Identification of Anxiety Endophenotypes Using Multidimensional Measures of Attention

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ABSTRACT

The relationship between attention bias and anxiety has been robustly supported across paradigms and disorders; however, most published studies have ignored the known multidimensional nature of attention, and instead proceeded in measuring attention bias as a unitary construct, resulting in a lack of clarity regarding which attentional mechanisms contribute to specific manifestations of anxiety. In the current study we addressed this by collecting response latency data on three basic attentional processes, (1) attentional orienting, (2) attentional disengagement, and (3) attentional control to evaluate their relationship to specific anxiety symptoms. In a final sample of 149 college undergraduates, who either completed the computer tasks in-lab (N = 28) or online (N = 121), we used an unsupervised clustering approach (k-means clustering) to assign individual cases to clusters, depending upon their performance on measures of attention. We used a supervised machine learning approach (random forest), to cross-validate the unsupervised classification results. Anxiety symptoms were then set as predictors, predicting cluster membership using multinomial logistic regression. With the unsupervised k-means clustering approach, we found four clusters in the data. The random forest algorithm suggested variable prediction accuracy, dependent upon cluster size. Anxiety symptoms were unrelated to attention cluster membership. Study results were limited, which may be influenced by potential data collection and analytic factors.

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GENERAL AUDIENCE ABSTRACT

Anxiety has been shown to be associated with enhanced attention for threatening information; however, most published studies have ignored the known multidimensional nature of attention, and instead proceeded in measuring attention as a unitary construct, resulting in a lack of clarity regarding which attentional mechanisms contribute to anxiety. In the current study we addressed this by collecting response latency data on three basic attentional processes: (1) attentional orienting for threatening information, (2) attentional disengagement from threatening infromation, and (3) attentional control to evaluate their relationship to specific anxiety symptoms. The final sample was 149 college undergraduates, who either completed the computer tasks in-lab (N = 28) or online (N = 121). We clustered individuals on these measures of attention (unsupervised k-means clustering). We used a supervised machine learning approach (random forest), to cross-validate the unsupervised classification results. Anxiety symptoms were then set as predictors, predicting cluster membership using multinomial logistic regression. We found four clusters of individuals in the data. The random forest algorithm suggested variable prediction accuracy, dependent upon cluster size. Anxiety symptoms were unrelated to attention cluster membership. Study results were limited, which may be influenced by potential data collection and analytic factors.

Table of Contents

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Introduction

The National Institute of Mental Health established the Research Domain Criteria (Insel et al., 2010), a research model that recasts psychiatric disorders in terms of fundamental underlying mechanisms of psychopathology. As such, the RDoC model largely abandons traditional diagnostic classification systems such as DSM and ICD-10, emphasizing instead neurobiological systems that cut across traditional diagnostic boundaries and correspond to observable clinical problems and symptomatology. Therefore, rather than relying on consensus-based diagnostic categories to guide research and ultimately treatment of psychiatric disorders, RDoC provides a roadmap to understanding dimensions of functioning (e.g., sustained threat, attention, arousal, and working memory) across multiple tiers of analysis including genetic, neurological, and behavioral levels. Attention has been a topic of intense interest in the context of RDoC, owing in part to previous and robust associations with various forms of psychopathology, particularly anxiety (Bar-Haim et al., 2007; Cisler & Koster, 2010; Mobini & Grant, 2007). For example, enhanced attention for threatening information may be pathognomonic of anxiety symptomatology broadly construed, a finding that has been widely supported across various traditional DSM and ICD-based classification approaches (Bar-Haim et al., 2007). Although the attention-anxiety association has been appreciated for some time now, no study has yet tested a central hypothesis that can be extrapolated directly from RDoC: that distinctive anxiety syndromes should be related to individual differences in the configuration of attention patterns (e.g. high/low initial orienting, high/low disengagement, high/low voluntary control [Bar-Haim et al., 2007; Insel et al., 2010]). If this assumption is correct, then the landscape of attention patterns at the individual (case wise) level should allow partitioning of cases into clusters that markedly differ in anxiety symptomatology (e.g., worry, social anxiety, obsessive anxious thoughts, or anxiety regarding physiological sensations of anxiety). Establishing distinctive syndromes of anxiety that can be partitioned along the lines of underlying mechanisms such as attention, is not only central to the theoretical basis of RDoC, but also a critical step toward development of treatments that will *directly target* the cognitive factors maintaining those syndromes. Accordingly, the purpose of the current study is to use a data-driven clustering approach to analytically determine whether data from several well-validated measures of attention can allow flexible, continuous and automatic clustering of cases into distinctive clinical syndromes, or intermediary (*endo*-) phenotypes of anxiety.

Attention is a fundamentally complex and multifaceted construct that has been traditionally viewed as the output of competitive interactions between cortical systems modulating access to visual stimuli. Given attention's dependence upon neural resources that are by definition limited in capacity, stimulus perception therefore necessitates a simultaneous reduction of attention to less important stimuli. Thus, conscious awareness could be described as the product of a "winner-take-all" competition that is biased for specific types of information (Desimone & Duncan, 1995). This process, referred to as biased competition, is thought to be the consequence of competitive interactions between two distinctive cortical networks that dynamically interact to modulate conscious access to stimuli (Corbetta, Patel, & Shulman, 2008). First, a dorsal-parietal network guides attention according to goals, or intentions toward stimuli in the environment, referred to as 'top-down' attention. For example, intending to read a sentence on a page and subsequently attending to the printed patterns of characters and spaces, reflects in part this top-down attentional process. Conversely, a ventral-parietal network is thought to handle basic ('bottom-up') computations related to fast-latency detection of previously unattended yet behaviorally relevant stimuli. As such, in order to successfully perform attention-demanding tasks, the dorso-parietal network, via likely the medial frontal gyrus, suppresses activation of the ventral-parietal network for unimportant information. However, if currently unattended objects in the environment require immediate attention, the re-orienting of attention from the attended stimulus to a previously unattended location involves an interaction between the dorso-parietal network (initiation of re-orienting) and the ventral-parietal network (later reconfiguration of dorso-parietal network). The dynamic, competitive interactions between these two networks collectively (either serially or in parallel) determine which stimuli are granted access to conscious awareness (Corbetta et al., 2008).

Several distinct cognitive processes are thought to be the natural output of the competitive interactions between the dorsal and ventral attention networks. For example, alerting, orienting, and executive control (Petersen & Posner, 2012) are conceptually distinct processes that are well-established (e.g., Fan, McCandliss, Sommer, Raz, & Posner, 2002; Raz & Buhle, 2006) and can be explained in terms of the dynamic, moment-to-moment changes in activation across dorsal and ventral networks of attention in the brain (Corbetta et al., 2008; Posner & Petersen, 1990). Alerting refers to a heightened level of vigilance, which is thought to be required for rapid stimulus detection. Alerting is thought to involve sustained activation of the ventral network, through modulations originating in the locus coeruleus, possibly mediated by the neuromodulator norepinephrine (Corbetta et al., 2008; Petersen & Posner, 2012). Orienting refers to the initial prioritization of sensory input following its presentation in the visual field, (Petersen & Posner, 2012; Posner & Petersen, 1990). Maintenance of orientation may invoke the dorsal network (intraparietal sulcus and superior parietal lobule), inasmuch as this process involves goal-directed (voluntary allocation of) attention to a fixed location in space. Executive control, or the top-down regulation of orienting and re-orienting processes, is associated with the fronto-parietal and cingulo-opercular networks (Dosenbach, Fair, Cohen, Schlaggar, & Petersen, 2008), which can effectively suppress the stimulus-driven attention when necessary to maintain top-down attention. As such, attention is not a unitary construct, but instead is comprised of multiple cognitive processes that are represented by related, yet independent neurological regions and networks.

A variety of these attentional processes, including but not limited to alerting, orienting and executive attention have been extensively examined in relation to anxiety (Bar-Haim et al., 2007; Cisler & Koster, 2010; Mobini & Grant, 2007). Because behaviorally relevant stimuli consume greater attentional resources than behaviorally irrelevant stimuli (Desimone & Duncan, 1995), and because fear-related stimuli are awarded preferential access to attentional resources compared to affectively neutral stimuli, it follows that chronically anxious individuals would demonstrate increased allocation of attentional resources toward behaviorally relevant environmental stimuli. This phenomenon has been described as an 'attention bias' for threat, and can be observed across diverse types of measurement paradigms (e.g., visual search, dot probe, and Stroop) and anxiety/anxiety-related disorders (e.g., generalized anxiety disorder; Bradley, Mogg, White, Groom, & Bono, 1999; social anxiety disorder, Gilboa-Schechtman, Foa, & Amir, 1999; specific phobias, Mogg & Bradley, 2006; panic disorder, McNally, Riemann, & Kim, 1990; obsessive compulsive disorder, Tata, Leibowitz, Prunty, Cameron, & Pickering, 1996; post-traumatic stress disorder, Bryant & Harvey, 1997). In a meta-analysis of the attention bias literature, Bar-Haim and colleagues (2007) found that the magnitude of attention bias is exceptionally similar across different anxiety disorders, prompting the question of how phenotypic differences in anxiety are so prevalent and diverse when attention for threat appears to be strikingly similar. To address this, Bar-Haim and colleagues (2007) propose that phenotypic differences in anxiety could be due to distinctive patterns of malfunction at different stages of attention, all of which could produce a similar ostensible attention bias when measuring with one paradigm. This conceptualization of attention bias is consistent with the broader model of attention as a multidimensional construct, dependent upon different stages of processing, including pre attentive biases (e.g., evaluation of stimuli outside of awareness and automatic attentional resource allocation) and later, top-down processes. In line with this, Bar-Haim and colleagues (2007) further propose that high trait anxiety and anxiety disorders could be due to a wide variety of attentional factors such as automatically evaluating objects as threatening, allocating resources to even mildly threatening stimuli, viewing that allocation as indicative of highly-threatening objects in the environment, or experiencing impaired ability to override these aberrant processes. Thus if attention bias is multi-dimensional, its measurement should faithfully reflect this. This has been addressed in the literature by examining different components of attention in relation to anxiety, such as attentional orienting, attentional disengagement, and attentional control (e.g., Cisler & Koster, 2010; Eysenck, Derakshan, Santos, & Calvo, 2007; Fox, Russo, Bowles, & Dutton, 2001). These distinct dimensions of attention bias are explained in greater detail below.

Attentional Orienting

Attentional orienting involves allocation of attentional resources toward a previously unattended location in the visual field (Corbetta et al., 2008). Attentional orienting has been conceptualized as automatic process or occurring at early stages of initial processing (Bar-Haim et al., 2007). One approach that has received some support in the literature is a model of enhanced initial orienting toward behaviorally relevant stimuli in anxiety disorders, broadly construed. Facilitated orienting of attention for threatening information has been supported across multiple theoretical models of attention and anxiety (e.g., Beck and Clark, 1997; Eysenck et al., 2007; Öhman, 1996) and empirically across multiple anxiety syndromes (see Bar-Haim et al., 2007 for review).

Attentional Disengagement

Attentional disengagement refers to the re-orienting of attention away from a previously attended location to another object in the visual field (Cisler & Koster, 2010). Slowed attentional disengagement is associated with high trait anxiety and suggests that an attended threatening stimulus inhibits re-orienting to other, non-threatening stimuli (e.g., Cisler & Koster, 2010; Fox et al., 2001). Attentional disengagement is believed to occur at later stages of processing. It is similar to the theorized attentional bias goal engagement system (Bar-Haim et al., 2007), which determines the allocation of attention, including attending to non-threatening stimuli while ignoring potentially negative stimuli.

Attentional Control

Attentional control, or executive control, is an individual difference variable that refers to one's ability to voluntarily allocate attention (Petersen & Posner, 2012). Attentional control has emerged as a potentially influential construct in anxiety literature. Eysenck and colleagues (2007) proposed that anxiety is associated with poorer attentional control due to increased stimulus-driven, bottom-up processing and inhibited goal-driven, top-down processing. When examining attentional control in attention biases, Derryberry and Reed (2002) found that anxious individuals high in attentional control were able to disengage their attention from threat earlier than anxious individuals low in attentional control. Similarly, individuals low in attentional control, showed difficulty disengaging attention from emotional faces during a rapid serial visual presentation task (Peers & Lawrence, 2009).

Theoretical Model

Some support has been found for these three distinctive attention allocation mechanisms (orienting, disengagement and attentional control) as they relate specifically to certain forms of anxiety syndromes. For example, enhanced attentional orienting for threat, even at the pre attentive level, is associated with post-traumatic stress disorder (Harvey, Bryant, & Rapee, 1996) and panic disorder (Lundh, Wikstrőm, Westerlund, & Őst, 1999), which may both be related to enhanced orienting toward aversive interoceptive sensations. Post-traumatic stress disorder involves hyper vigilance toward environmental threat, and similarly, panic disorder involves heightened sensitivity and threatening interpretation of physiological sensations of anxiety. Essentially, both disorders exhibit symptoms that involve increased threat sensitivity; one pertaining to environmental cues (post-traumatic stress disorder) and the other (panic disorder) related more to self-cues. Along similar lines, generalized anxiety disorder also demonstrates a unique facilitated attentional orienting for threatening stimuli, not present in depressive disorder (Mogg & Bradley, 2005). Social anxiety disorder is associated with impaired attentional disengagement from threat but not facilitated attentional orienting (Amir, Elias, Klumpp, & Przeworski, 2003). This may be due to the relationship between impaired attentional disengagement and the tendency to engage in post-event rumination often associated with social anxiety. Contamination fear, a common anxiety associated with obsessive-compulsive disorder, also is linked to impaired attentional disengagement from threat (Cisler & Olatunji, 2010), which reflects the intrusive and repetitive nature of obsessions (American Psychiatric Association, 2013). Collectively, these results suggest that different manifestations of anxiety potentially reflect differences in attentional mechanisms; however, there is limited research on which attentional mechanisms relate to specific anxiety syndromes.

Current Study

Despite preliminary evidence for mechanistic linkages between the configuration of individual strengths and weaknesses across specific components of attention, currently it is unknown how attentional orienting, disengagement, and control differentially contribute to distinct forms of anxiety symptomatology. Accordingly, the current proposed study will address the issue by testing the working hypothesis that specific components of attention: (1) attentional orienting, (2) attentional disengagement, and (3) attentional control should allow partitioning of individual cases into clusters that are defined by similar phenotypic anxiety syndromes, as measured by dimensional (self-report) scales of specific anxiety symptoms. Differential anxiety symptoms as measured by questionnaires will include anxiety sensitivity, social anxiety, worry, obsessive thoughts, and related avoidance behaviors. The proposed study will take a bottom-up approach to linking individual differences in attentional processes to anxiety symptom profiles.

To-date the majority of work in this area has used a mono-method approach, using a single paradigm within a study to measure a specific form of attention, despite the likely multidimensional nature of attention bias. An alternative approach to measuring the attention-anxiety interface involves using multiple paradigms to examine attention for threatening information in order to characterize linkages to anxiety symptom profiles. This could allow a determination of whether distinct patterns of attentional mechanisms are linked to individual differences in the (1) type and (2) severity of anxiety symptoms.

In light of preliminary, extant literature suggesting anxiety syndromes differ in regards to these attentional mechanisms (e.g., Amir et al., 2003; Cisler & Olatunji, 2010; Lundh et al., 1999; Mogg & Bradley, 2005), the classification of anxiety symptoms based on distinct configurations of attentional components is predicted. Four specific hypotheses will be tested:

1. Anxiety sensitivity, or fear regarding physiological symptoms of anxiety, will be associated with enhanced attentional orienting for threat. This attentional mechanism is associated with panic disorder (Lundh et al., 1999), and anxiety sensitivity is strongly linked to panic disorder (American Psychiatric Association, 2013). Moreover, the enhanced attentional orienting for threatening information reflects the consistent heightened sensitivity to physiological indicators of anxiety that is associated with anxiety sensitivity, which is unlike the perseverative nature of other anxiety symptoms.

2. Social anxiety, fear of negative evaluation and subsequent avoidance of social or performance situations (American Psychiatric Association, 2013), will be associated with inhibited attentional disengagement from threat, as attentional disengagement difficulties in the absence of facilitated attentional orienting have been linked to social anxiety disorder (Amir et al., 2003), and deficits in disengagement from threatening information reflect the post-event perseveration one with social anxiety often reports after a social event that was anxiety-inducing.

3. Obsessive thoughts and related compulsive behaviors will be associated with impaired disengagement of attention from threat and deficits in attentional control. Obsessive thoughts and compulsive behaviors for contamination have been associated with impaired disengagement of attention from threat (Cisler & Olatunji, 2010), which reflects the repetitive, intrusive nature of obsessions. Also, deficits in cognitive and behavioral inhibitory processes have been linked to obsessive-compulsive disorder (Chamberlain, Blackwell, Fineberg, Robbins, & Sahakian, 2005), which likely reflect the consistent compulsive behaviors associated with the obsessions.

4. Worry, often associated with generalized anxiety disorder, will be associated with enhanced attentional orienting for threat, inhibited attentional disengagement of attention from threatening information, and deficits in attentional control, given previous findings supporting facilitated orienting toward threat (Mogg & Bradley, 2005), post-task worrying (Paulesu et al., 2010), and attentional control deficits (Price, Eldreth, & Mohlman, 2011) associated with generalized anxiety disorder. This facilitated orienting of attention toward threat reflects the often diverse number of worries, while the inhibited disengagement of attention from threat and deficits in attentional control reflect the seemingly constantly re-occurring, preservative nature of worry.

If these hypotheses are supported, there is potential for a sustained beneficial effect on the field, as this study would be an initial step in identifying additional specific cognitive mechanisms underlying anxiety symptomatology. Moreover, it would facilitate work in the context of the RDoC proposition that underlying transdiagnostic mechanisms can and should be used as the bases of syndrome classifications. In order to test these hypotheses, the proposed study will utilize a machine learning approach applied to measures of attention, via a combination of both unsupervised and supervised learning methods in order to cluster individuals based on attentional processes. A multinomial logistic regression will then be used to characterize each discovered cluster in terms of anxiety symptoms (self-report measures).

Methods

Participants

University students at Virginia Polytechnic Institute and State University who were currently taking a psychology course signed up via the SONA Experiment Management System to receive course credit for their participation. One hundred and ninety nine individuals participated in the experiment. Of this initial 199, data from 16 individuals were not included in the final analyses, as they incorrectly responded to at least one of two questionnaire checks, designed to assess that the participant was reading the questions (e.g., “Please answer ‘3’ to this question”). Of the remaining 183, 10 individuals’ data were not included due to technical errors of task administration, and 24 individuals’ data were not included, as their performance scores were outliers of the sample (Z score > 2), which if not removed, resulted in single, outlier individuals being considered separate clusters from the rest of the sample, see Figure 1 for the study consort diagram. This resulted in a final sample of 149 individuals (74.5% female) with a mean age of 19.80 (SD = 2.00) years. The in-lab sample (N = 28) was 78.6% female with an average age of 20.54 (SD = 2.89) years. The online sample (N = 121) was 73.6% female with a mean age of 19.63 (SD = 1.70) years. The online and in-lab samples did not differ in gender or age. Of the final sample, 5% reported being diagnosed with an anxiety disorder (25% generalized anxiety disorder, 12.5% obsessive-compulsive disorder, 62.5% not specified), 4% reported being diagnosed with depression, and 3% reported being diagnosed with another disorder (attention-deficit disorder, eating disorder not specified, obsessive-compulsive personality disorder).

Computerized Tasks

Attention Paradigms We utilized a combination of web-based (remote) administration as well as lab-based (local) administration of the cognitive tasks proposed below, which were programmed with Inquisit (http://www.millisecond.com/), a software platform designed to administer tasks of attention with millisecond accuracy (De Clercq, Crombez, Buysse, & Roeyers, 2003). This allowed participants to remotely log onto the site, and complete tasks on their own computer.

Attentional network task (ANT)

We used the attentional network task (ANT; Fan, McCandliss, Sommer, Raz, & Posner, 2002*)* to assess attentional control. The ANT combines the Posner cued reaction time task (Posner, 1980) and the Eriksen and Eriksen (1974) flanker task to assess the alerting, orienting, and executive control components of attention (Posner & Petersen, 1990). During the task, a fixation cross (+) was presented during the entire trial. There were four cue (*) trial types: no cue, center cue, double cue (cue appeared above and below fixation cross), and spatial cue (cue appeared either above or below the fixation cross, indicating where the arrows would appear). During cued trials, cue(s) were present on the screen for 100ms. After the cue(s) was absent for 400ms, the behavioral probe appeared. The behavioral probe consisted of either a row of congruent arrows (five arrows facing in the same direction), a row of incongruent arrows (the middle arrow facing in the opposite direction of the four flanking arrows), or a center arrow without flanking arrows. Once the participant indicated the direction of the middle arrow by pressing the corresponding button, a new trial began after a variable duration (3,500ms – the participant's response latency). There were 24 practice trials prior to testing administration, during which each trial type was presented, and participants were informed of their response accuracy after each trial. Data from the practice trials were not included in the analyses. Following the practice, participants completed 288 trials, with equal presentation frequency of each of the 12 conditions: 4 (Cue: None, Center, Double, Spatial) x 3 (Flanking: None, Congruent, Incongruent). To create our attentional control index, we first removed each individual's incorrect trials. Following this, we removed each individual's outliers (responses that were > 2 Z scores, based on their response latencies for the task). We then calculated the difference between mean response latencies on incongruent and congruent arrow trials as our measure of attentional control, with smaller numbers (or more similar performance on these trials) reflecting greater attentional control.

Spatial cueing task

A modified spatial cueing task (e.g., Amir et al., 2003; Fox et al., 2001; Posner, 1980) was used to assess both attentional orienting for threat and attentional disengagement from threat. At the start of the trial, a fixation cross (+) appeared on the screen and remained on the screen for the duration of the trial. A neutral or angry face from a well-validated stimuli set (Ekman & Friesen, 1976) appeared on the screen on either the right or left side of the fixation cross 500ms after the start of the trial, and stayed on the screen for 200ms. After the face disappeared, a probe (*) appeared in either the same location as the face ("valid") or on the opposite location of the face ("invalid"). The participant was asked to indicate the location of the probe by pressing a corresponding button. Once pressing the button, the probe disappeared and the next trial began after 1000ms. Sixteen faces were chosen, consisting of 8 actors (4 female and 4 male). Actors appeared with equal frequency, and presentation order of actor, face valence, face location, and validity were randomized. One-fourth of the trials were invalid; the remaining were valid. There were 10 practice trials. Practice trials were identical to experimental trials except inanimate objects (stock images of chairs) were used as stimuli, and participants were informed of their response accuracy after each trial. Practice trials were not included in the final analyses. There were 256 experimental trials, consisting 64 invalid and 192 valid trials and 4 trial types: 2 (Validity: Valid, Invalid) x 2 (Valence: Neutral, Angry). To create our attentional orienting and attentional disengagement scores, we first removed each individual's incorrect trials. Following this, we removed each individual's outliers (responses that were > 2 Z scores, based on their response latencies for the task). Attentional orienting was then calculated as the difference in mean response latency for valid-angry trials and valid-neutral trials, with smaller numbers indicating enhanced orienting toward threat. Attentional disengagement was calculated as the difference in mean response latency for invalid-angry trials and invalid-neutral trials, with higher values indicating deficits in disengaging attention from threat.

Dot-Probe Task

We also collected data on the dot-probe task (Macleod, Mathews, & Tata, 1986), a common measure of attention bias. It has been used in anxious populations to assess selective attention for threatening stimuli (see Bar-Haim et al., 2007 for review). In a traditional dot-probe, two pictures (or words) of different valences appear on the screen simultaneously. When they disappear, a neutral probe (e.g., a dot or letter) replaces one of them, and the participant is asked to respond to that probe. It is proposed that response latencies will vary depending on which stimulus the probe followed, reflecting differences in attention allocation. For the current study, we used pictures of faces exhibiting either a neutral or angry expression (Ekman & Friesen, 1976). Similar to the spatial-cueing task, pictures consisted of 8 actors (4 male and 4 female), which appeared in random order, with equal frequency. Each trial began with the presentation of a fixation cross (+) on the screen for 500ms. Then two pictures (neutral and angry) appeared on the screen (one above the fixation cross and the other below the fixation cross) simultaneously and remained on the screen for 500ms. After the pictures disappeared, a letter (“E” or “F”) appeared in a prior location of one of the faces. The participant was instructed to indicate whether the letter was an “E” or “F” with a button press. After indicating which letter they believed it to be, another trial began with a fixation cross (Macleod, Mathews, & Tata, 1986; Price et al., 2014). Similar to the spatial-cueing task, there were 10 practice trials prior to the start of the task, during which, the practice trials were similar to the experimental trials, except pictures consisted of inanimate objects (stock images of chairs) and participants were given feedback of the accuracy of their response after each trial. Practice trials were not included in the analyses. There were 192 trials in total. Half of the trials, the probe followed the angry face, and on the other half of the trials, the probe followed the neutral face. To create our dot-probe measure of attention, we first removed each individual's incorrect trials. Following this, we removed each individual's outliers (responses that were > 2 Z scores, based on their response latencies for the task). We then calculated the difference between mean response latencies for the two trial types: when the probe followed the angry face and when it followed the neutral face. Smaller values are believed to be associated with a greater attention bias for threat.

Self-Report Measures

State-Trait Anxiety Inventory (STAI)

The State-Trait Anxiety Inventory (Spielberger, Gorsuch, Lushene, Vagg, and Jacobs, 1983) is a 40-item questionnaire that assesses current, transient (state) levels of anxiety (i.e., how the participant feels at the moment of answering the questionnaire) and more persistent (trait) anxiety tendencies (i.e., how the participant 'generally' feels). Potential responses range from 'Not at All' (1) to 'Very Much So' (4). Total scores were summed for state and trait separately; each subscale consisted of 20 items. Internal consistency for the state (Cronbach's $\alpha = .94$) and trait (Cronbach's $\alpha = .94$) inventories were within the acceptable range.

Anxiety Sensitivity Index (ASI)

The Anxiety Sensitivity Index (Reiss, Petersen, Gursky, & McNally, 1986) is a 16-item questionnaire that assesses anxiety sensitivity, fear of anxiety-related physiological sensations. Responses are on a 5-point scale, ranging from 'Very Little' to 'Very Much.' Anxiety sensitivity is commonly associated with panic disorder (McNally, 2002), an anxiety syndrome associated with recurrent and unexpected panic attacks and concern regarding future panic attacks (American Psychiatric Association, 2013). The questionnaire showed adequate internal consistency in the current sample, with a Cronbach's alpha of .89.

Leibowitz Social Anxiety Scale (LSAS)

The Leibowitz Social Anxiety Scale (Liebowitz, 1987) is a 24-item questionnaire that assesses fear and avoidance of a number of social and performance situations. It was originally created as an interview measure, but the self-report format is consistent with the interview version, and both are psychometrically sound (Fresco, Coles, Heimberg, Liebowitz, Hami, Stein, & Goetz, 2001). Item responses range from 'Not at All' (0) to 'Severely' (3). The LSAS has been widely used as a measure of symptoms associated with social anxiety disorder, which involves fear of negative evaluation and subsequent avoidance of situations, which might involve evaluation by others (American Psychiatric Association, 2013). The questionnaire showed acceptable internal consistency in the current sample (Cronbach's alpha = .96).

Penn State Worry Questionnaire (PSWQ)

The Penn State Worry Questionnaire (Meyer, Miller, Metzger, & Borkovec, 1990) is a 16-item, questionnaire that assesses worry tendencies on a 1 ('Not at All Typical of Me') to 5 ('Very Typical of Me') scale. Worry is conceptualized as 'apprehensive expectation,' and is one of the primary symptoms of generalized anxiety disorder, an anxiety syndrome associated with persistent, uncontrollable worry about a number of events in addition to related symptoms (e.g., muscle tension, difficulty concentrating, sleep disturbances, and etc.) more days than not (American Psychiatric Association, 2013). The Cronbach's alpha for the PSWQ in the sample was .82, within the acceptable range for internal consistency.

Obsessive Compulsive Inventory – R (OCI-R)

The Obsessive Compulsive Inventory – Revised (Foa et al., 2002), is an 18-item scale assessing the severity of distress associated with various obsessions and compulsions. Item responses range from 0 ('Not at All') to 4 ('Extremely') distressing. The OCI-R is a measure associated with obsessive-compulsive disorder, an anxiety-related syndrome associated with persistent and distressing obsessions and compulsive behaviors intended to reduce the discomfort associated with reoccurring obsessive thoughts (American Psychiatric Association, 2013). Internal consistency of the OCI-R (Cronbach's $\alpha = .87$) was within the acceptable range.

Beck Depression Inventory – II (BDI-II)

The Beck Depression Inventory – II (Beck, Steer, & Brown, 1996) is a 21-item questionnaire assessing a variety of depression symptoms (e.g., changes in appetite, abnormal energy levels, feelings of hopelessness, and etc.) on a 0 - 3 scale gauging severity. A total score is calculated by summing all items. The BDI-II has been widely used in clinical and non-clinical populations to assess depression symptomatology and has demonstrated strong psychometric properties. The BDI-II demonstrated adequate internal consistency in the current sample (Cronbach's $\alpha = .93$).

Experimental Procedure

All participants expressing interest in participating in the study were first e-mailed information about the study's procedures, including an electronic copy of the study's consent form. They were informed that they would be assigned to complete the computer tasks either in-lab or online. Immediately after consenting, prior to providing any data, individuals were informed of their task location assignment. Individuals who still wished to participate completed the aforementioned questionnaires in addition to demographic questions online through Qualtrics. Following questionnaire completion, the experimenter scheduled those assigned to complete the tasks in lab for their lab visit, which took place within two weeks of completing the questionnaires. For those assigned to complete the tasks online, the experimenter provided the Inquisit link for completing the tasks online, and informed participants to complete the tasks online within two weeks after completing the questionnaires and within normal waking hours (8am to 7pm). There were three different orders of attention task administration, see Table 1. Each participant was assigned a unique number, and each number was associated with a task order. The participant entered this number into the Inquisit program at the start of the tasks, which set the task order for the individual and linked participant's task data and questionnaire responses.

Data Analytic Plan

To assess for different attentional pattern configurations underlying anxiety symptoms, each participant's attentional orienting, disengagement, and control scores were first mean-centered and submitted to k-means clustering with the k value left to vary. K-means clustering established clusters by first arbitrarily choosing points in the data. The points (each point representing one individual's collective score on the three attentional measures) closest to the arbitrary initial points formed the clusters. A mean value was calculated for each cluster, and points closest to each mean value comprised the new clusters. This process was repeated until the creation of stable clusters. We then generated a silhouette coefficient (-1 to 1 range, with higher scores being preferable) for each individual, which measured that individual's distance to others in their cluster in comparison to their distance of others in the nearest neighboring cluster. The number of clusters resulting in the highest average silhouette coefficient was used to determine the optimal number of clusters for the data. For cluster validation, we submitted participant's scores and their corresponding cluster identification to a supervised learning approach, random forest. The random forest in this study utilized subsets of the data and the case wise cluster identities previously determined by k-means to estimate how well the findings would generalize to never-seen data. Random forest, a commonly used, decision-tree based machine learning method, has been shown to perform favorably (high accuracy and low generalization error rates) to similar classification methods (Breiman, 2001; Caruana & Niculescu-Mizil, 2006; Leistner, Saffari, Santner, & Bischof, 2009), particularly when predictors are non-independent. We then examined the prediction accuracy of the random forest, and plotted this by cluster in a confusion matrix for ease of interpretation. Following this, to assess how these different attentional configurations related to anxiety symptoms, we conducted a multinomial logistic regression. Total scores from the questionnaires of distinct anxiety symptoms (i.e., anxiety sensitivity, social anxiety, obsessive thoughts and compulsions, and worry) were submitted as predictors and the dependent variable was set as cluster identification.

Results

Comparison of In-Lab and Online Samples

To assess for potential task differences between individuals who completed the computer tasks online versus in lab, we conducted a series of independent t-tests on the attention response latency variables as well as response accuracy. We also assessed for potential group differences across anxiety measures as well. We found that the in-lab sample and online sample did not differ in performance on response latency attention measures. However, participants did significantly differ in accuracy on the spatial cueing task $t(147) = 2.55$, $p = .012$, with the in-lab sample ($M = 0.97$, $SD = 0.02$) demonstrating higher accuracy than the online sample ($M = 0.97$, $SD = 0.06$). Groups also did not differ in self-report measures of anxiety. See Table 2 for descriptive statistics of in-lab and online samples.

Relationships between Attention Variables

Initial examination of the relationships between the attention variables in the study involved a series of correlations between the attention variables used as the basis for k-means clustering: attentional orienting, attentional disengagement, and attentional control. We also correlated these measures with the most common current measure of attention for threat in the anxiety literature, the dot-probe attention bias measure. Correlations were calculated for the whole sample in its entirety (N = 149) and also separately for the in-lab (N = 28) and online samples (N = 121), see Table 3 for results. We found that attentional orienting and disengagement were positively correlated in the whole sample (r = .247, p = .002), as well as both in the in-lab (r = .532, p = .004) and online samples (r = .213, p = .019), such that individuals with slowed disengagement from threat also demonstrated slowed orienting toward threat, or individuals with relatively quicker disengagement from threat than neutral also showed quicker orienting toward threat than neutral. We also found that attentional orienting toward threat was positively correlated with the traditional attention bias measure, in the whole sample (r = .214, p = .009), in-lab sample (r = .377, p = .048), as well as online sample (r = .192, p = .034). Such that individuals who showed enhanced orienting for threatening information demonstrated a greater dot-probe attention bias in this sample. This positive relationship across tasks between attentional orienting and dot-probe attention bias is consistent with the literature conceptualizing the dot-probe as a measure of attentional orienting (see Bar-Haim et al., 2007 for review), providing preliminary support for the validity of our spatial-cueing paradigm.

Relationships between Psychopathology Measures

Initial examination of the relationships between the questionnaire variables in the study involved a series of correlational analyses, in the whole sample as well as in the in-lab and online samples separately. Overall, there were positive correlations between the questionnaire data, ranging from significant *r* values of .35 to .69. Some questionnaire relationships that were present in the online sample and whole sample were no longer statistically significant in the in-lab sample. This was evident for the relationship between the OCI-R and LSAS and the relationship between the OCI-R and ASI. This absence of significant relationship in the in-lab sample may be due to the reduced sample size of the in-lab sample as well as potentially a reduction in the range of clinical symptoms in the in-lab sample as well, see Table 4 for the correlations between the anxiety questionnaires.

Relationships between Attention Variables and Anxiety

To examine our hypotheses that different attentional patterns would be related to separate anxiety symptoms, we conducted a series of correlations between the anxiety questionnaire data (ASI, LSAS, OCI-R, and PSWQ) and attentional orienting, attentional disengagement, and attentional control. We again conducted these correlations in the whole sample and in the lab and online samples separately. Our first hypothesis was that anxiety sensitivity would be related only to enhanced attentional orienting toward threat. The correlational analyses between attentional orienting and anxiety sensitivity did not support this prediction (whole sample: $r = -.02$, $p = .818$, lab sample: $r = .19$, $p = .327$, online sample: $r = -.05$, $p = .577$). We also hypothesized that social anxiety would be related to deficits in attentional disengagement from threat. The correlational results provided preliminary support for this hypothesis. In the whole sample, attentional disengagement and social anxiety (LSAS) were positively correlated ($r = .19$, $p = .018$), suggesting that individuals who are slower at disengaging their attention from threat show higher levels of social anxiety symptoms. We conducted the same correlations in the lab sample as well as the online sample. The correlation remained in the online sample, $r = .21$, $p = .020$, but not in the in-lab sample, $r < -.01$, $p = .994$. In further support of the second hypothesis, no correlations were found between attentional orienting or control with social anxiety symptoms in the whole, in-lab, or online samples, suggesting social anxiety symptoms may be specifically related to difficulties in attentional disengagement. We also predicted that obsessive and compulsive symptoms would be associated with deficits in attentional disengagement and attentional control and that worry would be related to difficulties with all three aforementioned attentional processes. However, we found no preliminary support for these at the correlational level, see Table 5 for the results of these correlations.

K-Means Analyses

Attentional orienting, disengagement, and control scores for each participant were mean-centered and submitted to a series of k-means cluster analyses (two through ten possible cluster solutions). We conducted the k-means analyses in MATLAB, which utilizes the K++ algorithm for the selection of the seeds (Arthur & Vassilvitskii, 2007), which is a common algorithm for this data approach. Prior research has demonstrated that the K++ algorithm performs at a comparable level to several other seed-initiating algorithms (Celebi, Kingravi, & Vela, 2013). We used Euclidian distance as our difference metric of individual points and their relation to other points and clusters. In order to quantify the degree of model fit, we calculated a silhouette coefficient, which measures how close one's attention-based score is to other scores in the same cluster as well as scores in other clusters, for each individual. The average silhouette coefficient was calculated for each potential k-solution (two through ten), to find the optimal k value. A 4-k solution resulted in an average silhouette score of 0.38, the highest of all potential solutions, see Figure 2 for a graph of the four clusters and Figure 3 for the silhouette plot for this four-cluster solution. An average silhouette score of 0.38 is considered poor, suggesting that clusters in this study were weakly defined or potentially artificial. In line with this, the silhouette plot was narrow for each cluster, indicating poor fit. Moreover, the silhouette plot indicated that there was notable silhouette score variance within-clusters, suggesting that cluster-solution performance varied by individual (see Rousseeuw, 1987 for silhouette score and plot interpretation guide).

Random Forest

In light of the poor fit, we sought to determine whether the identified clusters could be replicated in an independent dataset. To cross-validate clusters, we conducted a random forest, predicting cluster membership with the three standardized attention variables as the predictors. We first randomly partitioned 70% of the data for training and 30% of the data for testing. We conducted the random forest using MATLAB's treebagger function on the training data. The treebagger function generated a set number of decision trees using sampling with replacement, and aggregated across them to produce the classifier used for prediction. We set the number of decision trees at 50. Misclassification probability, or mean squared error, remained stable at .02 after the addition of the 15th tree, see Figure 4 for graph. We set the minimum leaf size to 15 given the smallest cluster contained 19 individuals, see Figure 5 for an example of one of the decision trees generated. We then applied the classifier to the initial 30% of the data held out for testing and generated a confusion matrix to examine prediction accuracy, see Figure 6. The model correctly predicted all the individuals in clusters 1 and 3; however, it incorrectly predicted 60% of cluster 2 individuals and 14% of cluster 4. Cluster differences in prediction accuracy may be due to differences in cluster size, which resulted in a reduced number of observations in the training set. In support of this, the cluster with the lowest prediction accuracy was cluster two, which had the smallest sample size of 19 individuals. Following this, the second worst in prediction accuracy was the second smallest cluster, cluster 4 (n = 25) with 86% accuracy. Both cluster 1 (n = 51) and cluster 3 (n = 54), which demonstrated 100% prediction accuracy, were over twice the size of the smaller clusters. Therefore, random forest prediction performance was variable, showing good prediction accuracy when cluster size was relatively large. For the clusters that the classifier performed well on, these positive results suggest good predictive ability of these clusters when given a new individual's scores on attentional orienting, attentional disengagement, and attentional control. However, good classifier performance does not suggest that these clusters are well defined or that cluster membership is a valid measure of individual difference.

Comparison of Clusters

To determine whether clusters differed on attention variables, we first conducted three one-way ANOVAs on the clustered attention measures: attentional control, attentional orienting, and attentional disengagement, see Table 6 for descriptive statistics on these variables and other variables of interest. We found that clusters differed significantly on all three attention measures: attentional control (F (3,145) = 212.37, p < .001), attentional orienting (F (3,145) = 45.48, p < .001), and attentional disengagement (F (3,145) = 4.38, p = .006). To follow-up on these ANOVAs, we conducted a series of Bonferroni-corrected post hoc analyses, see Table 7 for post hoc results. In summary, we found that all clusters significantly differed on attentional control, except for clusters 3 and 4. Cluster 1 showed the smallest difference between congruent and incongruent trials (M = 57.22ms, SD = 10.88), or the highest attentional control performance. In comparison, cluster 2 demonstrated the lowest attentional control, with an average incongruent-congruent difference of 130.27ms (SD = 9.30). All clusters significantly differed on attentional orienting, except for clusters 1 and 2. Cluster 4 demonstrated the greatest attentional orienting for threat, represented as the smallest average difference value (M = -9.98ms, SD = 4.89), as orienting for threat is calculated as threat valid – neutral valid trials, and negative values indicate the individual was quicker on threat-cued trials. In comparison, cluster 3 demonstrated no attentional orienting for threat effect (M = 3.98ms, SD = 4.69). For attentional disengagement, cluster 4 (M = -13.69ms, SD = 17.97) was significantly better at attentional disengagement (threat invalid – neutral invalid) from clusters 1 (M = 1.82ms, SD = 18.32) and 3 (M = 2.19ms, SD = 20.82); however, standard deviation of attention disengagement in all clusters appeared high, suggesting cluster membership is less informative regarding this attention variable, see Figures 7, 8, and 9 for bar graphs representing cluster differences for these attention variables.

To assess for differences between clusters on self-report variables, we conducted a series of one-way ANOVAs on the following questionnaire data: trait anxiety (STAI-T), depression (BDI-II), social anxiety (LSAS), worry (PSWQ), anxiety sensitivity (ASI), and obsessive-compulsive symptoms (OCI-R). Results indicated that clusters did not significantly differ on these variables (trait anxiety [F (3,145) = 0.28, p = .840], depression [F (3,145) = 0.69, p = .558], social anxiety [F (3,145) = 1.77, p = .156], worry [F (3,145) = 0.63, p = .600], anxiety sensitivity [F (3,145) = 0.27, p = .847], obsessive-compulsive symptoms [F (3,145) = 0.99 p = .398]). As we hypothesized that clusters identification would relate to social anxiety, worry, anxiety sensitivity, and obsessive-compulsive symptoms, we conducted Bonferroni-corrected contrasts on these variables between clusters. Results also indicated no differences between any cluster contrasts on these variables (see Table 8 for these results).

Multinomial Logistic Regression

In order to assess whether attention symptom profiles are related to unique configurations of these attentional processes, we conducted a multinomial logistic regression predicting cluster identification with the following questionnaire scores entered as predictors: LSAS (social anxiety), PSWQ (worry), ASI (anxiety sensitivity), and OCI-R (obsessive-compulsive symptoms). The final model was not significantly different than the null (intercepts only) model (chi square = 16.22, df = 12, p = .181). As part of the initial planned analyses, the results of this model are presented in Table 9; however, the lack of the significant omnibus test of the overall model precludes the interpretation of the remaining model results.

Discussion

The purpose of this study was to test the hypothesis that differences in anxiety symptoms are associated with unique configurations of attentional patterns. Unlike prior studies, we took a multidimensional approach to our measurement of attention, assessing attentional control, attentional orienting toward threatening information, and attentional disengagement from threatening information. We submitted each individual's three measures of attention to an unsupervised k-means clustering analysis, which we cross-validated with a supervised classification approach, random forest. The k-means algorithm suggested a four-cluster solution was optimal; however, the silhouette coefficient and plot of the four-cluster solution suggested the clusters were not clearly defined. The random forest predicted cluster identification in a random selection of data held out for testing; however, there was variable performance by cluster, with two clusters showing perfect prediction compared two others with 86% accuracy (Cluster 4) and 40% accuracy (Cluster 2). To examine whether cluster membership was related to anxiety symptoms, we conducted a multinomial logistic regression predicting cluster number from the hypothesized anxiety measures (social anxiety, worry, obsessive-compulsive, and anxiety sensitivity). The overall model was found to not significantly improve upon the null model, limiting further interpretation of the regression results. Thus we found limited support that differences in anxiety symptoms are associated with unique attentional patterns.

Initial correlation results between our attention measures and different anxiety symptoms informed our study hypotheses. The correlation results between attentional disengagement and social anxiety symptoms provide some preliminary support for hypothesis two, which proposed that social anxiety symptoms would be uniquely associated with difficulties with attentional disengagement from threatening information. This is consistent with Amir and colleagues (2003), who used a similar spatial-cueing paradigm and found that social anxiety was related to deficits in attentional disengagement from threat, without enhanced orienting toward threatening information. However, social anxiety has also been associated with an attention bias for threatening information as measured with the dot-probe task, which is traditionally viewed as a measure of orienting for threatening information (see Bar-Haim et al., 2007 for review), despite more recent neurological findings suggesting it might instead measure attentional disengagement (Price et al., 2014). In the current study, we found that dot-probe performance was related to attentional orienting, not disengagement, and that social anxiety symptoms were only related to deficits in attentional disengagement, no other measure of attention. It should be noted, that we found this to be true in the entire sample as well as the online sample; however, we did not find this relationship in the in-lab sample. We anticipated that this was due to reduced range of both the attention predictors and social anxiety symptoms in the in-lab sample. However, when artificially restricting the range of the online sample, the relationship was maintained. Thus, it does not appear to be due to sample differences in range. It is unclear the nature of this null finding in the in-lab sample, but related studies have demonstrated that not all individuals with anxiety show an attention bias (Amir, Taylor, & Donohue, 2011). Thus, it is possible that there were not enough individuals with the cognitive bias in the in-lab sample.

We also hypothesized unique attentional patterns underlying anxiety sensitivity (enhanced attentional orienting for threat), obsessive-compulsive thoughts and behaviors (impaired disengagement of attention from threat and deficits in attentional control), and worry (enhanced attentional orienting for threat, inhibited attentional disengagement of attention from threatening information, and deficits in attentional control); however, we did not find support for these hypotheses. This may be because previous studies that have measured the attentional processes associated with these disorders and disorder-specific symptoms have used varied tasks. For example, Lavy, Van Oppen, and Van Den Hout (1994) used performance on an emotional Stroop task as a measure of attention for threat in individuals with obsessive-compulsive disorder. While Hunt, Keogh, and French (2006), used subliminal and supraliminal dot-probe tasks to measure attentional orienting for threatening stimuli in anxiety sensitivity. Although it is believed that conceptually similar but aesthetically different tasks measure the same or similar constructs, it is unclear how task differences might influence one's performance. It is rare for researchers to report on multiple tasks measuring the same or similar constructs, obscuring task overlap or distinguishing features.

Another factor that might have influenced the null finding between attention measures and other anxiety disorder symptoms might be the nature of the task stimuli. Social stimuli might be particularly salient for individuals with elevated social anxiety symptoms. Although other studies have used emotional and neutral face stimuli for measuring attention biases in non-social anxiety disorders and related symptoms (Bar-Haim et al., 2007), this difference in stimuli saliency might have contributed to a stronger signal for social anxiety. If so, this would result in a greater ability to detect attentional differences in social anxiety relative to other anxiety symptoms. Other studies have addressed this by using tasks with disorder-specific stimuli or with idiographic stimuli, where every individual chooses their own stimuli that they believe to be particularly threatening. For example, Moritz, Von Muehlenen, Randjbar, Fricke, and Jelinek, (2009) found that individuals with obsessive-compulsive disorder showed an attentional bias for obsession-related stimuli such as a picture of a dirty toilet for those with contamination concerns or a broken door for individuals with checking concerns. In the same study, they did not find that these same individuals had an attention bias for more general, non-specific threatening stimuli. Similarly, other researchers (Amir & Taylor, 2012) have used idiographic stimuli, where each individual completes the task with stimuli that are related to their specific worries (e.g., setting one threat stimulus as the word 'illness' for someone with concerns about their health or setting another threat stimulus as 'bills' for one who worries about their finances).

Before submitting the attentional measures to the k-means cluster analysis, we examined for potential relationships between attentional variables. We found that attentional orienting and disengagement were correlated, such that slower orienting to threatening information was associated with slower attentional disengagement from threatening stimuli, and similarly, quicker orienting for threatening information was associated with quicker disengagement. It is unclear why this relationship was found. One might even expect the inverse relationship, that one who experiences enhanced orienting toward threat might find it more difficult to disengage their attention from the stimulus. To our knowledge, no study has directly looked at the relationship between attentional orienting for threat and attentional disengagement from threat. However, the effect might be due to an error in measurement. One critique of the spatial-cueing paradigm has been that the task might be influenced by an emotion-related response slowing (Mogg, Holmes, Garner, & Bradley, 2008), in that individuals might be slower to respond on emotional trials in general, which would influence the difference scores. If this were the case, one would expect a positive correlation, as the scores are calculated as the difference between the threat and neutral trials (valid and invalid separately). Mogg and colleagues proposed an alternative task that included additional center trials, in which the participant responded to a probe following a single picture (threat or neutral) presented in the center of the screen. The researchers then used the difference between threat and neutral center trials to estimate the potential emotion-slowing effect, and then remove that from the scores. Unfortunately, center trials were not included in this task, so we were unable to account for a potential emotion-slowing effect. In the future, it would be beneficial to include these trials in the spatial-cueing paradigm to address this.

In addition to the positive relationship between attentional orienting and disengagement, we found that only enhanced attentional orienting (not disengagement) was associated with the dot-probe measure of attention bias. This is consistent with traditional attention bias literature that has viewed the dot-probe task as a measure of enhanced orienting of attention for threatening information (Bar-Haim et al., 2007), and might present as support for the validity of our attentional orienting measure. However, more recently, neuroimaging findings have suggested that the dot-probe task might actually be a measure of attentional disengagement and not orienting (Price et al., 2014). It is unclear why there is a discrepancy in the literature between purported attentional mechanisms underlying the dot-probe measure, and addressing measurement limitations of the dot-probe task is beyond the scope of this study. However, the findings of the current study support the distinction of these attentional processes.

In the current study, one near-null study finding that affected subsequent analyses was the poor performance of the k-means clustering analysis. The silhouette coefficient and plot indicated that the clusters that were created were ill defined, and that a clustering approach might not be the best analysis for the attention variables we calculated. When clusters are poorly defined at the start, cluster membership is less likely to be a valid, informative variable of interest. It then follows that using other measures such as questionnaire data to predict questionable cluster membership such as we did with the multinomial logistic regression would be challenging and likely to be unsuccessful. The poor cluster identification could be due to several reasons. As mentioned earlier, the attentional orienting and disengagement variables might have been influenced by an emotion-slowing effect, therefore increasing the noise in the metric, making it harder to detect the constructs of interest, attentional orienting and disengagement. In addition, response latency data in general can be noisy, in that many factors can influence one's behavioral response to a stimulus; however, only one numerical value is recorded for that response. With only one measurement per complex response, it can be difficult to parse out the effect of the construct of interest from other factors. In comparison, with physiology-based measurements, for a few-second trial one might have well into the thousands of data points, depending upon the methodology. To address response latency noise in this study, we removed outliers and did not include inaccurate trials, but it is unclear whether these corrections are enough to remove the noise and accurately detect the attentional construct. Moreover, the attentional processes or signals of interest operate on a fine-grained, millisecond level, which may be particularly difficult to parse from the noise of response latency data. An alternative explanation to the potential issues with measurement is that all three attention variables may operate on more of a continuum, without clear gaps in performance between individuals on any attentional process. This would suggest that maintaining the continuous nature of the data is important and attempting to split individuals into different groups might not be the best approach.

Limitations of the study include an entirely undergraduate student sample, thus the results might not be representative of the general population. In particular, this raised concerns about the range of anxiety symptoms that would be present. Although, the sample was limited to college students, there were several individuals meeting clinical cut-off scores across measures. However, even though there were individuals who met clinical cut-off, the means across the measures were subclinical and the distributions of questionnaire responses were all positively skewed, with much fewer individuals with elevated symptoms. This likely made it more difficult to detect the effects in such a limited sample. Another limitation of the study is that a large portion of the data was collected online, which leaves a number of extraneous factors such as time of day, screen size, screen orientation, computer hardware, and environmental distractions uncontrolled. This introduces additional noise into the measurements, which may have also contributed to the null findings. We took measures to address these such as requesting participants to complete the tasks during normal waking hours, setting task stimuli size to vary by screen size, and removing trials that were outliers or inaccurate; however, it is unclear the extent to which extraneous factors influencing the attention variables affected the study results. For future research on this topic, it would be beneficial to collect a larger in-lab sample and test effects in the in-lab sample before collecting online data.

As the project was an alternative approach to measuring attention's role in anxiety symptoms, I have learned a number of lessons, which I hope to carry forward in future work. One lesson I learned is that the measure of attentional orienting and disengagement, although used in the literature, might not be optimal. The initial positive correlations between the orienting and disengagement measures suggest that there might be an emotion slowing effect occurring, which has been raised as a critique against the paradigm (Mogg et al., 2008). Thus, if I desired to measure these constructs again, I would include the emotional center control they proposed in order to address this limitation. I also learned more about the countless potential extraneous influences on online data collection, which would make me more likely to propose a greater amount of in-lab data collection, in a better controlled setting. Finally, given the limited nature of response latency data (e.g., 2 measures for each trial: the reaction time and accuracy) and the potential limitations of the task, I would hope to include physiological measures to provide more data on the attentional constructs being measured, and ideally allow for greater understanding of the phenomena of interest.

In conclusion, in the current study, we tested whether distinct configurations of attentional patterns were associated with different anxiety symptom profiles. The cluster analysis poorly fit the data we collected, and this limited follow-up analyses relating anxiety variables to cluster membership. There are some preliminary correlational results between social anxiety, attentional subprocesses, and the dot-probe attention bias that might be explored further; however, a cluster approach is not suitable for the current attention variables we have calculated. The study's largely null findings suggest that response latency on these attentional tasks cannot be used to distinguish between different anxiety symptoms. It is unclear whether null findings are due to the aforementioned limitations of study methodology, analytic plan, and study design or the absence of relationships between constructs. For greater clarification, it would be beneficial to examine these phenomena in a sample collected in a more standardized environment, and to consider alternative methodologies and score indices (other than mean difference scores), which might be more resistant to metric noise.

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Tables

Table 1. *Administration orders of cognitive paradigms*

Order	Attention Paradigms		
1	Attentional Network	Spatial-Cueing	Dot-Probe
2	Spatial-Cueing	Dot-Probe	Attentional Network
3	Dot-Probe	Attentional Network	Spatial-Cueing

Table 2. *In-lab and online descriptive statistics*

Variable	In-Lab	Online
Response Latency Measures (seconds)		
Attention Orienting	0.68 (5.84)	-0.23 (7.08)
Attention Disengagement	-2.34 (14.98)	-0.45 (21.28)
Attentional Control	78.11 (19.93)	85.63 (26.98)
Accuracy Measures		
Spatial-Cueing*	0.97 (0.02)	0.95 (0.06)
Attentional Network Test	0.97 (0.03)	0.96 (0.04)
Anxiety Measures		
Trait Anxiety	37.77 (9.30)	39.98 (11.96)
Depression	8.55 (5.37)	9.28 (9.80)
Social Anxiety	32.08 (16.77)	37.40 (25.70)
Worry	48.49 (6.14)	50.50 (6.28)
Anxiety Sensitivity	19.91 (9.65)	20.57 (11.28)
Obsessive-Compulsive	12.79 (9.62)	13.08 (10.85)

Note: Response latency variables are in milliseconds. Means are presented, followed by standard deviations in parentheses. Significant differences are denoted by an asterisk following the variable name. Attentional Orienting (Angry Valid – Neutral Valid), Attentional Disengagement (Angry Invalid – Neutral Invalid), Attentional Control (Incongruent – Congruent), Trait Anxiety (STAI-Trait), Depression (BDI-II), Social Anxiety (LSAS), Worry (PSWQ), Anxiety Sensitivity (ASI).

Table 3. *Correlations between attention variables*

Whole Sample				
	Control	Orienting	Disengagement	Dot-Probe
Control	1	.01	-.03	<.01
Orienting		1	.25**	.21**
Disengagement			1	-.01
Dot-Probe				1
In-Lab Sample				
	Control	Orienting	Disengagement	Dot-Probe
Control	1	-.01	-.17	-.29
Orienting		1	.53**	.38*
Disengagement			1	-.01
Dot-Probe				1
Online Sample				
	Control	Orienting	Disengagement	Dot-Probe
Control	1	.01	-.01	.04
Orienting		1	.21*	.19*
Disengagement			1	-.01
Dot-Probe				1

Note: Note: *r* values are presented. * Denotes significant at < .05 level. ** Denotes significance at the <.01 level.

Table 4. *Correlations between questionnaires*

	STAI-T	LSAS	PSWQ	ASI	OCI-R
Whole Sample					
STAI-T	1	.56**	.55**	.36**	.52**
LSAS		1	.55**	.51**	.46**
PSWQ			1	.42**	.45**
ASI				1	.46**
OCI-R					1
In-Lab Sample					
	STAI-T	LSAS	PSWQ	ASI	OCI-R
STAI-T	1	.62**	.35	.40*	.51**
LSAS		1	.69**	.46*	.13
PSWQ			1	.43*	.01
ASI				1	.27
OCI-R					1
Online Sample					
	STAI-T	LSAS	PSWQ	ASI	OCI-R
STAI-T	1	.55**	.58**	.35**	.52**
LSAS		1	.53**	.52**	.52**
PSWQ			1	.42**	.55**
ASI				1	.49**
OCI-R					1

Note: Note: *r* values are presented. * Denotes significant at < .05 level. ** Denotes significance at the <.01 level. Trait Anxiety (STAI-Trait), Social Anxiety (LSAS), Worry (PSWQ), Anxiety Sensitivity (ASI), Obsessive-Compulsive Thoughts and Behaviors (OCI-R)

Table 5. *Correlations between attention variables and psychopathology*

	Control	Orienting	Disengagement
Whole Sample			
Trait Anxiety	-.01	.10	.06
Depression	-.06	.08	-.09
Social Anxiety	-.14	.08	.19*
Worry	.09	-.01	.07
Anxiety Sensitivity	.09	-.02	.06
Obsessive-Compulsive	-.02	.07	.14
In-Lab Sample			
Trait Anxiety	-.22	.11	-.21
Depression	-.11	.02	-.18
Social Anxiety	-.12	.18	< -.01
Worry	.34	.16	.21
Anxiety Sensitivity	-.01	.19	.08
Obsessive-Compulsive	-.24	.04	.03
Online Sample			
Trait Anxiety	< .01	.11	.10
Depression	-.06	.09	-.08
Social Anxiety	-.16	.07	.21*
Worry	.04	-.04	.04
Anxiety Sensitivity	.11	-.05	.05
Obsessive-Compulsive	.01	.07	.15

Note: *r* values are presented. * Denotes significance at < .05 level.

Table 6. *Descriptive statistics by cluster*

	Cluster 1 (N = 51)	Cluster 2 (N = 19)	Cluster 3 (N = 54)	Cluster 4 (N = 25)
Attentional Variables				
Control	57.22 (10.88)	130.27 (9.30)	91.84 (9.74)	87.83 (15.70)
Orienting	0.64 (4.91)	-0.38 (5.95)	3.98 (4.69)	-9.98 (4.89)
Disengagement	1.82 (18.32)	0.59 (21.03)	2.19 (20.82)	-13.69 (17.97)
Attention Bias (Dot-Probe)	0.62 (17.09)	5.53 (14.91)	-0.72 (20.59)	-15.09 (26.51)
Questionnaire Data				
Trait Anxiety	39.82 (12.14)	38.95 (9.66)	40.32 (12.58)	37.87 (9.28)
Depression	9.57 (9.59)	7.31 (7.59)	10.07 (10.10)	7.68 (6.72)
Social Anxiety	40.75 (25.35)	26.75 (17.84)	37.30 (26.02)	32.88 (21.12)
Worry	49.63 (6.22)	51.32 (5.79)	50.60 (6.80)	49.17 (5.69)
Anxiety Sensitivity	19.82 (10.93)	22.46 (11.57)	20.42 (10.99)	20.24 (11.04)
Obsessive-Compulsive	12.53 (10.21)	10.42 (9.99)	14.81 (10.52)	12.12 (11.91)
Demographic Variables				
Age	19.90 (2.26)	19.53 (1.31)	19.70 (1.73)	20.00 (2.43)
Gender	64.7% Female	84.2% Female	77.8% Female	80% Female

Note: Response latency variables are in milliseconds. Means are presented, followed by standard deviations in parentheses. Significant differences are denoted by an asterisk following the variable name. Attentional Orienting (Angry Valid – Neutral Valid), Attentional Disengagement (Angry Invalid – Neutral Invalid), Attentional Control (Incongruent – Congruent), Trait Anxiety (STAI-Trait), Depression (BDI-II), Social Anxiety (LSAS), Worry (PSWQ), Anxiety Sensitivity (ASI).

Table 7. *Bonferroni-corrected post hoc tests for attention variables*

Attentional Control			
Cluster	2	3	4
1	-73.05 (3.03)**	-34.62 (2.20)**	-30.61 (2.75)**
2		38.43(3.01)**	42.44 (3.43)**
3			4.01 (2.73)
Attentional Orienting			
Cluster	2	3	4
1	1.02 (1.34)	-3.34 (.97)*	10.62 (1.21)**
2		-4.36 (1.33)*	9.61 (1.51)**
3			13.96 (1.20)**
Attentional Disengagement			
Cluster	2	3	4
1	1.23 (5.26)	-0.37 (3.82)	15.51 (4.78)*
2		-1.60 (5.22)	14.28 (5.95)
3			15.88 (4.73)*

Note: Response latency variables are in milliseconds. Mean differences are reported, followed by standard error in parentheses. * Denotes a significant contrast the < .05 level. ** Denotes a significant contrast at the <.01 level.

Table 8. *Bonferroni-corrected contrasts for questionnaire data*

Social Anxiety			
Cluster	2	3	4
1	14.00 (6.49)	3.45 (4.71)	7.87 (5.89)
2		-10.55 (6.44)	-6.13 (7.34)
3			4.42 (5.84)
Worry			
Cluster	2	3	4
1	-1.68 (1.69)	-0.97 (1.23)	0.47 (1.54)
2		0.71 (1.68)	2.15 (1.92)
3			1.44 (1.53)
Anxiety Sensitivity			
Cluster	2	3	4
1	-2.65 (2.97)	-0.60 (2.16)	-0.42 (2.70)
2		2.05 (2.95)	2.22 (3.36)
3			-0.18 (2.67)
Obsessive-Compulsive Symptoms			
Cluster	2	3	4
1	2.11 (2.85)	-2.28 (2.07)	0,41 (2.59)
2		-4.39 (2.83)	-1.70 (3.23)
3			-2.69 (2.56)

Note: Response latency variables are in milliseconds. Mean differences are reported, followed by standard error in parentheses. No contrasts were significantly different.

Table 9. Multinomial logistic regression parameter estimates

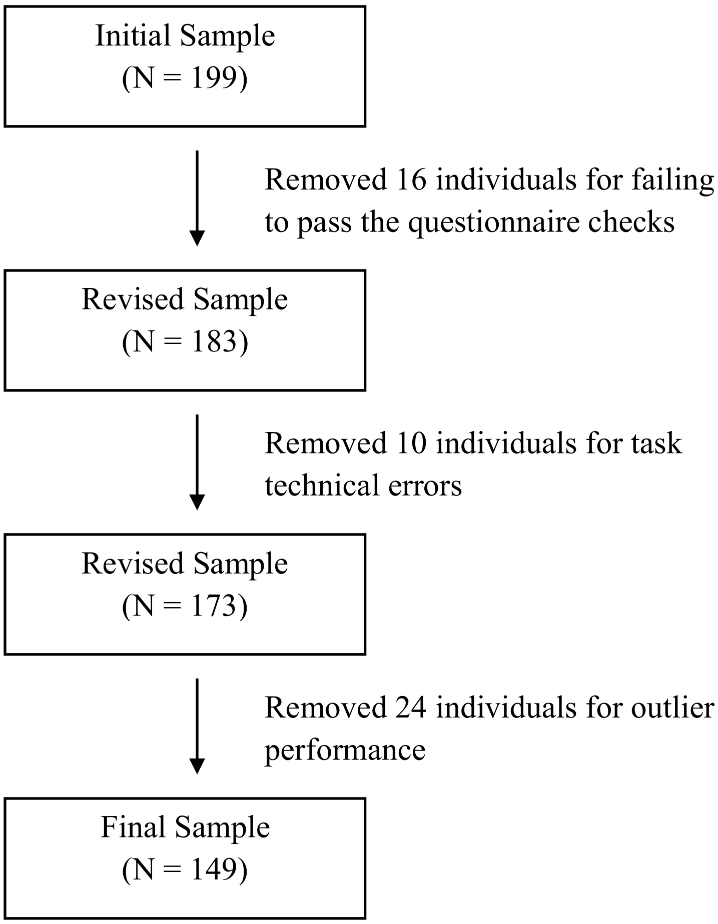
		95% CI for Odds Ratio		
	β (SE)	Lower	Odd Ratio	Upper
Cluster 1 vs. Cluster 2				
Intercept	-3.91 (2.40)			
LSAS	-0.4 (.02)	0.93	0.96	0.99
PSWQ	0.07 (.05)	0.97	1.07	0.18
ASI	0.06 (.03)	1.00	1.06	1.13
OCI	-0.03 (.04)	0.90	0.97	1.04
Cluster 1 vs. Cluster 3				
Intercept	-1.14 (1.64)			
LSAS	-0.01 (.01)	0.97	1.00	1.01
PSWQ	0.03 (.04)	0.96	1.03	1.10
ASI	< - .01 (.02)	0.96	1.00	1.05
OCI	0.03 (.02)	0.98	1.03	1.07
Cluster 1 vs. Cluster 4				
Intercept	-0.31 (2.00)			
LSAS	-0.02 (.01)	0.96	0.98	1.01
PSWQ	-0.01 (.04)	0.91	1.00	1.08
ASI	0.02 (0.03)	0.97	1.02	1.08
OCI	< 0.01 (0.03)	0.95	1.00	1.06

Table 9 (cont.). Multinomial logistic regression parameter estimates

		95% CI for Odds Ratio		
	β (SE)	Lower	Odd Ratio	Upper
Cluster 2 vs. Cluster 3				
Intercept	2.77 (2.37)			
LSAS	0.03 (0.02)	1.00	1.03	1.06
PSWQ	-0.04 (0.05)	0.87	0.96	1.06
ASI	-0.06 (0.03)	0.89	0.94	1.00
OCI	0.06 (0.04)	1.00	1.06	1.14
Cluster 2 vs. Cluster 4				
Intercept	3.60 (2.62)			
LSAS	0.02 (0.02)	0.99	1.02	1.06
PSWQ	-0.07 (0.06)	0.84	0.93	1.04
ASI	-0.04 (0.03)	0.90	0.97	1.03
OCI	0.04 (0.04)	0.96	1.04	1.12
Cluster 3 vs. Cluster 4				
Intercept	0.83 (2.00)			
LSAS	-0.01 (0.01)	0.97	0.99	1.02
PSWQ	-0.03 (0.04)	0.89	0.97	1.06
ASI	0.02 (0.03)	0.97	1.02	1.08
OCI	-0.02 (0.03)	0.93	0.98	1.03

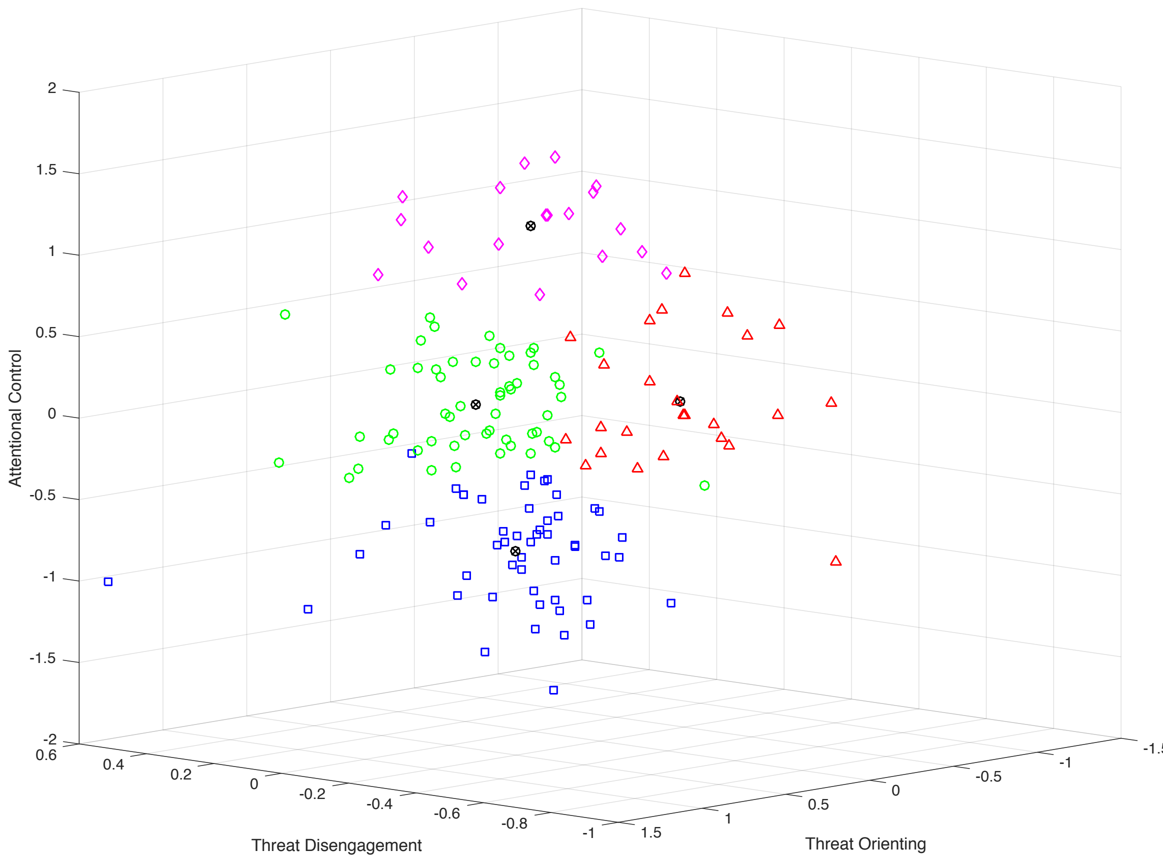
Figures

Figure 1. *Diagram of data cleaning steps*



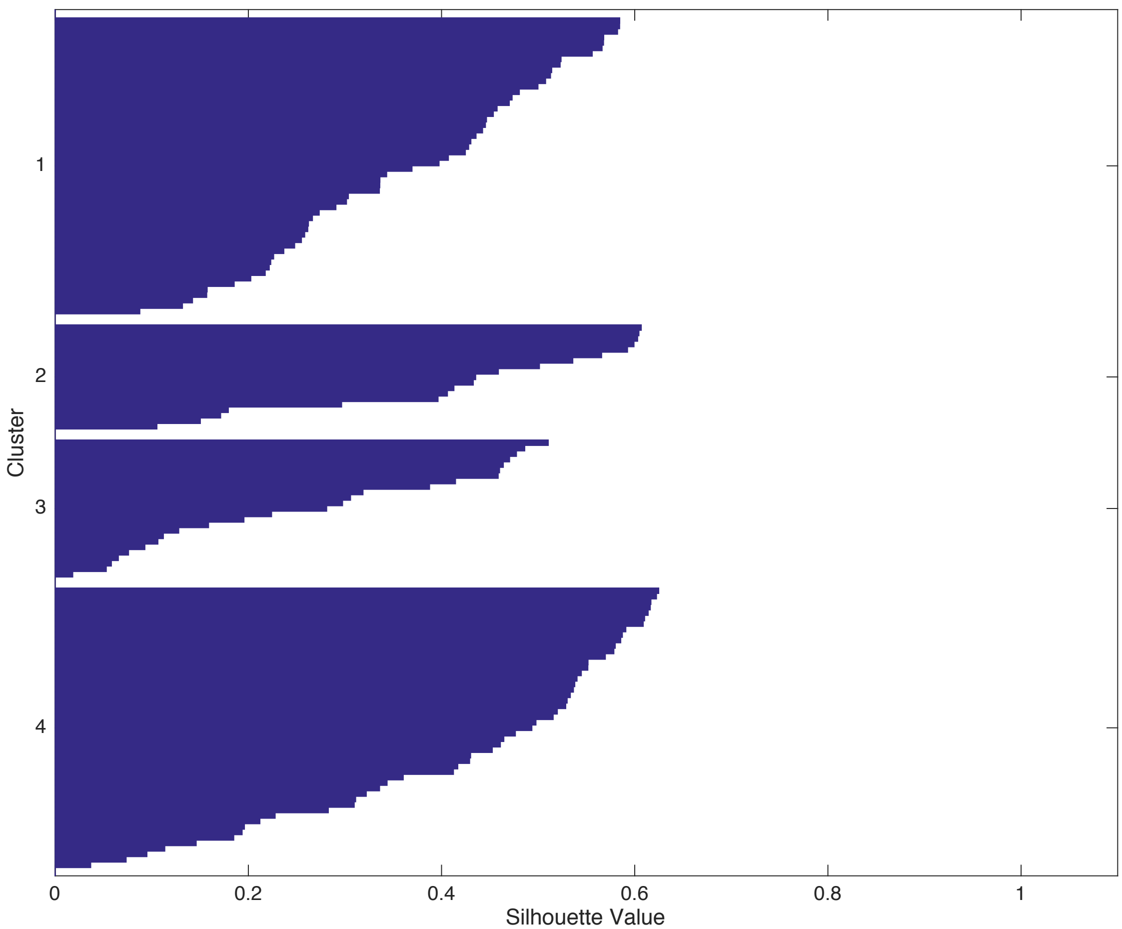
Note: Diagram represents the participants removed from the sample at each step of data cleaning. The final sample was used in the reported study analyses.

Figure 2. *3D plot of four-cluster solution*



Note: Clusters are represented as points with a different color (blue, red, green, and magenta) as well as point shape (circle, triangle, square, diamond). The black X's in the circles represent the centroids.

Figure 3. *Silhouette plot of four-cluster solution*



Note: The average silhouette score was 0.38. The Y-axis indicates the individual's cluster membership.

Figure 4. *Mean squared error as a function of decision trees added to the model*

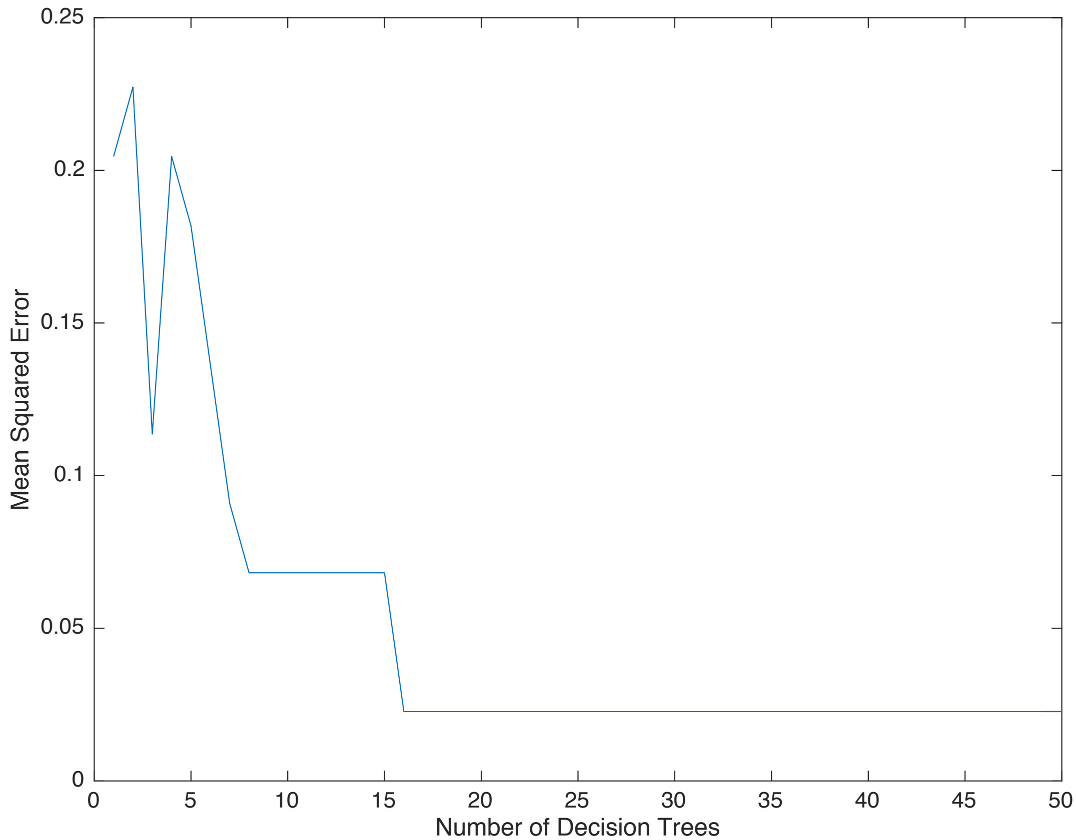
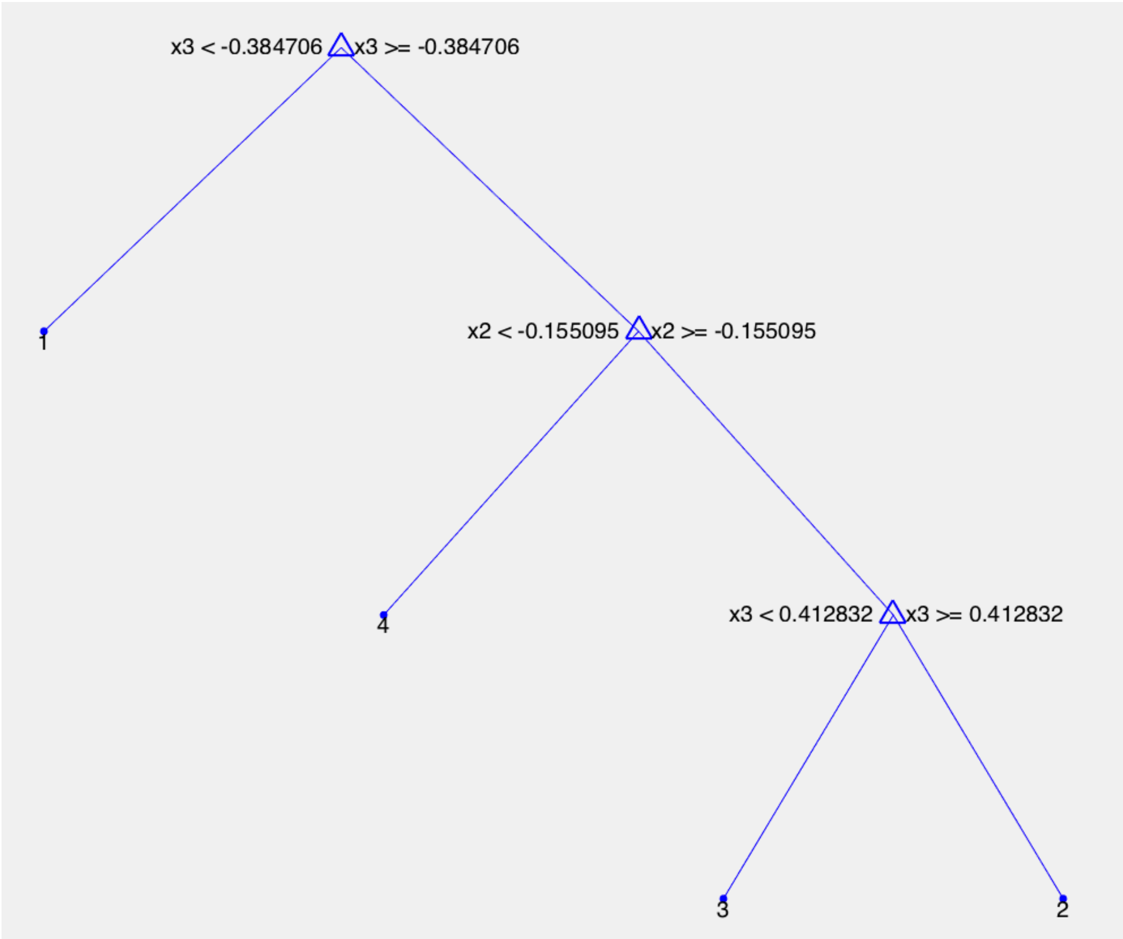
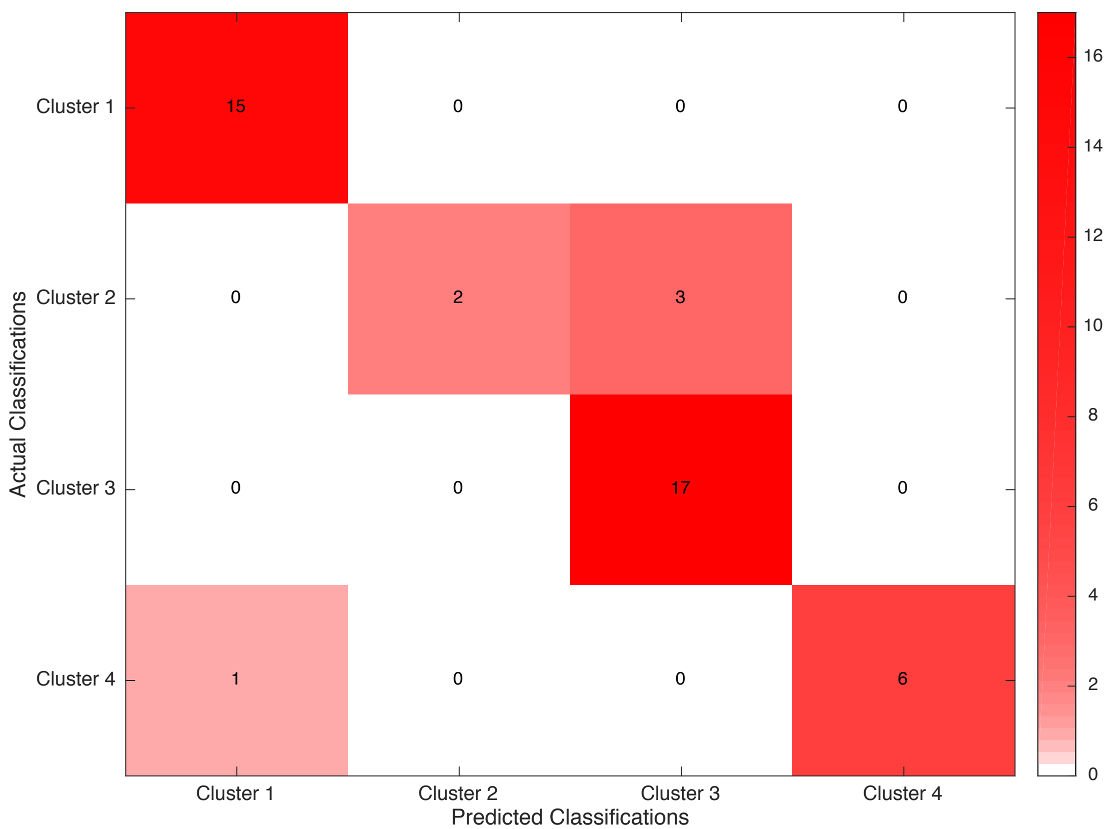


Figure 5. *Example of decision tree in random forest*



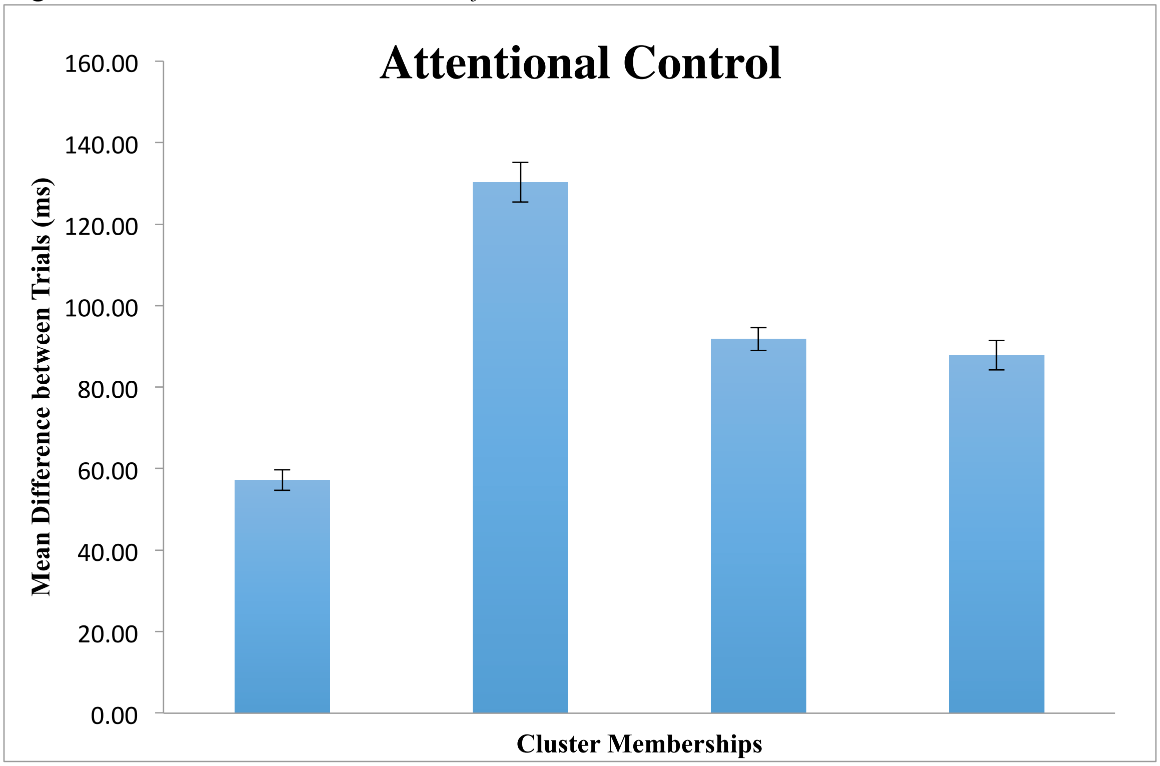
Note: The predictors are ‘x2’ (attentional orienting) and ‘x3’ (attentional control). The end numbers are the resulting cluster identifications.

Figure 6. *Confusion matrix depicting cluster prediction accuracies*



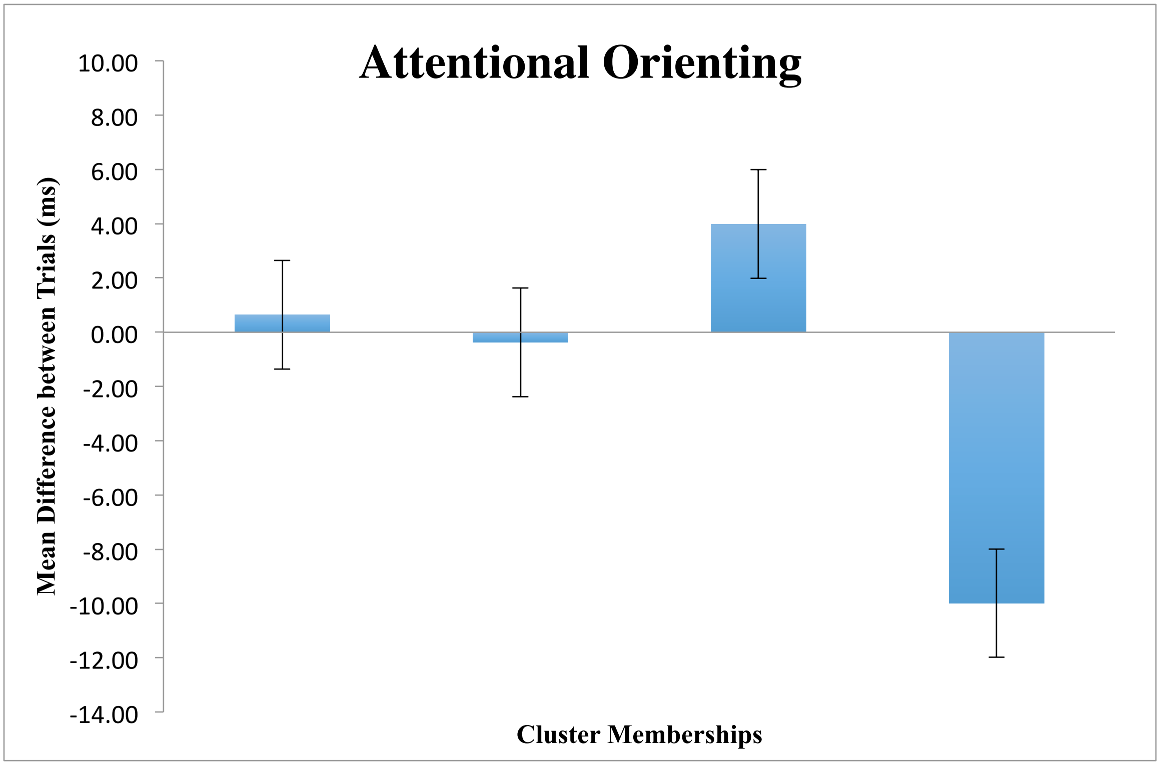
Note: Each square denotes the number of individuals predicted to belong to the cluster by their actual cluster membership. Perfect accuracies would be represented as a single diagonal line.

Figure 7. *Attentional control values for clusters 1 - 4*



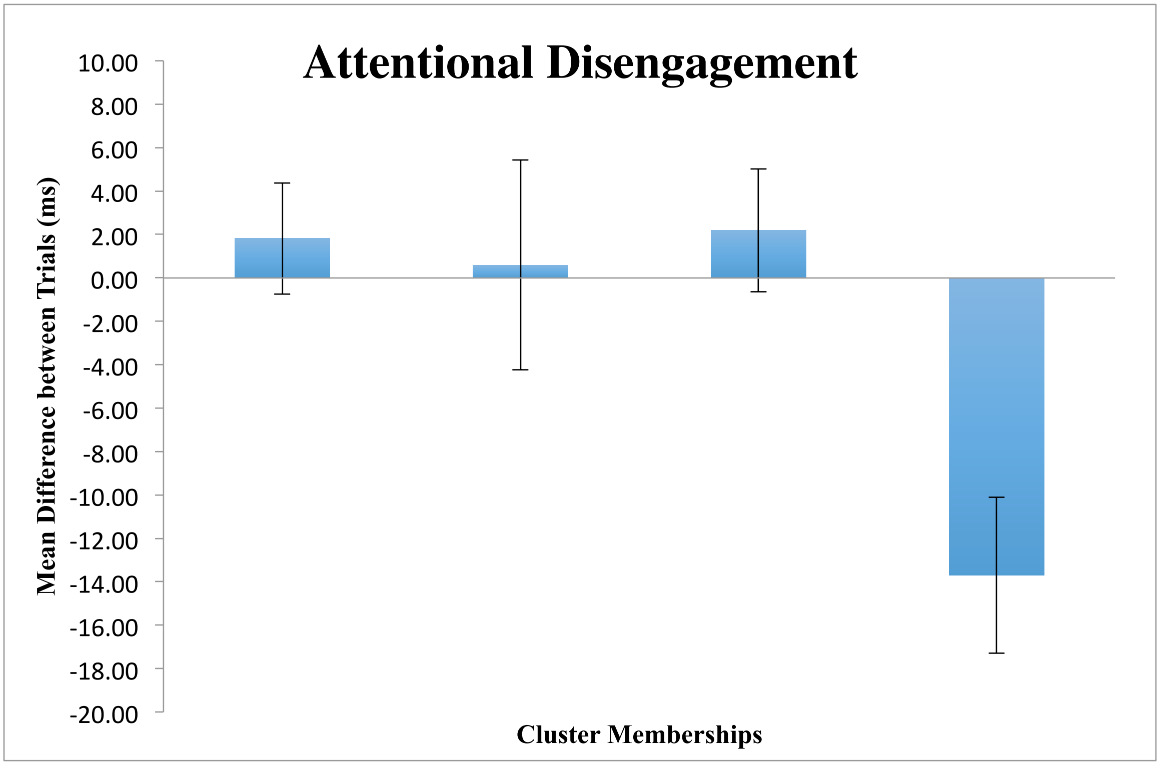
Note: Greater difference scores (incongruent – congruent trials) reflect worse cognitive control.

Figure 8. *Attentional orienting values for clusters 1 - 4*



Note: Lower scores (threat valid – neutral valid trials) reflect enhanced attentional orienting for threat.

Figure 9. *Attentional disengagement values for clusters 1 - 4*



Note: Higher scores (threat invalid – neutral invalid trials) reflect worse attentional disengagement from threat.