a dialogue box reading “You must click BOTH buttons at the SAME time.” Then the fixation point returned for 500 ms before “Solution?” appeared on the screen. Participants had four seconds to report whether they solved the anagram by insight or analytically. Half of the participants pressed the left mouse button to indicate insight and the right button to indicate analytical solutions; the other half pressed the left button to indicate analytical solutions and the right button to indicate insight. This procedure was used for 15 practice trials and 180 experimental trials.

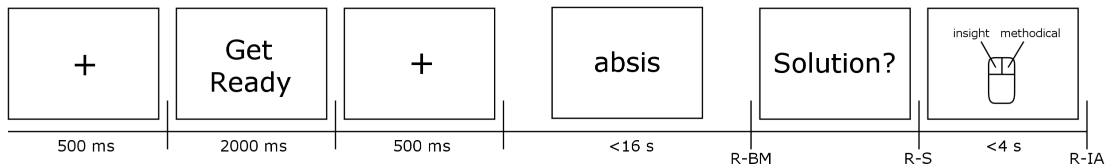

Figure 1: Anagrams trial procedure
Time course of a single anagram trial, in seconds (s) and milliseconds (ms). After a fixation, ready screen, and fixation, the anagram stimulus was shown for 16s (timeout, at which point the next trial was initiated) or until the subject made a bimanual response button click (R-BM) indicating they had a solution. The subject was then prompted to verbally report the solution (here "basis") and the experimenter scored the response (R-S). A visual strategy prompt of the button mapping for insight and methodical (e.g., analytic) strategies immediately followed, lasting for 4s or until the subject responded with a left or right mouse button click (R-IA).

2.6 Resting State

Each experimental session began with a resting-state EEG recording. Participants were instructed to relax and allow their minds to wander freely during four 2.5-min blocks of alternating eyes-open and eye-closed EEG recordings (with eyes-open always first). There was a 20-sec break between each block. During the eyes-open blocks, participants gazed at a white fixation cross against a black background on a computer monitor. To help minimize eye movements during the eyes-closed blocks, participants were instructed to imagine that they were still fixating on the fixation cross.

2.7 EEG Acquisition and Data Preprocessing

84-channel electroencephalographic data were acquired using silver silver-chloride electrodes embedded in a nylon cap (MANSCAN system, SAM Technology, Inc., San Francisco, CA) using International 10-20 system locations with additional electrodes and linked-mastoid reference. Preprocessing was performed in MATLAB 7.14 (Mathworks, Inc., Natick, Massachusetts, USA) using functions from the EEGLAB toolbox (Delorme & Makeig, 2004). Data within eyes condition were merged for each session and bandpass-filtered from 2 to 55 Hz. Data were regularly epoched at 1-second intervals, and bad channels were removed by visual inspection of the time course and FFT. Data were passed through a semi-automatic artifact detection tool (Delorme, Sejnowski, & Makeig, 2007), and epochs were classified as clean or artifactual by the following methods: threshold (+/- 300mV), joint-probability (channel/global limit 5SD/3SD), kurtosis (6.5SD/3SD) and spectral profile (exceeding -100 to 25db over 20 to 55Hz), followed by manual review. These parameters were tuned to detect primarily very large artifacts and electromyographic (EMG) activity - the removal of which improves ICA decomposition quality - while retaining stereotypical artifacts such as eye blinks and eye movements for correction by independent components analysis (ICA). ICA weights were calculated using EEGLAB's FASTICA algorithm. The ADJUST toolbox (Mognon, Jovicich, Bruzzone, & Buiatti, 2011) was used to automatically detect and remove artifactual ICA components representing blinks, eye movements and spatial discontinuities. ADJUST detections were limited to the third of the components with the highest mutual information to ensure that only reliable and important components were removed. The remaining components were manually reviewed. Data were then passed through the semi-automatic artifact detection tool again with more conservative parameters: threshold (+/- 40mV), joint-probability (channel/global limit 4SD/3SD), kurtosis (6.5SD/2SD) and spectral profile (exceeding -100 to 25db over 20 to 55 Hz), followed by manual review. Channels previously removed were then recovered through interpolation. EEG data were preprocessed using ICA artifact correction and manual review in EEGLAB 12. Analyses were conducted in the SPM12 M/EEG toolbox (Litvak et al., 2011). The FFT of 1s regularly epoched sensor-level RS data was calculated from 2 to 50 Hz in frequency steps of 2 Hz (Hamming windowed), robust averaged and log transformed within session.

2.8 SPM Model Structure

Spectral data were averaged within-session and log transformed, and transformed to 3D Scalp x Frequency .nii format images ([x,y], mm; [z], Hz). All SPM analyses were conducted at sensor-level. Importantly, SPM images were Z-transform normalized within frequency step, across electrodes. EEG absolute power within frequency bands varies between subjects due to variations in skull thickness and white/gray matter density which affect cortical signal power (Smit, Boomsma, Schnack, Hulshoff Pol & de Geus, 2012) as well as individual differences. Z-transformed relative power has been shown to correlate more closely with PET perfusion than absolute power (Cook, O'Hara, Uijtdehaage, Mandelkern, & Leuchter, 1998) and improves the validity of between-subject comparisons.

There are several possible methods for computing statistical parametric maps, including one sample, two-sample and paired models. All of these models are simplifications of the *flexible factorial* (flexfac) model. The flexfac model allows inputting of multiple scans (scalp-frequency image files) per subject. Each scan is associated with a matrix of binary or integer values specifying which condition it represents. In this study, each scan was assigned a value for group (insight, analytic) eyes condition (open, closed); day of testing (1-4); and gender (M,F). The flexible factorial model partitions between and within-subject error. Depending on whether the subject term is included in the model, either the between or within-subject error term will be used to compute the F-statistic. Because day of testing and eyes condition are within-subject effects, flexfac models testing these factors (as confounds) included the “subject” factor. Tests on the gender confound and the main effect of group are between-subject effects and do not include the subject term. The flexfac method is more sensitive than comparable options, such as two-sample or regression tests on within-subject averages, as it both partitions within and between subject variance and models confound variables.

2.9 Grouping

Subjects in the middle of the distribution of I/A ratios do not strongly represent either group, and could have moved to one side or the other with very little change in their number of solutions. This makes median split ineffective at defining well differentiated groups (Kozhevnikov, 2007). To isolate groups with the greatest potential to reveal different solution-style related RS-EEG patterns, we calculated the log ratio of the number of anagram insight solutions to the number of analytic solutions (I/A ratio) and removed subjects representing the middle quintile of the distribution of this ratio. The remaining subjects formed the Insight and Analytical groups.

CRAs also have an insight – analytic judgement, and could have been used to group subjects. CRAs were not used for two reasons. First, CRA accuracy was fairly low (averaging 51% across included subjects). Insight analytic ratios are unstable when solution counts are very low (<10), meaning that one more or fewer solution of either type would dramatically change the ratio. This issue is compounded by the explicit focus of this analysis on the most extreme subjects. The much higher anagrams task accuracies (averaging 71%) resulted in much more stable ratios. Secondly, because the anagrams task was delivered on day 3 before any mention of creativity or insight versus analytic judgements, during anagrams subjects were relatively naïve. Response bias may have increased on day 4 (CRAs) due to the intervening period in which subjects may have contemplated the insight analytic judgement.

Gender was balanced across all participants included in the final analysis, but not between-groups. As the genders were ultimately shown to vary significantly in their anagram I/A ratio ($p=.038$) across all subjects, between-group gender balancing would have unavoidably conflicted with and critically weakened I/A group construction. Gender was instead included and explored as a covariate in an SPM flexible factorial model.

2.9 Hypotheses

2.9.1: Strategic Consistency: since I/A ratio is purported to index a consistent cognitive style trait, different problem-solving tasks should elicit similar I/A ratios. Therefore, I/A ratios for the CRA task were expected to correlate with those from the Anagrams task.

2.9.2: PANAS group differences: Prior work has shown that positive mood predicts higher I/A ratios, consistent with a body of work linking creative cognition and positive mood (Subramaniam et al., 2009). Therefore, PANAS scores were expected to be higher for the insight groups than for the analytic group across sessions.

2.9.3: Resting-state group differences: it was hypothesized that contrasts of RS-EEG data by group membership would reveal clusters of significant differences. Specific predictions about the scalp-frequency profile of significant differences were not made. It was expected that RS-data would differ by eye condition over frontal-temporal and occipital regions, but that eye condition would not interact with group differences (Hagemann et al., 2002).

Chapter 3: Results

3.1: Intersession Period

To ensure that the analysis represented a durable, traitlike factor, the inter-session period was kept to 1 day at minimum. Average durations between sessions are described in Table 1.

Table 1: Days elapsed between sessions by group
Time elapsed between sessions, averaged within and between subjects by group.

	Insightfuls	Analytics
	mean ± SD	mean ± SD
Intersession period (days)	15.0 ± 15	16.7 ± 10

3.2: PANAS

Subjects completed the PANAS mood questionnaire on each day of testing immediately after resting-state EEG recording. Consistent with prior work linking mood, insight and creativity, we found a significant difference between the insight and analytic groups on day one through three average PANAS scores ($p=.022$; three-day averages were used to maintain consistency with the main analysis). This result suggests several possible relationships between trait RS-EEG, mood and I/A ratio. Most simply, the content or degree of subjects' mind-wandering could transiently bias mood immediately prior to collection of PANAS data; in this case, mood acts as an intermediate variable between trait factors and I/A ratio. Alternatively, an independent trait bias in mood valence could have more complicated interactive effects on RS-EEG, PANAS scores and/or I/A ratio. Our experimental design did not permit full exploration of these relationships because

PANAS data was only collected once per session. However, any potential confounding effect of mood was explored by entering Anagram I/A ratio and day 1 to 3 averaged PANAS scores as covariates against day 1 to 3 within-subject RS-EEG averages. In this model, no clusters survived an F-test of the main effect of mood or mood*I/A ratio interaction with a standard cluster forming threshold p_clust = .001. Thus, while the source and effect of I/A related differences in mood remains uncertain, in our data they do not predict RS-EEG or interact with RS-EEG prediction of I/A ratio.

3.3: Morning-Eveningness Questionnaire

Subjects completed the MEQ on their first day of testing. The MEQ scores participants on their preference for and propensity to be active at different periods of the day. A significant group difference was observed on scores of the morning-eveningness questionnaire, p=.011, indicating that insightfuls prefer morning activities relative to analytics. These measurements scored insightfuls overall in the "neither" type, while analytics scored overall as "moderately evening" type. Despite the interesting group difference in this survey, our results are unlikely to be explained by morning or evening preference as sessions were scheduled almost exclusively for afternoons. MEQ differences in insightfuls and analytics is a promising topic for future analysis.

3.4: Edinburgh Handedness Inventory

Since several components of our experimental design involved language function, subjects were prescreened with a question about their handedness and also performed the Edinburgh Handedness inventory on the first day of testing. All subjects were right handed, and the groups did not significantly differ in the extremity of their handedness (p=.248)

3.5: Anagram and CRA behavioral data

3.5.1: Response Accuracies

Mean response accuracies are shown in Table 2. There were no significant group effects (Fs < 1.0). Anagram insight/analytic ratio was not correlated with solving accuracy (r(32) = .05, t[1,30] = .274, p = .39; Figure 2a). CRA insight/analytic ratio was significantly positively correlated with solving accuracy (r(32) = .39, t[1,30] = 2.33, p = .01; Figure 2b). 42 subject analyses were qualitatively similar (figure 2c & 2d).

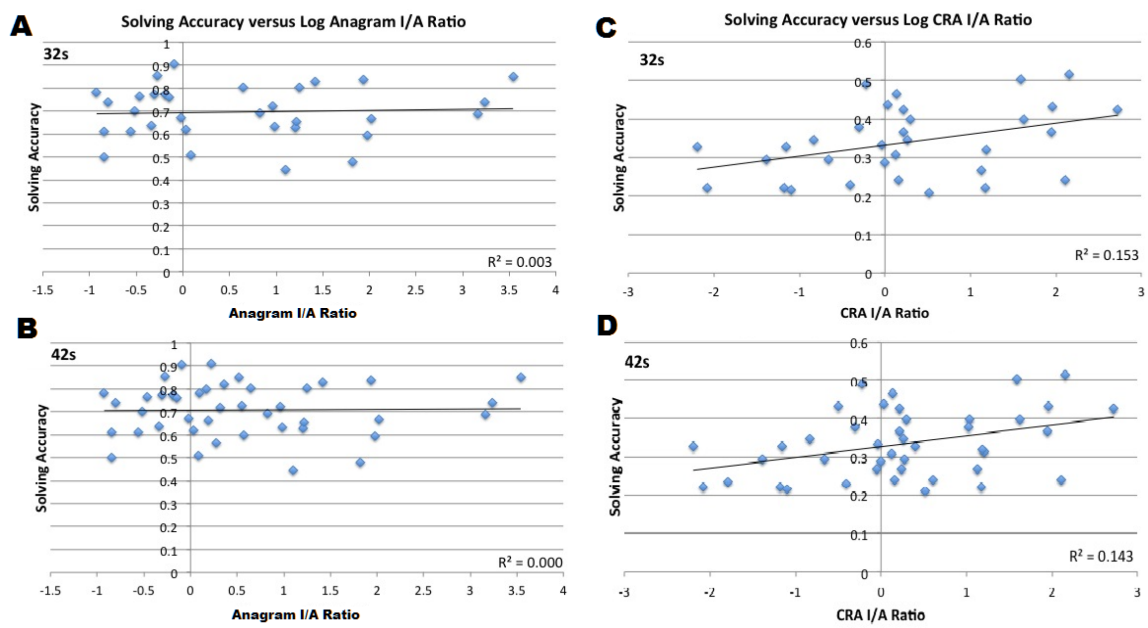

Figure 2: Correlation of solving accuracy and insight/analytic bias
(A) Solving accuracy versus anagram I/A ratio for 32s (middle quintile removed). No correlation present. (B) Solving accuracy versus anagram I/A ratio for 42s (middle quintile retained). No significant correlation. Middle quintile variance is similar or equal to insightful and analytic groups. (C) Solving accuracy versus CRA I/A ratio (middle quintile removed). Moderate, significant (p = .01) correlation favoring insightfuls. (D) Solving accuracy versus CRA I/A ratio (middle quintile retained). Correlation is only slightly weakened. Added subjects are distributed across CRA I/A ratios since middle quintile is defined by anagram I/A ratio.

Table 2: Response timeouts and accuracies.
Timeouts are the proportion of trials not generating a response in 16s. Accuracy was assessed as proportion of all trials and as a proportion of trials generating a response. No group effects were significant.

	Insightfuls		Analytics	
	Task – Anagrams	Task – CRAs	Task – Anagrams	Task – CRAs
	mean ± SD	mean ± SD	mean ± SD	mean ± SD
% Timeout	.28 ± .12	.54 ± .14	.28 ± .11	.56 ± .15
% Correct of all trials	.69 ± .12	.35 ± .08	.70 ± .11	.32 ± .10
% Correct of all responses	.96 ± .04	.79 ± .15	.98 ± .02	.77 ± .14

3.5.2: Response Times

Mean response times are shown in Table 3. For both tasks, analytic solution times were slower than insight solution times. Specifically, for the anagram task, a repeated-measures analysis of variance (ANOVA) showed a significant main effect of solution type ($F[1,30] = 27.90$, $p < .001$). There were no significant group or group*solution-type effects ($F[1,30] < .66$, $p = .43$). For the CRA task, there was also a significant main effect of solution type ($F[1,30] = 19.20$, $p < .001$). The group effect approached significance ($F[1,30] = 3.75$, $p = .06$), but the group*solution-type interaction did not ($F[1,30] = .003$, $p = .95$).

Table 3: Response times.
Response time in milliseconds of the Insightful and Analytic groups on the anagram and CRA tasks, separated by insight and analytic response types, including correct and incorrect responses.

	Insightfuls		Analytics	
	Task - Anagrams	Task - CRAs	Task - Anagrams	Task - CRAs
	mean ± SD	mean ± SD	mean ± SD	mean ± SD
Insight Response time (ms)	4950 ± 3684	5861 ± 2920	4465 ± 3688	5537 ± 2678
Analytic Response time (ms)	6689 ± 3881	6972 ± 2876	5815 ± 3653	6691 ± 2564

3.6: Anagram SPM Results

Three flexfac models were created to test the hypothesis of interest and confounding variables. Potential confounds were included in the final model if they produced a significant main effect or interacted with the Insightful/Analytic group variable. All tests on flexfac models were corrected at a cluster forming threshold of $p<.001$, which conforms to assumptions of Random Field Theory that may be violated with less conservative thresholds (Gehrig, Wibral, Arnold, & Kell, 2012). This parameter addresses concerns recently raised about the validity of random field theory multiple comparisons correction, upon which SPM methods rely (Eklund, Nichols, & Knutsson, 2016).

The first model tested Gender as a potential confound, since this factor was not balanced across participants. Image files were entered into a between-subjects flexfac model with factors Group (insightful/analytic) and Gender. No clusters survived a test of the main effect of Gender or the Group*Gender interaction; therefore, gender was not included in the final model.

Second, a within-subjects flexfac model was created with factors Subject, Group, Eyes and Day. This design is valid for within-subject main effects and within-between factor interactions. An F-test revealed an expected main effect of Eyes condition in several broad clusters spanning multiple frequency ranges over occipital, parietal and frontal cortex (all clusters $p<.0001$). Follow-up directional t-tests confirmed greater broadband occipito-parietal activity in eyes-closed condition, versus greater broadband fronto-temporal activity in eyes-open condition (Figure 3; all clusters $p<.0001$). Therefore, the eyes factor was retained in the final model. No Group*Eyes interaction was observed. No main effect of Day or Group*Day interaction was observed, so Day was not included in the final model.

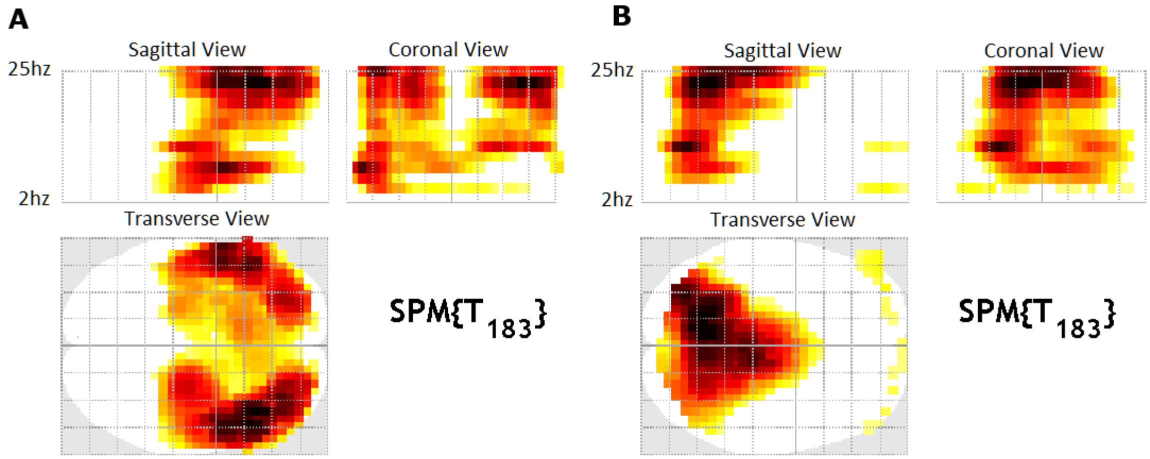

Figure 3: SPM significance maps of flexible factorial contrast for eye condition main effect.

Sagittal, coronal and transverse views of significant voxels. Views are through transparent scalp-frequency space, with pixel color representing the most significant voxel in the plane. Results were thresholded at p_clust = .001 and interpreted at the cluster level. Brain image in transverse view is representative. (a) T-contrast of eye open > closed condition revealing significant broadband clusters over frontotemporal areas, particularly in beta frequency. (b) T-contrast of eye closed > open condition revealing significant broadband clusters over occipito-parietal areas, particularly in beta (midline) and alpha (lateral-posterior).

Based on the above models, a between-subjects flexible factorial model was created with factors Group and Eyes and subjected to a group main effect F-test. This model revealed group differences in the left-parietal region in beta frequency (16hz to 22hz), P_FWE = .008, and in frontal midline in beta frequency (16Hz to 22Hz) at P_FWE = .015. The direction of these effects was explored through T-tests. Analyst > Insightful scans revealed clusters of significantly greater activity in mid-frontal beta (P_FWE = .034, 16Hz to 20Hz), and right-frontal beta (P_FWE = .025, 14Hz to 22Hz; marginally significant in F-test, p=.052; Figure 4a). Insightful > Analyst scans revealed clusters of significantly greater activity in left-parietal beta (P_FWE = .008, 16hz to 20hz), and a marginally significant cluster in left-temporal alpha (P_FWE = .073, 10hz to 12hz; Figure 4b).

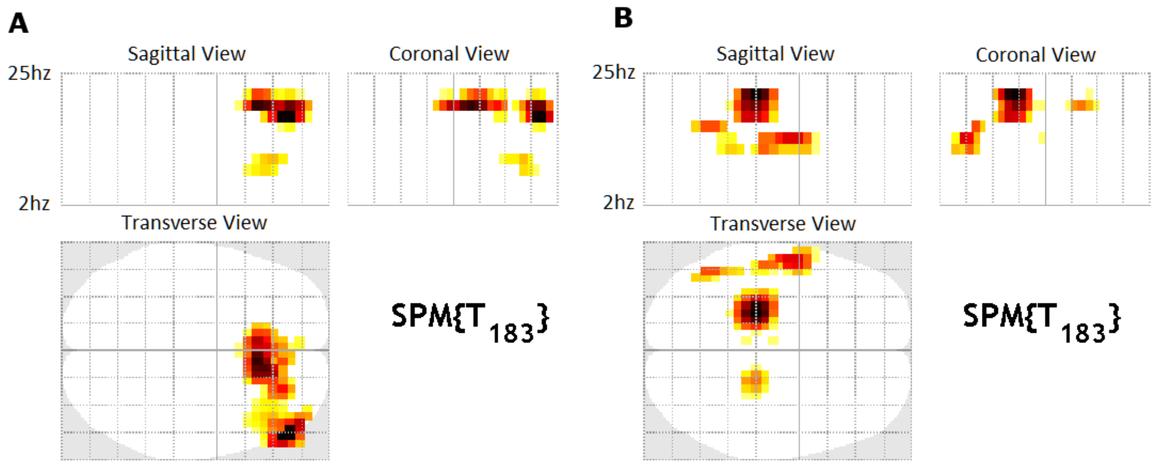

Figure 4: SPM significance maps of flexible factorial contrast for group main effect. Sagittal, coronal and transverse views of significant voxels. Views are through transparent scalp-frequency space, with pixel color representing the most significant voxel in the plane. Results were thresholded at p_clust = .001 and interpreted at the cluster level. All significant clusters are in beta frequency. Brain image in transverse view is representative. (a) T-contrast of analytic > insightful group revealing two significant beta-frequency clusters over midline-frontal and right-frontal cortex. (b) T-contrast of insightful > analytic group revealing one significant beta frequency cluster over parietal cortex, and one marginally significant alpha frequency cluster over left temporal cortex.

3.7: Regional Relationships and Transient Hypofrontality

A correlation analysis was performed to explore the relationships between the significant cluster regions. RS data from days 1 through 3 (including both eye conditions) was averaged within-subject, and power values were extracted from the scalp-frequency locations of the peak voxel of each of the three significant regions (left-temporal alpha was explored in a separate analysis, below). The three regions were significantly correlated, positively between the two frontal clusters and negatively between both frontal regions and left-parietal (Figure 5a).

3.8: Predictive Modeling

To determine if the three significant clusters contributed independently or if their correlations were causal to the I/A ratio, we explored whether regression on multiple predictors and their interactions better characterized the anagram I/A ratio data than any one region independently. In a stepwise multiple regression we found the most parsimonious model of anagram I/A ratio included right-frontal and left-parietal regions while excluding mid-frontal. Interaction terms between the three regions were not significant. The final model correlated with Anagram I/A ratio with r_adjusted = .777 and RMSE = .819 (Figure 5b). This correlation and RMSE outperforms a model using only the parietal peak voxel, r_adjusted = .693, RMSE = .921.

To demonstrate robustness, the final stepwise regression model was subjected to K-fold cross validation with 8 folds. Over 100 iterations, the average RMSE of the K-fold model increased only slightly, to .885. By contrast, a similar cross-validated model trained on only the parietal peak voxel predictor resulted in an RMSE of .941. The RMSE is in the units of the outcome variable (I/A ratio). The standard deviation of the I/A ratios included in the 32 subject analysis was 1.23. Therefore, using the two-predictor model, a subject's I/A ratio can be predicted to within .66 standard deviations.

The model was additionally trained using values from sensor space. The CP3 and F10 electrodes were closest to the peak voxel locations of the parietal and right-frontal clusters, respectively. The power spectra of these electrodes was averaged across all days and eye condition within-subject, and frequency power at the peak voxel frequencies (both 20Hz) was extracted. A model retrained on this data with the same cross-validation methodology as described above resulted in r_adjusted = .30, RMSE = 1.05, or .85 standard deviations.

To test the generalizability of our model we additionally applied it to prediction of day-3 CRA I/A ratios over the 32 subjects included in the original analysis. Despite the lower stability of CRA I/A ratios and differences between the tasks, our model is still a significant predictor of CRA I/A ratio (R=.43, p=.0128, RMSE = 1.1999).

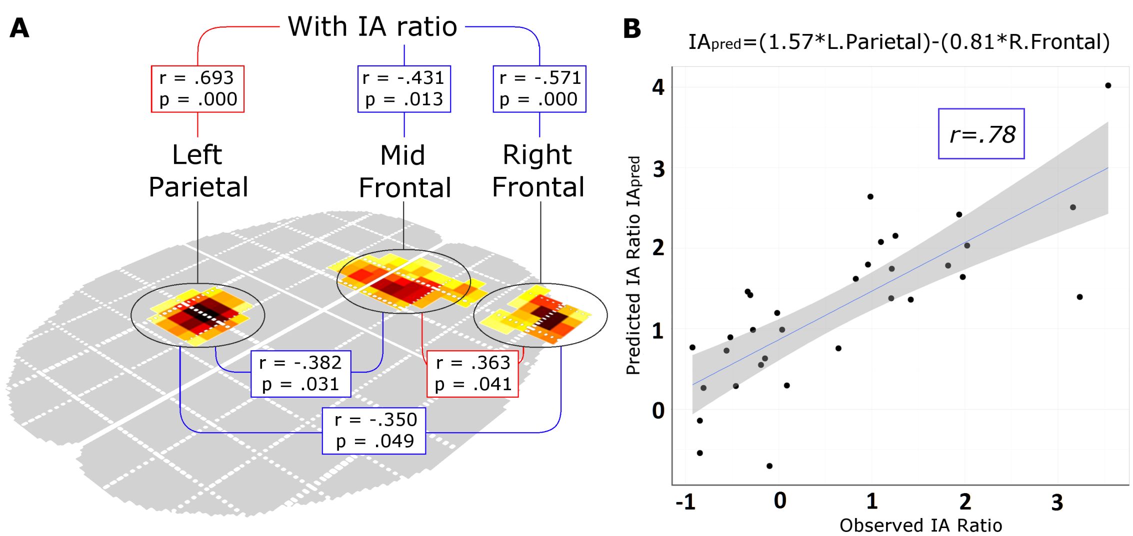

Figure 5: Relationships between predictor clusters and performance of model
(A) Schematic representation of intercorrelations between the significant clusters (lower boxes), and the correlation of each cluster independently with the IA ratio (upper boxes). Blue and red connectors indicate positive and negative correlations, respectively. (B) I/A ratio predicted by two-cluster stepwise linear regression model versus observed (actual) I/A ratio. Multiple linear regression model equation includes only the left-parietal and right-frontal clusters as predictors. Regression coefficient of MLR model is a significant improvement over any individual predictor (r=.78).

3.9: Model Generalizability

To assess the generalizability of our model, we tested its performance on a dataset with these subjects reincluded (42 subjects total). This test revealed that the model significantly predicts I/A ratio, r=.406, p=.021, RMSE=1.02. Therefore, our left-parietal - right-frontal model generalizes, with some loss of accuracy, to the full range of I/A ratios. We additionally tested whether a new model, retrained on the three predictors across all subjects, would better predict the I/A ratio than our original model. A stepwise multiple regression eliminated both mid-frontal and right-frontal predictors, retaining only the left-parietal predictor, but was slightly less accurate in describing I/A ratio than our original model, r=.377, p=.033, 100 iteration average k-fold (8 folds) validated RMSE=1.10. Our original two predictor model is thus slightly better at predicting I/A ratio across all participants.

3.10: Left-temporal Alpha

While left-temporal alpha was not significantly correlated with anagram I/A ratio, correlation with CRA I/A ratio was highly significant, r=.690, p<.0001. Therefore, we reran the stepwise multiple regression against CRA I/A ratio including the left-temporal alpha peak voxel as a predictor. The stepwise model rejected all predictors except left-temporal alpha, achieving a correlation of r=.690, p<.0001, 100 iteration average k-fold (8 folds) validated RMSE=.952. When interactions are allowed, stepwise multiple regression includes predictors left-temporal alpha and its interaction with left-parietal beta, which is not independently significant, r=.766, p<.0001, 100 iteration average k-fold (8 folds) validated RMSE=.911; slightly more predictive than the linear model alone.

3.11: Alternative SPM Regression Analysis

To investigate the nature of the middle quintile in relation to the insightful and analytic groups, a between-subjects SPM regression analysis including all subjects with acceptable behavioral and EEG data (n=42) was performed with factors Group and Eyes, and subjected to a Group main effect F-test. This model revealed no significant clusters, although non-significant clusters in left-parietal beta and right-frontal beta were prominent at P_FWE = .084 and P_FWE=.165, respectively.

To better explain the effects, fitted responses of this model are plotted at the peak voxel locations of the parietal and right-frontal clusters from the main 32 subject analysis (Figure 6). These plots reveal that the middle quintile group had substantially higher activity in the parietal cluster than would be predicted by the 32 subject analysis – as high as the most insightfully-biased subjects. Results for right-frontal cluster were less clear, and generally follow a pattern of increasing variance with decreasing I/A ratio; however, these results are for only one voxel and may not be representative of the overall pattern.

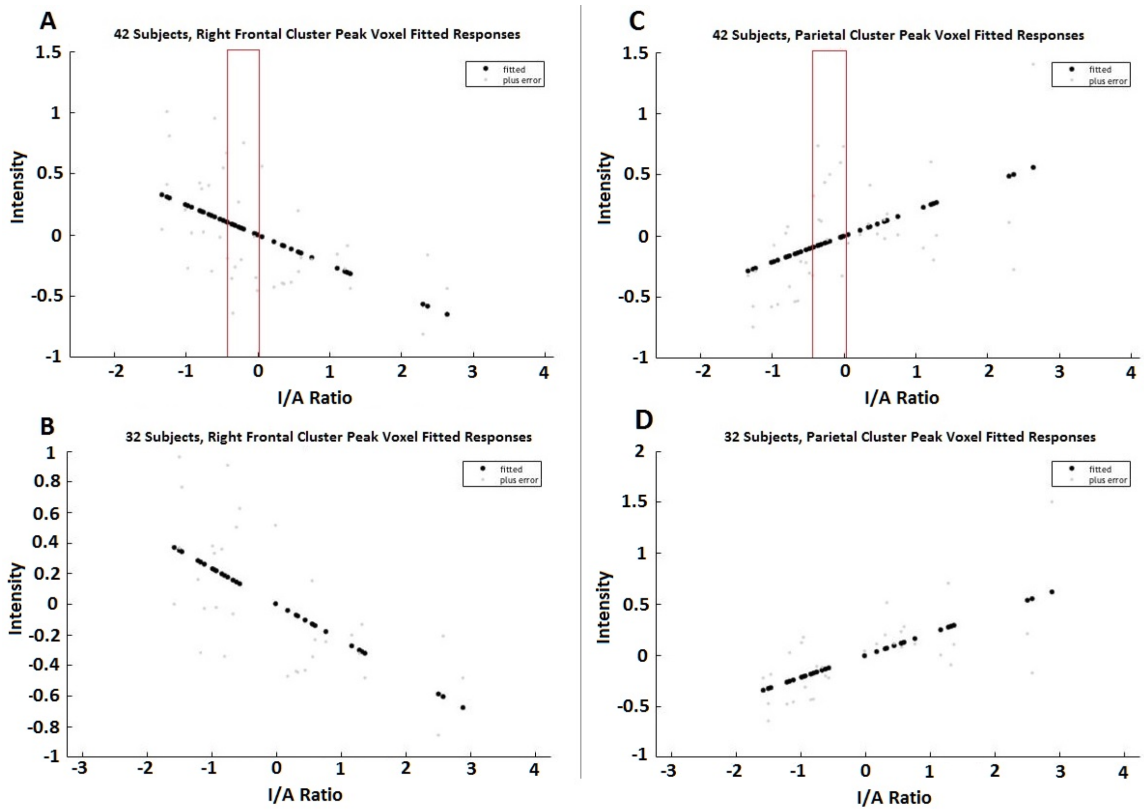

Figure 6: 32 versus 42 subject fitted responses at parietal and right-frontal peak voxels. I/A ratio versus intensity at selected peak voxels. Gray dots are intensity values; black dots are fitted (predicted) responses by linear regression. Intensity is unitless. (A) 42 subject model fitted responses at right-frontal cluster peak voxel, approximate middle quintile in red outline. (B) 32 subject model fitted responses at right-frontal cluster peak voxel (C) 42 subject model fitted responses at parietal cluster peak voxel, approximate middle quintile in red outline. (D) 32 subject model fitted responses at parietal cluster peak voxel.

<u>3.12: Weak versus Extreme Cognitive Style</u>

If subjects with a weak bias towards one or the other strategy have qualitatively different RS profiles from insightfuls and analytics, these differences might be related to weak versus extreme cognitive style, as opposed to the particular direction of style bias. To test this theory, a flexible factorial model including factors group and eyes was created with groups formed from the 16 most strategically unbiased versus the 16 most biased subjects. This analysis revealed no significant clusters.

3.13: Effect of Data Length

Isolation of the traitlike RS activity associated with strategy selection bias may not require all four sessions. We performed the same model creation and K-fold analysis procedure described above on data averaged over different numbers of RS sessions, from one to four. RMSE follows an exponential decline as more RS sessions are included, demonstrating the effect of averaging on the “state” noise components of RS EEG (Table 4). Practical improvement in predictive power is not gained with more than 3 or 4 sessions, except potentially in individuals with unstable RS activity.

In sum, our results describe an insight / analytic “cognitive style axis”, and more generally demonstrate that it is possible to isolate traitlike variation in resting-state recordings and use multi-dimensional predictors to titrate estimates of personality factors and cognitive style. With refinement, this technique may have specific value as an applied predictor of cognitive problem solving style and associated phenomena. The richness of the traitlike RS EEG signal suggests that the trait-activity isolation method may be applicable to identification of traitlike neural predictors of other tasks and constructs.

Table 4: Model improvement as a function of data length

Root mean squared error (RMSE) of stepwise regression model (32s) with an increasing number of included sessions per subject. As additional sessions of resting state data are added to the within-subject averages from which power values are drawn, the RMSE of the model decreases. Practical improvement is not gained with more than 3 days of data.

	RMSE
Day 1 only	1.073
Days 1 to 2	.922
Days 1 to 3	.881
Days 1 to 4	.875

Chapter 4: Discussion

4.1: Predictive Implications

These results demonstrate consistent, trait resting-state differences between individuals who approach problems insightfully versus analytically, in data collected days to weeks before the grouping task. The results are considered below in the context of the anagram task and the insight / analytic ratio. However, the paradigm described for extracting trait-like RS predictors of on-task cognitive features is also extensible to other cognitive features of interest. Fox, Spreng, Ellamil, Andrews-Hannah and Christoff (2015) commented "[…] different forms and content of mind-wandering entail at least partially dissociable neural correlates. […] the investigation of specific functional roles for the various brain networks and regions involved has undoubtedly begun in earnest." The paradigm described here may serve as a general mechanism for advancing that goal. The deep linkage between RS and task suggests future applications in which simple RS recordings could stand in as a simpler proxy for on-task measures and diagnostics.

4.2: Variable Engagement in Mind-Wandering

It is now well understood that subjects are not cognitively idle just because they have not been given an instruction. They produce "stimulus independent thought", or mind-wandering (Smallwood & Schooler, 2006). Mind-wandering is the decoupling of attention from sensory input and task-related processing to episodic memory retrieval, planning and problem solving (Schooler, Smallwood, Christoff, Handy, & Reichle, 2011). In the context of RS, mind-wandering is "spontaneous cognitive operations during conscious rest" (Laufs et al., 2003). Individuals vary in their propensity to engage in mind-wandering in daily life (Killingsworth & Gilbert, 2010), suggesting similar variation in RS. Therefore, group RS differences could reflect different amounts of engagement in mind-wandering behavior. The propensity to produce mind-wandering may be related to ability to maintain vigilance or exogenous attention (Schooler et al., 2011). Strength or flexibility of attention is also centrally implicated in behavioral differences in creative output and ability (Carson, Peterson, & Higgins, 2003; Ansburg & Hill, 2003; Zabelina, O'Leary, Pornpattananangkul, Nusslock, & Beeman, 2015), and specifically in the I/A ratio (Wegbreit, Suzuki, Grabowecky, Kounios, & Beeman, 2012). Attentive faculties could act as a hidden variable that affects RS behavior, by how much mind-wandering occurs, and I/A ratio, by perception and processing of the stimuli.

4.3: Approach to Resting State

More subtly, although subjects in RS are not behaving differently, they may be thinking differently. Cognition during RS depends on ongoing cognitive and affective processes, and the focus of attention. This is well summarized by Laufs et al. (2003), who remarked that "the default mode of brain activity at rest has a specific functional connotation with cognitive and emotional processes revolving around the subject's internal state." The instructions in RS in this study were simply to "remain still and relaxed." Subjects in a task-free period could choose any behavior between vigilant mindfulness and unconstrained mind-wandering (Fox et al., 2015). These opposing modes of thought (Mrazek, Smallwood, & Schooler, 2012; Dixon, Fox, & Christoff, 2014; Lebuda, Zabelina, & Karwowski, 2016) have been previously linked to I/A strategy selection in a study showing that greater self-reported trait mind-wandering predicted more CRA problems solved by insight, and that when instructed to use an analytic strategy, participants with higher scores of trait mindfulness were more accurate overall (Zedelius

& Schooler, 2015). Thus, RS differences could as easily arise from differences in interpretation of the instructions as from the amount of mind-wandering occurring, or raw ability to focus attention.

One explanation for the link between mind wandering and insight is that release of attention from the problem, known as an “incubation period”, is necessary to admit new stimuli and memory retrieval essential to unconscious task-relevant processing (Schooler et al., 2011). However, this theory does not explain insight facilitation on short insight/analytic strategy tasks such as are used in Zedelius & Schooler (2015) and the present work, because these problems are (presumably) too short for meaningful impasse and mind wandering to occur. Thus, the RS predictors of strategy selection we observe are more likely to be a function of subjects’ basic approach to task-free periods.

4.4: Considerations for Interpretation of Scalp-Frequency Results

EEG has high temporal and frequency resolution. In the present analyses, all observed contrast differences are in beta frequency. Beta is known as a signature of active, higher-order cognitive processing (Ray & Cole, 1985) linked to perception, motor control (Sherman et al, 2016) and perceptual feature binding (Jaušovec & Jaušovec, 2000). There also exists evidence for a more general and unifying role for beta oscillations in “maintaining the status quo” (Engel & Fries, 2010). Beta oscillations may reflect a region increasing its resistance to input, in order to maintain the current state or processing task. This interpretation would fit with a theory of cognitive style as a persistent attentional scope or mode of processing that might shape other aspects of ongoing thought.

Interpreting the scalp locations of the observed group differences is complicated by the low spatial resolution of EEG. Electrochemical voltage changes in a particular area of cortex (a "source") spread effectively instantaneously to all areas of the scalp, falling off in amplitude with the inverse of the distance from the generator to the recording site. The scalp, skull, and other intervening tissues further smear the scalp voltage profile. Therefore, scalp EEG is a spatial average of a large number of diffuse signals. Because adjacent areas of the brain may have very different functions and connections, this spatial imprecision makes functional interpretation difficult. Therefore, it is desirable to unmix scalp EEG signals to a more precise approximation of the original sources (source localization or "the inverse problem"). However, most source localization techniques depend on EEG phase information, which is lost during scalp-frequency transformation such as is applied in this work. Localization analysis is the primary direction for future work on this analysis (see 5.1: Future Work), as most functional hypotheses depend on a finer spatial resolution than is achieved with a raw scalp topography.

4.5: DMN/DAN Modulation

Mind-wandering is positively correlated with default mode network (DMN) activity (Mason et al., 2007). If insightfuls and analytics engage in RS mind-wandering at different rates, we would expect to observe differential recruitment of the DMN. Our data are partially consistent with this theory, assuming that the peak voxels of the significant clusters generally approximate the scalp location of the true sources. Frontal beta in medial and inferior regions could indicate increased DMN and mind-wandering activity (Christoff et al., 2016), but these regions are also implicated in externally directed cognition (Dixon et al., 2014). Right inferior frontal areas are also strongly linked to inhibition. Although this linkage has mostly been explored through active (go-no-go) tasks rather than resting state, there is evidence that the inferior frontal region also responds to endogenous signals related to cognitive control (Aron, Robbins, & Poldrack, 2014), such as might be required to "stop thinking." These signals are primarily encoded in beta band (Swann et al., 2009). Midline frontal beta oscillations have also been linked to top-down endogenous cognitive control of attention (Van de Vijver, Ridderinkhof, & Cohen, 2011). The superior parietal area is implicated in endogenous, sustained top-down orienting of attention toward current goals as a component of the dorsal attention network (DAN; Corbetta, Patel, & Shulman, 2008). In the present analysis the group variable did not significantly interact with eye condition as might be expected of an attentional modulation, but in fact this is consistent with evidence that the DAN is functionally connected even in eyes-closed resting-state (Fox, Corbetta, Snyder, Vincent, & Raichle, 2006; Patriat, Molloy, Meier, Kirk, & Nair, 2013). However, there are also broad implications of parietal function in episodic memory retrieval (Wagner, 2005). Notably, medial-frontal and fronto-parietal regions are among areas found most predictive of subject identity (that is, expressing the most idiosyncratic yet consistent cross-session activity) in prior studies of RS (Finn, et al., 2015).

Clearly, spatial interpretation without Laplacian or other source-localization is adventurous. "Raw" EEG scalp signals are not only diffuse, but depending on the orientation of the structure or section of gyri that produces them, may appear at some distance from the actual generator or on the opposite side of the head ("paradoxical lateralization"). Even without these complications, it is not possible to support whether our data are more consistent with a DMN or DAN modulation without better localization.

The distance between parietal and frontal clusters, and their anticorrelation (see below), makes it clear that they originate from separable sources. Although it is not possible to say certainly without localization, it is likely that these sources originate in the lobes (parietal and frontal) they appear over. Thus, at present our results could inform theories that rely on only the broad functionality of each lobe.

Correlation between frontal regions is consistent with findings that medial frontal cortex cognitive control function is linked to inferior frontal structures tractographically (Li et al., 2013) and in active task paradigms (Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004). In the context of the broad inhibitory function of the frontal cortex, the anti-correlation between power in frontal and parietal regions suggests that the insightful/analytic dynamic may be partly traceable to cognitive control that can inhibit or release parietal activity. This interpretation supports the *Matched Filter Hypothesis* (MFH) advanced by Chrysikou, Weber and Thompson-Schill (2013). "Matched filter" is a signal processing term referring to a filter that ideally parses signal from noise. In the MFH, prefrontal cortex (PFC) cognitive control is conceptualized as a filter that acts on low level information, such as perceptual stimuli or subconscious associations. While many tasks benefit from increased cognitive control to screen out irrelevant data, tasks that are more implicit and creative may in fact rely on low-level information. For ideal performance, the PFC filter must be "matched" to the task demands. CRA's are a salient example of a task that relies on weak associations. Insight solutions to CRAs are theorized to rely on simultaneous activation of the weak associates of each of the three stimulus words, and subsequent discovery of their overlap. Anagram insight solutions may rely on unconscious parallel processing of possible letter and bigram positions

(Novick & Sherman, 2003) which are weak “associations” of the stimulus string. Because solution by insight relies on these weak associations, it can only be achieved when PFC filtering is relaxed.

The MFH is supported by studies showing that reduced involvement of the PFC due to dual-task demands, frontal lesions, disorders and age (childhood) can improve performance on tasks requiring bottom-up, data-driven implicit processing, as opposed to more explicit tasks that utilize rulesets and working memory. This dichotomy echoes the concept of cognitive style. With further localization and network analysis, the results presented here could extend MFH to subjects’ resting-state cognition. This would imply that creative and analytic “types” of people engage different levels of PFC filtering at rest. This is consistent with earlier studies advancing transient hypofrontality as a main mechanism of creative thought (Dietrich, 2002), but suggests that hypofrontality is partly chronic and related to individual traits.

4.6: Left Temporal Alpha

Although the SPM results in the left temporal alpha cluster were not significant, the scalp-frequency location of this cluster is intriguing. First, we found that left temporal alpha peak voxel power significantly correlated with each of the three other significant regions, positively with left-parietal and negatively with both frontal regions. This result links the exploratory left-temporal alpha result to the insightful > analytic state. Creativity theory has long postulated a special role for the right hemisphere (Kounios & Beeman, 2014), and prior work on CRAs has revealed a burst of temporal gamma in right anterior superior temporal lobe at the moment of solution (Jung-Beeman et al., 2004). Thus it was interesting to explore whether any correlation existed between the I/A ratio of the tasks in this experiment, and the marginally significant RS left temporal alpha cluster. Since alpha is primarily implicated as an inhibitory frequency (Klimesch, Sauseng, & Hanslmayr, 2007), such a result might indicate a right-dominant temporal lobe state.

4.7: Alternate SPM analyses

The SPM results and stepwise multiple regression model were based on a dataset with subjects in the middle quintile of anagram I/A ratios removed. Subjects with middling I/A ratios (who thus do not strongly rely on one strategy or the other) might represent an a different "fast switching" type that quickly moved between insight and analytic modes. These subjects could exhibit a different resting state pattern which not lying on a continuum with highly insightful and analytic solvers. Regardless of the underlying phenomena, subjects with middling I/A ratios could easily have been included in either group with a few more insight or analytic solutions, and their inclusion weakens the group separation (Kozhevnikov, 2007). Ideally, an inflection point or "transition zone" would be identified which defined "no style" individuals from both insightfuls and analytics. An obvious candidate is the value log I/A ratio = 1, where the numbers of solutions by each method are equal. However, it is not clear that an "average" solver should have a log ratio of 1; insight or analysis might be more prevalent as a solving method, defining the other extreme. Since little is known about cognitive style, the actual distribution of these inflection points is unknown. Alternatively, if I/A ratio does not contain critical inflection thresholds as a proxy for cognitive style, then a continuous regression including the middle quintile might be more appropriate.

However, an alternate version of the SPM analysis was performed using all subjects with acceptable data (including the middle quintile) as a regression on I/A ratio to explore whether the results depended on removal of the middle quintile. No significant clusters resulted from this analysis. It is not possible to support a detailed interpretation of this null result, but it is in line with the assumption that the middle quintile subjects' resting state pattern is not on the same continuum as the extreme subjects.

A related question is whether the most biased subjects have a different pattern of resting-state activity than the most unbiased. This explores any predictors of the presence of a cognitive style versus individuals who are agnostic. This strikes at the concept of "cognitive flexibility". For instance, individuals with no cognitive style might be engaging in fast set-switching between a creative versus analytic mindset. However, an analysis repartitioning the subjects in this manner found no significant voxels. This is an interesting avenue for future exploration. Many high-level treatments of the phenomenon of creativity suggest that alternating between a highly divergent and open frame of mind that generates possibilities, and a structured or convergent mindset in which those possibilities are rigorously tested or value-assessed is a possible mechanism for creative genius, especially of the type encompassing long creative projects which involve both technical and creative aspects. Ultimately, an extremely insightful or analytic mindset may not be the most productive, although in the context of this study it is the most informative.

Ideally, a three-way comparison between insightful, middle, and analytic subjects would be performed to clarify these questions. This study did not have enough subjects to achieve sufficient power for such an analysis.

4.8: Predictive Modeling

The stepwise predictive model exceeded the predictive power of any of the regional predictors by a significant margin. Given SPM scalp-frequency maps, the cross-validated model could predict I/A ratio to within .66 standard deviations – given only sensor data, it could predict I/A ratio to within .85 standard deviations. With future improvements, this opens the door to assessment of cognitive style without laborious cognitive tasks, and to the potential generalization of the cognitive style fronto-parietal predictor to other creative tasks. It should be noted that these results were obtained with a 32 subject model (middle quintile removed). With the middle quintile re-added, the predictive stepwise regression model was still fairly accurate, but it is questionable whether the inclusion of these subjects in the model is appropriate given the failure to observe significant SPM clusters at those locations with these subjects re-included. The middle quintile remains an unexplained source of variance.

Chapter 5: Conclusion

This thesis has demonstrated a technique for isolation of trait resting-state neural signatures of cognitive style. General considerations for designing and implementing investigations of other cognitive traits are summarized with an overview of an EEG processing and analysis pipeline for preparing and investigating these data. The analysis of insight/analytic cognitive style revealed group differences over frontal and parietal lobes that occur days to weeks before the grouping task, and thus are predictive rather than descriptive of the variance in anagram solution style bias. The lack of source localization makes the specific pattern of these results difficult to interpret. However, at a lobe-level, the spatial results are in agreement with the Matched Filter Hypothesis, and could represent differential levels of chronic executive inhibition during resting state in insightfuls and analytics. Finding these signals in isolations of trait-like resting state suggests that these differences in executive inhibition could be deep and influential to individuals' approaches to a wide domain of problem solving. This is supported by the applicability of the fronto-parietal model to CRA data as well as anagrams.

5.1: Future Directions

Replication with a greater subject count would make possible a more detailed consideration of subjects in the middle quintile of the insight/analytic distribution. In the future, replication with a different insight/analytic judgment task would help to generalize these results.

Source localization and network analysis are important for improving the specificity of the conclusions of this work. Efforts to complete these analyses are underway. Because scalp-frequency transformation of the type used here destroys phase information, an alternative Laplacian transformation will be used (Nunez et al., 1994). Because EEG signals fall off nonlinearly as a function of their distance from the source generator, scalp areas where voltage changes rapidly are likely to approximate the true sources. Laplacian transformation calculates the second spatial derivative of scalp-frequency power, or the rate of change of the rate of change in EEG scalp power. This is a form of high-pass spatial filter. The Laplacian enhances focal voltage changes and attenuates the smoother signal change that is likely to represent uninformative smearing and signal diffusion. The Laplacian does not provide the three dimensional source approximations that model-based techniques like LORETTA and beamforming do. However, it relies on very few assumptions compared to model-based methods. Laplacian transformation and SPM analysis will be performed on these data in the near future.

Network analysis will be performed via the MultiVariate Granger Causality (MVGC) toolbox (Barnett & Seth, 2014). Because granger causality analysis is biased by highpassing at even low values (.1Hz), alternate preprocessing has been developed for this analysis. As an alternative to highpassing, linear detrending is used to remove slow drift (Delorme et al., 2011). The Cleanline plugin is used to remove line-noise as an alternative to lowpassing (Mullen, 2012). Standard preprocessing as described in the main methods followed, with the exception that all gross-artifact identification and rejection was performed automatically. The results of this analysis may shed light on the network connectivity between right frontal and left parietal lobes in solvers with different cognitive styles, and provide additional evidence for or against integration of these results with the matched filter hypothesis.

This work supports the role of resting-state recording as a source of predictors for psychological and cognitive style variables. The methods described are applicable to uncovering resting-state predictors of any cognitive style exposed by a similar free-strategy problem. Resting state analysis may develop to encompass a personal diagnostic that can be used to assess many dimensions of individual differences without response bias through quick and non-invasive neural recording. Future work should explore advanced machine-learning classification algorithms to form more accurate and detailed predictions about cognitive style from rich scalp-frequency EEG statistical parametric maps, rather than peak voxel intensities.

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Appendix A: Anagram and CRA Insight / Analytic Ratios by Subject

Group	Subject	Anagram I/A	CRA I/A
Neither	104	0.17	-0.05
Neither	106	0.19	0.61
Neither	114	0.22	1.03
Neither	117	0.57	-0.49
Neither	118	0.32	1.21
Neither	126	0.36	0.25
Neither	203	0.28	-1.79
Neither	209	0.52	0.41
Neither	216	0.10	1.03
Neither	222	0.55	0.27
Analytic	102	-0.56	-1.18
Analytic	103	-0.19	-0.30
Analytic	105	-0.93	0.14
Analytic	108	0.09	-1.15
Analytic	110	-0.02	-0.41
Analytic	111	-0.85	1.18
Analytic	115	-0.15	-0.84
Analytic	120	-0.46	0.27
Analytic	123	-0.81	0.03
Analytic	124	-0.85	-1.10
Analytic	204	-0.28	0.22
Analytic	210	-0.33	0.30
Analytic	212	-0.30	0.16
Analytic	214	-0.52	-1.39
Analytic	220	0.04	-2.08
Analytic	225	-0.10	-0.22
Insight	107	1.42	2.15
Insight	109	3.54	1.63
Insight	112	1.21	0.13
Insight	122	3.23	2.11
Insight	125	1.25	0.00

Insight	202	3.16	0.51
Insight	206	0.96	1.59
Insight	208	0.83	-2.20
Insight	211	0.64	-0.04
Insight	215	1.22	1.95
Insight	217	1.94	2.72
Insight	218	1.10	-0.66
Insight	219	1.98	1.13
Insight	221	0.98	1.96
Insight	223	1.82	0.22
Insight	224	2.02	1.19