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Anxiety Enhances Threat Processing Without Competition Among Multiple Inputs: A Diffusion Model Analysis

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Enhanced processing of threatening information is a well established phenomenon among high-anxious individuals. This effect is most reliably shown in situations where 2 or more items compete for processing resources, suggesting that input competition is a critical component of the effect. However, it could be that there are small effects in situations without input competition, but the dependent measures typically used are not sensitive enough to detect them. The present study analyzed data from a noncompetition task, single-string lexical decision, with the diffusion model, a decision process model that provides a more direct measure of performance differences than either response times or accuracy alone. The diffusion model analysis showed a consistent processing advantage for threatening words in high-anxious individuals, whereas traditional comparisons showed no significant differences. These results challenge the view that input competition is necessary for enhanced threat processing. Implications for theories of anxiety are discussed.

Keywords: diffusion model, lexical decision, anxiety, threat bias, processing competition

Numerous studies have demonstrated that individuals high in anxiety show enhanced processing of threatening information over nonthreatening information compared to their low-anxious counterparts. This phenomenon, often termed a *threat bias*, has been repeatedly demonstrated in clinically anxious samples and in nonclinical samples of individuals high in trait anxiety (see Bar-Haim, Lamy, Pergamin, Bakermans-Kranenburg, & van IJzendoorn, 2007, for a meta-analytic review). Such biased processing of threat is thought to play a significant role in the development and/or maintenance of anxious states (e.g., Beck & Clark, 1997; Bishop, 2007; Eysenck, 1992; Mathews & Mackintosh, 1998; Mogg & Bradley, 1998; Williams, Watts, MacLeod, & Mathews, 1988, 1997). Accordingly, there has been much empirical and theoretical work devoted to understanding the exact nature of this bias.

The present study focuses on the conditions in which anxiety-related threat bias does and does not manifest. In particular, we investigated whether competition for processing resources is necessary to demonstrate threat bias in individuals high in anxiety. It has been suggested that the bias only occurs when threatening information competes with nonthreatening information for processing resources (e.g., MacLeod & Mathews, 1991; Mathews, 1990; Mathews & Mackintosh, 1998; Williams et al., 1997). For example, Mathews and Mackintosh (1998) stated, “Thus, it is the attentional priority accorded to threat in preference to other cues, rather than the efficiency of processing threatening information per se, that characterizes anxiety” (pp. 540–541).

In support of this view, the tasks that reliably show threat bias do indeed involve more than one stimulus (or stimulus aspect) that competes for processing resources. For example, in the widely used probe detection (e.g., MacLeod, Mathews, & Tata, 1986) and probe discrimination tasks (e.g., Bradley, Mogg, Falla, & Hamilton, 1998), two stimuli (e.g., words or faces), one threatening and one neutral, are briefly presented at different locations on the screen. Then a probe is presented at the location of one of the stimuli, and participants must indicate the presence of the probe or determine its type or location. In individuals high in anxiety, responses are typically faster when the probe replaces the threatening stimulus and slower when it replaces the neutral stimulus, suggesting that attention is preferentially allocated to threat for these individuals. Because participants can attend to either of the two stimuli cues in the tasks, there is competition for processing resources.

Similar results have been demonstrated in other paradigms such as emotional Stroop and dichotic listening tasks, both of which involve competition for processing resources (see Bar-Haim et al., 2007). In the emotional Stroop task, participants must name the color of presented words, some of which are threatening or emotional. In this task, individuals high in anxiety show slower responses to the colors of threatening compared to nonthreatening words (e.g., Fox, 1993). Although only one stimulus is presented at a time, the meaning of the word can compete with the color of the word and affect responses. In dichotic listening tasks participants must attend to one of two auditory streams that are presented simultaneously in different ears, so the two streams compete for attention. Participants who are anxious show significant interference when threat-related words are presented in the unattended stream (e.g., Mathews & MacLeod, 1986; Wenzel, 2006).

Each of the above tasks involves processing competition, and each reliably reveals threat bias. In contrast, evidence for threat bias in tasks that do not involve competition is rare, providing further support for the claim that processing competition is necessary for threat bias. Perhaps the most consistent support for this

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claim comes from lexical decision tasks, in which participants must determine if letter-strings are words or not. MacLeod and Mathews (1991) compared patients diagnosed with generalized anxiety disorder (GAD) and healthy controls on two versions of lexical decision and showed threat bias for the patients, but only when there was processing competition. The critical distinction in the study was between single- and double-string versions of the task. In the single-string version, one string of letters was presented at a time and participants responded *word* or *nonword*. In the double-string version two letter-strings were presented simultaneously and participants responded *word* if one or both of the strings was a word, or *nonword* if neither was a word. For both versions of the task, threat bias was defined as faster responses to trials with one threatening word compared to trials with one nonthreatening word.

In the double-string design there are two inputs that compete for attention. In the single-string design, on the other hand, there is only one stimulus to process so there was no competition among inputs. MacLeod and Mathews' (1991) results showed a threat bias for patients with GAD, but only in the double-string version. Individuals who are anxious had faster responses to trials containing a threatening word paired with a nonword relative to trials with a nonthreatening word paired with a threatening word. In contrast, participants who are anxious did not show faster responses to threatening words relative to nonthreatening words when they were presented by themselves. The authors took this as evidence that, for individuals who are anxious, threatening information is assigned processing priority over competing input, but it is not more accessible than nonthreatening information in general. Thus the advantage for threatening information is only present when there is competition for processing resources.

It is important to be clear on the type of competition implied by MacLeod and Mathews' (1991) results. Although there is competition between the responses (word and nonword) it is present in both versions of the task. There is also competition among internal representations, in that the decision depends on whether a letter-string sufficiently matches a word in lexical memory. However, this type of competition is also present in both versions of the task. The type of competition that does differ between the two versions of the task is input competition: In the double-string task there are two inputs that can be processed, whereas in the single-string tasks there is only one. Thus we refer to MacLeod and Mathews' (1991) hypothesis as the input competition hypothesis for clarity. This hypothesis states that anxiety affects the cognitive control systems involved in selecting threatening over neutral stimuli for processing, but it does not facilitate the availability of threat-related information in general. Consequently, threat bias will only manifest in conditions involving multiple, competing inputs.

In support of the input competition hypothesis, several other studies with lexical decision have failed to demonstrate a threat bias in individuals who are anxious. Mogg, Mathews, Eysenck, and May (1991) found a threat bias in participants who are anxious when comparing threatening and categorized nonthreatening words in double- but not single-string lexical decision. Hill and Kemp-Wheeler (1989) used positive and threatening words in single-string lexical decision and found no threat bias in participants who are anxious. Calvo, Eysenck, and Estevez (1994) found larger semantic priming of threatening words as a function of test anxiety, but no effects in the basic single-string lexical decision task. Pauli, Dengler, and Wiedemann (2005) had patients with panic disorder and healthy controls study threatening and neutral words and used single-string lexical decision to assess implicit memory for the studied words, and they did not find a threat bias in the patients with panic disorder. Ferraro, Christopherson, and Douglas (2006) used single-string lexical decision to compare blood-fearful, spider-fearful, and nonfearful controls, but failed to find any threat bias to spider- or blood-related words. Mathews and Milroy (1994) had participants with high- and low-anxiety make valence decisions (e.g., "is this word pleasant or unpleasant?") about threatening and neutral words, but found no differences in response times (RTs) as a function of anxiety. Similar tasks without input competition, like affective decision or identification, have shown evidence of response bias for threat in participants with high anxiety, but no evidence of greater discriminability or accessibility for threatening stimuli (Becker & Rinck, 2004; Eysenck, 1992; Manguno-Mire, Constans, & Geer, 2005; Windmann & Kruger, 1998; Winton, Clark, & Edelmann, 1995).

Taken together, these studies suggest that the anxiety-related threat bias does not occur unless threatening information competes with other input for processing resources. However, recent studies have demonstrated anxiety-related threat bias using a variant of the probe detection task in which only one stimulus cues the potential probe location. Thus rather than displaying one threatening and one nonthreatening stimulus simultaneously to cue the probe location, only one stimulus is presented that can correctly or incorrectly cue the location of the upcoming probe. Threat bias has been demonstrated for individuals who are anxious in this task with both threatening words (Amir, Elias, Klumpp, & Przeworski, 2003; Fox, Russo, Bowles, & Dutton, 2001) and threatening pictures (Koster, Crombez, Verscheure, Van Damme, & Wiersema, 2006). At first glance these findings might be taken to challenge the input competition hypothesis because only one stimulus is used to cue the probe location; thus the threatening stimulus does not compete with a nonthreatening stimulus for processing resources. However, there is still potential input competition between the cue and the probe. In fact, one proposed source of threat bias in this task, an impaired ability to disengage attention from the threatening stimulus, implies competition between the threatening stimulus and the probe (Amir et al., 2003; Fox et al., 2001). Thus there is potentially some input competition in this task, so it cannot strongly challenge the input competition hypothesis.

As noted above, the input competition hypothesis is an explicit component of several theories of threat bias (Mathews, 1990; Mathews & Mackintosh, 1998; Williams et al., 1997). It also appears to be implicit in other models, including those of Eysenck (1992); Beck and Clark (1997); Mogg and Bradley (1998); and Frewen, Dozois, Joanisse, and Neufeld (2008), in that these models have been formulated to account for why attention is selectively allocated to threat cues over neutral cues and thus imply competition between such cues.

However, in many of these theories input competition is not necessarily a core component. In their simplest form, these models all appear to include some form of what Williams et al. (1997) termed the affective decision mechanism (ADM), which determines the threat value of input and which triggers a secondary resource allocation mechanism (RAM), which assigns priority to processing of stimuli deemed potentially threatening. As noted by Mathews and Mackintosh (1998), the 1988 version of the Williams et al. model "seemed to predict that high trait/state anxious individuals should be faster to respond to threatening stimuli even in the absence of competing stimuli" (p. 541). They noted that the 1997 revised model was altered to accommodate the apparent requirement for processing competition. Specifically, they conceptualized the ADM as a parallel distributed processing network in which the activation of representations of threatening stimuli is strengthened by adding an emotional "tag." This tag gives such representations an advantage over competing stimulus representations. Mathews and Mackintosh (1998) noted, "Without any competition, however, no particular advantage would be apparent, because a single threat stimulus would always effectively control the output from that network, regardless of whether it carried a tag or not" (p. 541).

Although the consistent failure to find evidence of threat bias using tasks not involving input competition (e.g., lexical decision) suggests a need for this hypothesis, we note that it rests on a pattern of null findings that are not conclusive. We suggest this pattern may be an artifact of insensitive measures and so suggest that enhanced processing of threatening stimuli in individuals who are anxious should be expected even in the absence of processing competition.

To illustrate this point, we focus on a recent neurocognitive model of anxiety (Bishop, 2007). This model was chosen because it was informed by research on attentional biases and is formalized in terms of underlying neural substrates (see Frewen et al., 2008, for similar principles in a neural-network model). Bishop's (2007) model builds on the hypothesis of Mathews and Mackintosh (1998) that individuals who are anxious have more sensitive threat appraisal than their nonanxious counterparts. In brief, the model posits that individuals who are anxious are characterized by heightened responsiveness of the amygdala, and this leads to increased activation of the representations of threatening cues in the temporal cortex, effectively enhancing the saliency of threat in the environment. This element of Bishop's model parallels the ADM in the Williams et al. model. This increased amygdala activity is coupled with decreased attentional regulation from prefrontal cortex, which reduces the ability to inhibit processing of threatening distractors. Consequently, cortical representations of threatening information are more easily activated relative to nonthreatening information for anxious individuals, leading those individuals to selectively attend to threat. In terms of attentional biases, enhanced activation of the amygdala facilitates engagement, whereas impaired regulation from prefrontal cortex delays disengagement.

In Bishop's (2007) model the increased activity of threat representations leads to preferential processing of threat over competing input for anxious individuals. When there are multiple inputs competing for attentional resources, the model predicts that threatening information will win the competition, consistent with the results reviewed above. However, the central mechanisms of the model should presumably operate with or without input competition. In particular, there is no apparent reason why the amygdala would respond to threat when two or more inputs are presented, but not when one threatening stimulus is presented in isolation. It would be more parsimonious to assume that anxious individuals have hyperactivity of the amygdala in response to threatening information, regardless of whether there are other concurrent inputs. Similarly, we should expect the ADM to lead to enhanced processing of threat regardless of concurrent inputs. If so, threat bias should still occur with multiple-competing inputs, but it should also occur in the absence of additional inputs. That is, the cortical representations of threatening information should be more active relative to neutral information, even if only one stimulus is being processed. Of course, such an account does not address why threat bias is not found without competition among inputs, which we investigated in the present study.

The failure to find reliable threat bias in tasks without input competition suggests that models such as Bishop's (2007) should only be formulated for situations with multiple inputs. In contrast, we hypothesize that threat bias is present regardless of input competition, but the effects are smaller, and thus more difficult to detect, when there is no input competition. According to this hypothesis, there are small effects of threat bias in noncompetition tasks, but traditional analytical methods are not sensitive enough to detect them. If this were true, it would allow for broader and more parsimonious models of anxiety in which selective processing of threat over concurrent input is simply one manifestation of more general underlying processes.

In support of our hypothesis, there is some evidence for anxiety-related differences in lexical decision without input competition. Hill and Kemp-Wheeler (1989) found a nonsignificant trend suggesting an advantage for positive words in participants with low-anxiety but not participants with high anxiety. Pauli and colleagues (1997) showed a marginally significant difference between patients with panic disorder and healthy controls in identifying rapidly presented threatening words, however, they failed to replicate the effect (see Becker & Rinck, 2004). Last, Vythilingam et al. (2007) compared patients with posttraumatic stress disorder (PTSD) to healthy controls on single-string lexical decision and showed a significant threat bias in patients only.

These studies support the claim that there might be small effects in noncompetition tasks that are hard to detect. There are several aspects of research in this domain that can limit statistical power, thus reducing the ability to detect such small effects. First, there are often practical limitations to participant recruitment with clinical populations, resulting in relatively small sample size. For example, in the MacLeod and Mathews (1991) study, there were only 16 participants in each group. Although this size of sample might be sufficient to show large effects of a manipulation, small effects could require more participants to reach significance. Second, there is often a limit to the number of relevant stimuli that are available. Although researchers might use a large pool of threatening words in an experiment, it is unlikely that every word is equally salient to anxious participants. Thus although the word *cancer* is deemed threatening by the experimenter, it might not be sufficiently threatening or relevant to a particular individual who is anxious. Last, the dependent measure used to assess threat bias, typically mean RT, is not a direct measure of difficulty of stimulus processing. As we will discuss in the next section, response speed across individuals is determined by several factors that are independent of the stimulus, so RTs might not be precise enough to detect small effects.

Given the limitations to research discussed above, it is possible that there are small effects of threat bias in noncompetition tasks that are undetected. A straightforward way to test this is to increase the power of a design and assess whether threat bias emerges. The present study employed this approach to determine if threat bias could be reliably demonstrated in single-string lexical decision.

Based on the limitations listed above, there are three primary methods to increase the chance of significance in lexical decision: increase sample size, increase the number of critical stimuli, or use a more sensitive dependent measure. Because there are practical limitations to increasing the number of participants with high anxiety or threat-related stimuli that are relevant to those participants, we focused on using a more sensitive dependent measure. We used a cognitive decision model, the diffusion model (Ratcliff, 1978; Ratcliff & Smith, 2004), to produce a more direct measure of lexical processing than traditional RTs and accuracy values. Before the diffusion model is introduced we review the limitations of traditional analyses of lexical decision and how they can obscure effects.

Dependent Measures for Lexical Decision

Lexical decision involves two dependent measures, accuracy and RTs. We focus primarily on RTs because accuracy is rarely compared in lexical decision due to ceiling effects, though the following concerns hold for both measures. If certain stimuli, such as threatening words, provide a strong match to lexical memory, responses to them will be fast and accurate. Thus RTs are used to assess the speed or quality of access to lexical representations. Unfortunately, RTs are affected by other components of the decision that are not related to the construct of interest. For example, some individuals tend to perform these tasks relatively slowly, not because they are slow to process the information, but because they are more cautious when responding. Although this difference in response caution is presumably independent of word accessibility, it is absorbed into the measures used to assess lexical processing. Therefore, two participants who have similar lexical processing could still have substantially different RTs. Other aspects of an individual's response style can affect the behavioral data as well. Some individuals might be slower at the response stage of the task (e.g., pressing the button), whereas others might have a bias for one response (e.g., prefer to respond *word*), making it faster and more probable than the other.

In this sense, RTs are only an indirect measure of lexical processing because they reflect more than just the quality of information extracted from a stimulus (Ratcliff, Van Zandt, & McKoon, 1999; White, Ratcliff, Vasey, & McKoon, 2009). If the size of an effect between conditions or groups is relatively small, such an indirect measure might be too obscured to detect the effect. Thus RT and accuracy comparisons can show null differences even when there is an underlying effect. This limitation holds for other two-choice response time tasks, not just lexical decision.

The potential problem of different levels of response caution, reflected in speed/accuracy tradeoffs, is typically addressed by regressing accuracy on RTs to assess a systematic relationship. Although this method can detect group differences in response caution, it does not produce a direct measure of lexical processing; RTs still reflect more than lexical access. Even if there are no apparent group differences in speed/accuracy settings, individual differences in response style can still affect RTs (Ratcliff et al., 1999; White et al., 2009).

Ideally, an individual's response style would be identified and separated out to produce a more direct measure of lexical processing. Sequential sampling models allow for such analyses. Sequential sampling models are designed to account for the processes involved in making a simple decision (Ratcliff & Smith, 2004). One of the most widely applied models within this class is the diffusion model, which decomposes data from two-choice tasks into processing components (Ratcliff, 1978; Ratcliff & Rouder, 1998; Ratcliff et al., 1999). The model provides estimates for the several components of the decision process: response caution, response bias, encoding and response output time, and the quality of information provided by a stimulus. As a result, the effects of the components are disentangled, allowing more direct comparisons than are possible with the RTs and accuracy alone. In the next section, we provide a brief explanation of the diffusion model. For a more detailed description, readers should see Ratcliff and Tuerlinckx (2002); Ratcliff and Smith (2004); Ratcliff and McKoon (2008), or Wagenmakers (2009).

The Diffusion Model

The diffusion model (Ratcliff, 1978) is a sequential sampling model designed to explain the processes involved in making simple decisions. The model is designed to apply to fast (RTs under 1 to 1.5 s) two-choice decisions that involve a single-stage decision process. A schematic of the model is shown in Figure 1. Panel A of Figure 1 shows the entire process from presentation of the stimulus to the execution of a response. When making a decision in a two-choice task, an individual must encode the information, make a decision, and produce a response. The diffusion model does not address encoding and response, but it incorporates a parameter for these nondecision components, *Ter* (mean time for encoding and response), that estimates the total time for these processes.

The main focus of the model is the decision component of the response, shown in Figure 1B. The diffusion model assumes that information is accumulated until there is sufficient evidence for a response. The process starts at some point, z, and evidence is sampled over time until the process reaches a boundary (a or 0), at which point a response is initiated. The evidence is noisy so although the mean rate of accumulation (i.e., the slope of the line, v) always approaches the top boundary, the actual process is stochastic, represented by the nonmonotonic line in Figure 1B. Because evidence accumulation is noisy, responses with the same accumulation rate terminate at different times, producing RT distributions. Further, sometimes the noise drives the process to the wrong boundary, producing errors.

The main parameters of the model are the nondecision component, *Ter*, the starting point of the decision process, z, the distance between the two boundaries, a (i.e., a – 0), and a drift rate, v, for each condition in an experiment. These parameters have straightforward behavioral interpretations. Drift rate indexes the quality of information from the stimulus. A high value of drift rate means that the process reaches the boundary sooner and is less likely to be driven across the wrong boundary by noise, producing fast responses and few errors. Boundary separation, a, indexes the amount of information an individual requires to reach a decision (i.e., speed/accuracy settings or level of caution). A large boundary separation is indicative of a cautious response style and means that processes take longer to reach a boundary, but are less likely to cross the wrong boundary by mistake, leading to slower but more accurate responses. The position of the starting point, z, indexes response bias. If the starting point is closer to the top boundary

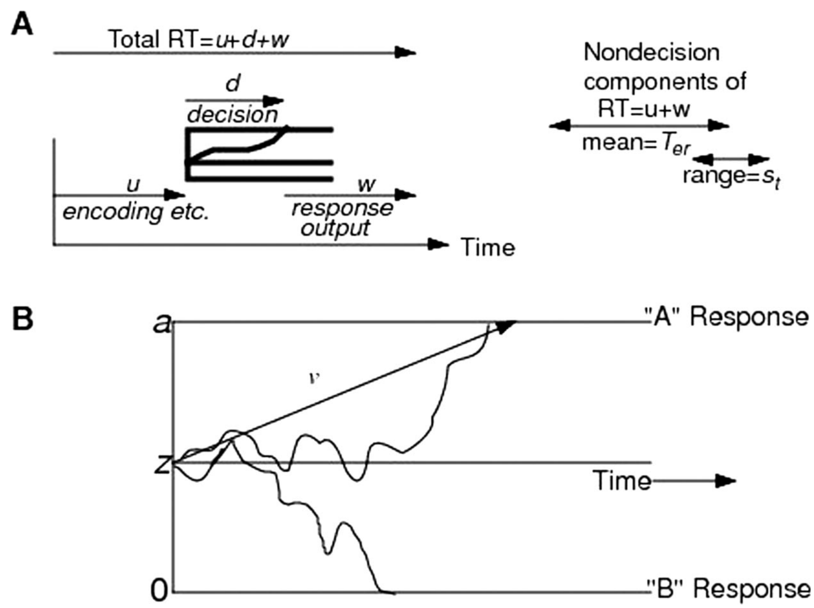

Figure 1. An illustration of the diffusion model. Panel A shows the total response process, including encoding and response output. Panel B shows the diffusion process for the decision component of the response process. Parameters of the model are: *a*, boundary separation; *z*, starting point: *Ter*, mean value of the nondecision component of reaction time; η, *SD* in drift across trials; s_z, range of the distribution of starting point (*z*) across trials; *v*, drift rate; p_0, proportion of contaminants; s_t, range of the distribution of nondecision times across trials; and *s*, *SD* in variability in drift within trials.

those responses will be faster and more probable than those corresponding to the other boundary.

The components are assumed to have variability associated with them, based on the assumption that they fluctuate throughout the course of an experiment. The parameter s_t captures variability in the nondecision component, s_z captures variability in the starting point, and η captures variability in drift rates across trials. The parameter p_o represents the proportion of contaminants in the data (e.g., due to lapses in attention), which allows the model to accommodate outlier responses that are not removed through data trimming (see Results).

The diffusion model is fit to all aspects of the behavioral data, including accuracy and the correct and error RT distributions for each condition. In this regard it is highly constrained by the data, and all possible effects are captured. To fit the model, researchers need the quantile RTs for correct and error responses and accuracy for each condition (see Ratcliff & Tuerlinckx, 2002, for a full description of the fitting method). To ease use of the model, it has recently been implemented in a MATLAB toolbox (Vanderkerckhove & Tuerlinckx, 2008).

The diffusion model provides several advantages over analyses of RTs and accuracy. First, all of the data are used by the model. Whereas a traditional analysis might only compare mean RTs for correct responses, the model incorporates accuracy values and the RT distributions for both correct and error responses. Second, the model separates components of processing, allowing researchers to compare measures of response caution, response bias, nondecision time, and stimulus evidence across groups of subjects. Third, and most important for present purposes, the variability associated with each component does not affect the other measures. It has been shown empirically and through simulations that individual differences in response caution and bias can affect RTs and accuracy but not drift rates (Voss, Rothermund, & Voss, 2004; White, Ratcliff, Vasey, & McKoon, 2010). Also, the correlations among parameters across subjects are typically small, suggesting that components extracted by the model are relatively independent of each other (see Ratcliff, Thapar, & McKoon, 2010). Further support for the use of drift rates to index differences in lexical processing comes from Ratcliff, Gomez, and McKoon (2004), who analyzed a series of lexical decision experiments with the diffusion model and showed that manipulations of word frequency, word repetition, nonword type, and stimulus proportionality all mapped onto changes in drift rates. Thus each of the manipulations in that study produced changes in the quality of evidence in the decision process. Taken together, these studies suggested that compared to RTs or accuracy values, drift rates provide a more direct measure of lexical processing that is not contaminated by other decision components.

Another advantage of a diffusion model analysis is that it can be applied to conditions with relatively few observations. This is particularly relevant here because researchers often have a limited pool of threatening words to use when assessing threat bias. With a limited number of observations for these conditions there will be greater variability in the estimates used to compare processing. This limitation can be overcome with the diffusion model by including filler conditions with hundreds of observations. By fitting the model to all conditions simultaneously, the filler conditions with many observations constrain estimates for the target conditions with fewer observations (e.g., threatening words), as we describe in more detail in the Model Fitting section.

With the diffusion model to assess anxiety-related differences in threat processing, two questions can be addressed. First will drift rates reveal a threat bias for anxious participants in a lexical-decision task without input competition? Second, are there differences between participants with high anxiety and low anxiety in response criteria or nondecision time? More generally, this approach can demonstrate the utility of applying cognitive modeling techniques, encouraging their use in the exploration of other clinical phenomena.

Experiment 1: Threat Bias in Single-String Lexical Decision

Experiment 1 was designed to determine if individuals with high-trait anxiety show a processing advantage for threatening information in a lexical-decision task. Threatening and matched nonthreatening words were presented sporadically among many neutral fillers. The sporadic presentation of these words was intended to reduce the probability that they would be noticed as the stimuli of interest and to prevent the threatening words from priming each other. The study was replicated with two separate sets of participants to ensure that the results were robust across participants. Rather than combine the participants into one large group, we chose to treat them as separate groups because studies involving psychopathology are often limited to a small sample of participants, and we wanted to ensure that our findings were replicable in typical samples. However, the pattern of data was the same for the two groups.

Method

Stimuli. The stimuli were divided into two categories, filler and target. Filler stimuli were included to constrain the model fitting and hide the target words as stimuli of interest. There were three filler stimuli pools: 366 high frequency words with frequencies from 78 to 10,600 per million ($M = 287.5$, $SD = 476$, Kucera & Francis, 1967), 599 low frequency words with frequencies of four and five per million ($M = 4.41$, $SD = 0.017$), and 434 nonwords, which were created by replacing all of the vowels with other vowels (except for *u* after *q*) from the word pools.

Target stimuli consisted of threatening words and matched nonthreatening words. The words were taken from a previous study investigating memory bias in anxiety (Mathews, Mogg, May, & Eysenck, 1989) and an online database for the attentional probe task (www.psy.uwa.edu.au/labs/cogemo/AttProbe1.html). There were two, 120 word pools, one threatening (e.g., cancer, embarrassment) and one nonthreating (e.g., planet, avacado), that were matched for letter-length and frequency of usage. Target and filler stimuli were chosen randomly from the word pools without replacement for use in the task.

Anxiety measure. The trait portion of the Spielberger Trait Anxiety Inventory (STAI, Spielberger, Gorsuch, & Lushene, 1970) was used to assess differences in anxiety. Trait scores from the STAI were used to group participants, with the upper and lower third of scores grouped as high- and low-anxiety, respectively. The lower cutoff for the high-anxiety group was 43 and the upper cutoff for the low-anxiety group was 34.

Participants. All participants were Ohio State University students who received credit in an introductory psychology course for participation. In the first set there were 63 total participants. The low-anxious group consisted of 21 participants (12 women) with mean STAI 28.2 ($SD = 2.3$), and the high-anxious group consisted of 21 participants (14 women) with mean STAI 47.2 ($SD = 4.9$). In the second set there were 57 total participants, with 21 participants (13 women) in the low-anxious group, mean STAI 30.3 ($SD = 3.4$), and 21 participants (14 women) in the high-anxious group, mean STAI 48.9 ($SD = 6.1$).

Procedure. Participants performed a lexical-decision task in which they were shown single strings of letters and told to respond *word* if the letters formed an English word or *nonword* if they did not. Stimuli remained on the screen until a key was pressed. To discourage guessing, the word *ERROR* was shown for 750 ms after incorrect responses. There were 12 blocks consisting of 36 words and 36 nonwords each. Of the 36 words in each block, there were 24 filler words (12 high frequency, 12 low frequency) and 12 target words (six threatening words, six nonthreatening). Each target word was separated by at least four trials of filler stimuli to avoid priming effects and each was preceded by a high frequency word to control sequential effects. After finishing the task participants completed the STAI–T.

Model fitting. All responses faster than 250 ms or slower than 3 s were excluded from the analyses (less than 0.7% of the data) to remove apparent outliers. Although the diffusion model incorporates a parameter, p_o, to account for lapses in attention, data trimming is still performed to remove responses that are substantially outside of the range of normal responses. Thus p_o captures any responses (e.g., due to lapses of attention) that fall within the normal response window.

The diffusion model was fit individually to each participant's data, which allowed the parameters to be subjected to analysis of variances (ANOVAs) in the same manner as RTs and accuracy values. The data entered into the fitting routine for each condition were the accuracy value and the five quantiles of the RT distribution for correct and error responses (see Appendix). The model was fit to all conditions simultaneously, including the filler and target conditions. The use of all of the conditions is an important methodological advantage afforded by the model. Because there were relatively few observations in the target conditions, RT and accuracy estimates for threat and nonthreat conditions have higher variability. However, by using hundreds of observations from the filler conditions to constrain estimates for response criteria and nondecision time in the diffusion model, the drift rates for the target conditions can be accurately estimated (White et al., 2009). In other words, the model was used to determine an individual's nondecision time and response caution based on hundreds of responses to filler conditions, and that information was then used as a reference to determine the quality of evidence (drift rates) for the target conditions with fewer observations. Thus we were able to decrease the variability of the drift-rate estimates without adding more target observations.

The quality of fit can be assessed by the chi-square values reported in Table 2. With five conditions and 12 model parameters, the degrees of freedom were 43 with a critical value of 59 (see Appendix). Thus Table 2 shows there are significant misfits of the model. However, the power of the chi-square statistic increases with the number of observations, meaning a small misfit can produce a significant chi-square (see Ratcliff, Thapar, Gomez, & McKoon, 2004). As a rule of thumb, we generally find that for experiments with up to 1,000 observations, chi-square values that are less than twice the critical value indicate good accord with the data, so long as there are no systematic misses from the model's predictions (see Appendix). In the present experiment, all of the values were well under twice the critical value, and were comparable to previous applications of the model to lexical decision (Ratcliff et al., 2004; White et al., 2009), allowing for confident comparison of the parameter values. The appendix includes a more detailed account of fit quality, including visual assessment of the fits.

Results

Differences in lexical processing were assessed by comparisons of mean RTs, accuracy, and drift rates. The two sets of participants are presented separately (Group 1 and Group 2). The behavioral data are shown in Table 1 and the diffusion model parameters are shown in Table 2. We performed ANOVAs on the filler stimuli, but there were no main effects or interactions involving anxiety so they are not discussed further.

When comparing threatening and nonthreatening words, we found evidence for a threat bias in both of the high-anxiety groups. Specifically, participants with high anxiety had larger drift rates for threatening compared to nonthreatening words whereas participants with low anxiety did not. More important, these effects were only significant in drift rate comparisons, though RT and accuracy comparisons showed small, nonsignificant differences in the expected direction.

Comparisons of target stimuli were performed using 2 $\times$ 2 mixed ANOVAs on each measure (mean RTs, accuracy values, and drift rates), with stimulus type (threatening, nonthreatening) as the within-factor and anxiety group as the between-factor. Overall, participants had an advantage for threatening compared to nonthreatening words. For accuracy comparisons, there was a main effect of stimulus type, with more accurate responses to threatening words in Group 1, $F(1, 40) = 7.57$, $p < .01$, $\eta^2 = .16$, but the effect did not reach significance in Group 2, $F(1, 40) = 1.5$, p .1, $\eta^2 = .04$. Similar results were found with RT comparisons; Group 1 showed faster responses to threatening words, $F(1, 40) = 9.62$, $p < .01$, $\eta^2 = .19$, but the difference was not quite significant for Group 2, $F(1, 40) = 3.16$, $p = .08$, $\eta^2 = .07$. Consistent with these results, drift rates were significantly higher for threatening compared to nonthreatening words in Group 1, $F(1, 40) = 23.63$, $p < .001$, $\eta^2 = .35$, and Group 2, $F(1, 40) = 7.25$, $p = .01$, $\eta^2 = .13$.

The primary effect of interest was the interaction between anxiety and stimulus type. Figure 2 shows the results plotted as the difference between threat and nonthreat conditions (i.e., threat bias) for mean RTs, accuracy, and drift rates. Although there were small differences in the direction of a larger threat bias for the high-anxious groups with RTs and accuracy, the interactions were not significant for either measure (all Fs < 1). However, drift rate comparisons did show the predicted interaction in both groups: Group 1, $F(1, 40) = 4.72$, $p < .05$, $\eta^2 = .07$; Group 2, $F(1, 40) = 4.92$, $p < .05$, $\eta^2 = .09$. Subsequent paired t tests confirmed that both of the high-anxious groups had significantly higher drift rates for threatening compared to nonthreatening words: Group 1, $v_{threat} - v_{nonthreat} = .064$, $t(20) = 4.84$, $p < .001$, $\eta^2 = .539$; Group 2, $v_{threat} - v_{nonthreat} = .034$, $t(20) = 3.26$, $p < .01$, $\eta^2 = .347$, whereas the difference did not reach significance for the either of the low-anxious groups: Group 1, $v_{threat} - v_{nonthreat} = .023$, $t(20) = 1.77$, $p = .09$, $\eta^2 = .061$; Group 2, $v_{threat} - v_{nonthreat} = -.001$, $t(20) = -.29$, $p > .1$, $\eta^2 = .004$.

To assess differences in response criteria and nondecision time, we performed direct comparisons between the low- and high-anxious groups on each of the components listed in Table 2. None of the components differed between participants with high anxiety and low anxiety (all ts < 1.5).

Discussion

Consistent with predictions, the results from Experiment 1 demonstrate enhanced processing of threatening words for participants with high anxiety. Drift rate comparisons revealed a significant

Table 1
Accuracy and Reaction Times Averaged Across Participants for Experiment 1

	Low anxiety			High anxiety		
	Accuracy	Mean correct RT	Mean error RT	Accuracy	Mean correct RT	Mean error RT
Group 1						
Fillers						
HF	.963 (.03)	611 (217)	609 (290)	.964 (.03)	629 (231)	565 (178)
LF	.832 (.05)	726 (283)	738 (327)	.839 (.06)	752 (312)	759 (367)
NW	.922 (.04)	703 (288)	771 (358)	.937 (.03)	733 (305)	748 (351)
Targets						
Threat	.924 (.03)	654 (232)	784 (336)	.935 (.03)	675 (240)	713 (286)
Nonthreat	.911 (.03)	673 (258)	825 (372)	.908 (.04)	699 (280)	821 (392)
Group 2						
Fillers						
HF	.975 (.02)	627 (264)	599 (184)	.977 (.02)	609 (212)	570 (190)
LF	.833 (.06)	732 (307)	732 (350)	.854 (.07)	724 (276)	785 (375)
NW	.926 (.04)	712 (292)	762 (378)	.930 (.03)	722 (277)	777 (382)
Targets						
Threat	.891 (.03)	693 (268)	701 (333)	.915 (.03)	691 (261)	700 (398)
Nonthreat	.886 (.04)	700 (274)	756 (351)	.900 (.03)	711 (280)	850 (436)

Note. Standard deviations are given in parentheses. Groups 1 and 2 refer to separate groups of participants. RT = response time; HF = high-frequency words; LF = low-frequency words; NW = nonwords.

Table 2
Diffusion Model Parameters Averaged Across Participants for Experiment 1

Group 1								
	Filler stimuli					Target stimuli		
	High frequency	Low frequency	Nonword			Threat	Nonthreat	
Drift rates								
Low anxiety	.438 (.12)	.189 (.06)	.275 (.09)			.277 (.10)	.254 (.08)	
High anxiety	.469 (.11)	.211 (.05)	.285 (.05)			.331 (.10)	.267 (.07)	
	a	Ter	z	s_t	s_z	η	p_o	χ^2
Response parameters								
Low anxiety	.137 (.02)	.437 (.04)	.068 (.01)	.159 (.06)	.060 (.03)	.123 (.05)	.011 (.02)	62 (27)
High anxiety	.148 (.03)	.448 (.04)	.074 (.01)	.162 (.06)	.082 (0.04)	.135 (.04)	.013 (.03)	63 (30)
Group 2								
	Filler stimuli					Target stimuli		
	High frequency	Low frequency	Nonword			Threat	Nonthreat	
Drift rates								
Low anxiety	.474 (.12)	.207(.05)	.278 (.06)			.262 (.08)	.263 (.08)	
High anxiety	.444 (.09)	.184 (.06)	.276 (.06)			.259 (.08)	.225 (.06)	
	a	Ter	z	s_t	s_z	η	p_o	χ^2
Response parameters								
Low anxiety	.137 (.03)	.444 (.03)	.069 (.01)	.151 (.07)	.068 (.04)	.125 (.06)	.015 (.02)	68 (26)
High anxiety	.141 (.03)	.442 (.04)	.066 (.01)	.155 (.04)	.048 (.03)	.113 (.05)	.016 (.03)	63 (23)

Note. Standard deviations are shown in parenthesis. Groups 1 and 2 refer to separate sets of participants. Drift rates for nonwords are originally negative (corresponding to the bottom boundary of the diffusion process), but the absolute values are presented for display purposes. a = boundary separation; Ter = nondecision component; z = starting point; s_t = variability in the nondecision component; s_z = variability in starting point; η = variability in drift across trials; p_o = probability of an outlier.

processing advantage for the threatening words in the high-anxious but not the low-anxious groups. The interaction between stimulus type and anxiety group was significant only for drift rates, though accuracy and RTs showed small differences in the expected direction. Because there are large individual differences in the processing components (e.g., nondecision time and response caution) that affect RTs and accuracy values (Ratcliff & McKoon, 2008), these measures are less sensitive than drift rates when used to assess lexical processing, accounting for the discrepant findings among the measures.

The present results indicate that input competition is not necessary to demonstrate anxiety-related biases for threatening information, consistent with recent results with patients with PTSD (Vythilingham et al., 2007). Demonstrating this effect in nonclinical participants with high anxiety suggests that it is a general phenomenon for anxiety that is not restricted to patients with PTSD. Although the threat bias was in the right direction with RTs and accuracy, it was not strong enough to be statistically significant.

Comparisons of the processing components extracted through the diffusion model show that there were no differences between low- and high- anxious groups in boundary separation (caution), nondecision time (encoding and response output), or starting point (response bias). However, because the experiments were designed with many more filler than target stimuli, these processing components were determined more heavily by nonthreatening information in the model fits. In other words, the trials with threatening words did not greatly contribute to the estimates for the response components (aside from drift rates for those conditions), so we cannot make any claims about how or if threatening information affects these components of processing. To address this, we also fit the diffusion model to the target conditions alone, without constraints from the filler conditions. In short, the results were consistent with fits to the full data set: There were no differences in response criteria or nondecision time between participants with high and low anxiety. Regardless, we designed Experiment 2 to further explore the possibility of differences in decision components associated with threatening words.

Experiment 2: Response Criteria and Threatening Information

The results of Experiment 1 show one advantage of using the diffusion model to analyze data from these tasks. The between-groups differences in threat processing were consistently significant in comparisons of drift rates, but not in comparisons of RTs and accuracy. Because drift rates are a direct measure of lexical processing, small differences that were not apparent in traditional analyses were able to be detected. Further, because the diffusion model incorporates accuracy values and RT distributions for both

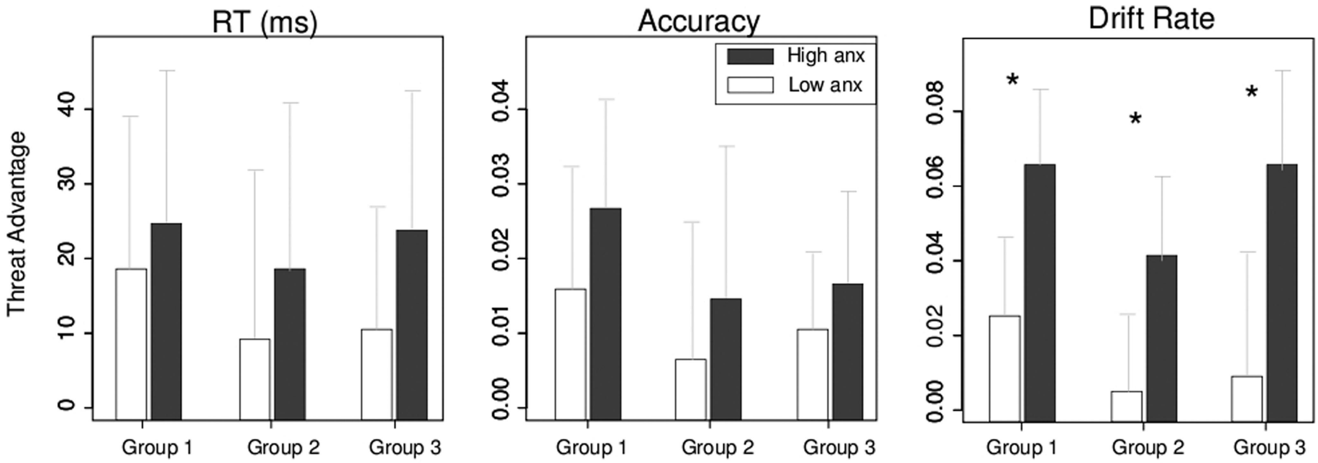

Figure 2. Plots of the threat bias in each measure across groups of participants. Groups 1 and 2 were from Experiment 1, Group 3 was from Experiment 2. Threat bias is computed as the difference between responses to threatening and matched nonthreatening words, with a bigger difference indicating a bigger advantage for the threatening words. Differences are shown for reaction times (RTs), accuracy, and drift rates extracted by the diffusion model (see text). Error bars are ±2 *SE*s. * Significant difference in threat bias between high and low anxiety groups ($p < .05$). Anx = anxiety.

correct and error responses, all of the behavioral data were taken into account when estimating the processing components, whereas a comparison of RTs does not account for effects in accuracy (and vice versa).

In addition to extracting drift rates that are more direct measures of lexical processing than accuracy or RTs, the diffusion model allows comparison of response components. One goal was to assess if threatening information differentially affects nondecision time, response caution, or response bias in participants with low and high anxiety. However, the design of Experiment 1 was not conducive to this type of comparison. As previously mentioned, the filler stimuli greatly outnumbered the target stimuli and had a greater influence on the estimates for the decision components. Thus the response criteria estimates obtained in Experiment 1 did not reflect any potential effects of the threatening words. Further, response criteria usually do not systematically change from trial to trial (e.g., Ratcliff et al., 1999), so we would not expect large differences based on the sporadic presentation of threatening words. However, a block of trials (e.g., 60) that contained a larger proportion of threatening words could be sufficient to induce criteria shifts in the high-anxious group.

Method

Experiment 2 increased the proportion of the target stimuli in the blocks to assess potential criteria changes. In the experiment, half of the blocks contained a relatively high proportion of threatening words (threat blocks), whereas the other half contained a high proportion of matched nonthreatening words (nonthreat blocks). Under this design, threat and nonthreat blocks could be modeled separately to compare processing components, allowing us to assess differences in response criteria and nondecision time as a function of threatening stimuli. The reasoning is as follows: Although the sporadic presentation of threatening words in Experiment 1 did not result in differences between participants with high and low anxiety in nondecision time, response caution, or response bias, grouped presentation of threatening words could result in differential changes in these components. Further, we could also assess threat bias in the same manner as Experiment 1 to determine if the results replicate in a third group of participants.

Procedure. The lexical-decision task in Experiment 2 was the same as the task in Experiment 1, except for the blocking manipulation and the exclusion of low frequency words. The entire experiment consisted of 12 blocks of 60 trials. Half of the blocks were threat blocks, in which the proportion of threatening words was high, and the other half were nonthreat blocks, in which the proportion of matched nonthreatening words was high. Threat and nonthreat blocks were presented in randomized order. Each block consisted of 30 words and 30 nonwords. Threat blocks consisted of 10 high frequency words and 20 threatening words, whereas nonthreat blocks consisted of 10 high frequency words and 20 nonthreatening words. Thus one third of the total trials and two thirds of the words in each block were target words. The same presentation rate and error feedback were used as in Experiment 1. After completing the task, participants filled out the STAI. The entire experiment lasted less than 30 min.

Stimuli. The same filler stimuli were used, except that low frequency words were no longer included in the test list. The low frequency words were excluded because the new design required fewer filler observations than Experiment 1 because the proportion of target trials was increased. To allow for more responses to target words, all of the 120 words from the threatening and nonthreatening pools were shown to each participant (compared to 72 in Experiment 1).

Participants. There were 61 total participants, all students at Ohio State University who participated for credit in an introductory psychology course. The low-anxious group consisted of 21 participants (15 women), mean STAI = 29.4 (SD = 3.1), and the high-anxious group consisted of 21 participants (13 women), mean STAI = 47.1 (SD = 6.3).

Results

The diffusion model was fit in the same manner as Experiment 1, except that threat and nonthreat blocks were modeled separately for each participant. Behavioral data are shown in Table 3 and diffusion model parameters are shown in Table 4. The fit quality was similar to Experiment 1. The ANOVAs for filler conditions had anxiety group (low, high) as the between-factor, and stimulus type (high frequency word, nonwords) and block (threat, nonthreat) as within-factors. Consistent with Experiment 1, there were no main effects or interactions involving anxiety group for filler conditions (all Fs < 2.5). Although we found no group differences in response criteria or nondecision time, drift rates were significantly higher for threatening words compared to nonthreatening words in the participants with high anxiety but not participants with low anxiety, replicating the results from Experiment 1. Similar to Experiment 1, this threat advantage was only significant for drift rate comparisons, though RTs showed a small difference in that direction.

Threat bias was assessed by a 2 × 2 mixed ANOVA, with anxiety group as the between-factor and stimulus type (threatening, nonthreatening) as the within-factor. The results were consistent with Experiment 1. The main effect of stimulus type was significant for all three measures: RT, $F(1, 40) = 10.55$, $p < .01$, $\eta^2 = .20$; accuracy, $F(1, 40) = 7.57$, $p < .01$, $\eta^2 = .11$; drift rates, $F(1, 40) = 6.98$, $p < .01$, $\eta^2 = .09$, showing an advantage for threatening compared to nonthreatening words. There were no main effects of anxiety group for any measure (Fs < 1).

For the interaction between anxiety group and stimulus type, there was a small difference in RTs that did not reach significance, $F(1, 40) = 2.3$, $p > .1$, $\eta^2 = .04$, and no significant difference in accuracy ($F < 1$). More important, the interaction was significant for drift rates, $F(1, 40) = 4.40$, $p = .04$, $\eta^2 = .13$. Subsequent paired t tests on drift rates confirmed a threat advantage in the high-anxious group, $v_{threat} - v_{nonthreat} = .063$, $t(20) = 3.52$, $p < .01$, $\eta^2 = .382$, but no advantage in the low-anxious group, $v_{threat} - v_{nonthreat} = .007$, $t(20) = .328$, $p > .1$, $\eta^2 = .005$. Thus Experiment 2 provides a replication of the threat bias found in Experiment 1.

Differences in response criteria were assessed by performing 2 × 2 mixed ANOVAs on response caution (a), response bias (z/a), and nondecision time (Ter), with anxiety group as the between factor and block (threat, nonthreat) as the within factor. There were no significant main effects or interactions for any of the parameters (all Fs < 2), suggesting that the threat blocks did not differentially affect these components for the high- and low-anxious groups.

Because each participant performed both threat and nonthreat blocks, we were able to compare parameter values between the two to assess the stability of response style. We expected that an individual's settings on these response components would be similar for both the threat and nonthreat blocks. There were strong correlations ($p < .01$) between the blocks for boundary separation (a), $r(40) = .65$, nondecision time (Ter), $r(40) = .80$, bias for a response (z/a), $r(40) = .66$, and average drift rates collapsed across target and filler conditions, $r(40) = .40$. These results show that the individual differences in response style and overall performance were highly stable between the threat and neutral blocks.

Discussion

The blocking manipulation did not produce different decision criteria for participants with low and high anxiety. This might be due to the fact that the target stimuli, though more prominent than in the first two experiments, still only accounted for one third of trials in each block. It would be hard to increase this proportion significantly while still maintaining an equal number of word and nonword stimuli and providing different conditions to constrain the model parameters. Alternatively, the null differences in processing components might reflect the fact that processing of threatening words does not differentially alter response criteria in participants who are anxious. However, previous research has shown increased response bias associated with anxiety and threatening words (e.g., Windmann & Kruger, 1998), thus the null findings from the present study should be interpreted cautiously.

Although we did not find any differences in response criteria, the experiment did replicate the processing advantage for threatening information in the high-anxious group, whose drift rates were significantly higher for threatening compared to nonthreatening words. Again, this processing bias was only

Table 3
Behavioral Data Averaged Across Participants From Experiment 2

	Low anxiety			High anxiety		
	Accuracy	Mean correct RT	Mean error RT	Accuracy	Mean correct RT	Mean error RT
Fillers						
HF–N	.958 (.04)	642 (203)	586 (197)	.948 (.04)	636 (216)	553 (245)
HF–T	.939 (.04)	646 (214)	604 (279)	.943 (.04)	635 (212)	550 (175)
NW–N	.952 (.02)	686 (232)	691 (291)	.939 (.04)	699 (247)	741 (275)
NW–T	.960 (.02)	689 (235)	648 (268)	.946 (.04)	696 (248)	742 (376)
Targets						
Threat	.946 (.03)	681 (240)	646 (249)	.925 (.07)	678 (240)	756 (423)
Nonthreat	.937 (.03)	690 (235)	754 (351)	.909 (.06)	701 (265)	790 (425)

Note. Standard deviations are shown in parentheses. RT = response time; HF–N = high frequency words in nonthreat blocks; HF–T = high-frequency words in threat blocks; NW–N = nonwords in nonthreat blocks; NW–T = nonwords in threat blocks.

Table 4
Diffusion Model Parameters Averaged Across Subjects for Experiment 2

	Filler stimuli: High frequency	Filler stimuli: Nonword	Target stimuli
Drift rates			
Low anxiety			
Threat Bl	.359 (.12)	.300 (.10)	.309 (.11)
Nonthreat Bl	.396 (.14)	.311 (.10)	.302 (.11)
High anxiety			
Threat Bl	.400 (.13)	.309 (.11)	.324 (.10)
Nonthreat Bl	.394 (.17)	.285 (.08)	.261 (.07)

	a	Ter	z	s_t	s_z	η	p_o	χ^2
Response parameters								
Low anxiety								
Threat Bl	.131 (.02)	.446 (.04)	.065 (.01)	.161 (.05)	.081 (.04)	.105 (.09)	.007 (.02)	30 (18)
Nonthreat Bl	.132 (.03)	.451 (.03)	.066 (.02)	.154 (.04)	.086 (.04)	.131 (.08)	.006 (.02)	32 (19)
High anxiety								
Threat Bl	.140 (.03)	.442 (.03)	.070 (.02)	.172 (.03)	.081 (.04)	.139 (.08)	.009 (.02)	33 (21)
Nonthreat Bl	.133 (.02)	.444 (.03)	.066 (.02)	.161 (.04)	.082 (.04)	.124 (.08)	.008 (.02)	28 (18)

Note. Standard deviations are shown in parentheses. Drift rates for nonwords are originally negative (corresponding to the bottom boundary of the diffusion process), but the absolute values are presented for display purposes. Threat Bl = threat blocks; nonthreat Bl = nonthreat blocks; a = boundary separation; Ter = nondecision component; z = starting point; s_t = variability in Ter; s_z = variability in starting point; η = variability in drift across trials; p_o = probability of an outlier.

significant in comparisons of drift rates, though the differences approached significance in RTs. It could be argued that there was a confound related to word categorization effects, in that the threat blocks contained many words from the same category, whereas the nonthreat blocks did not (e.g., Mogg et al., 1991). Although this possibility cannot be ruled out completely, it should not detract from the findings. First, the pattern of threat bias in Experiment 2 was similar to the pattern in Experiment 1, where categorization effects were reduced by sporadic presentation of the target stimuli. Second, word categorization effects would not account for the difference in threat bias between anxious and nonanxious participants, unless anxious individuals have a more developed category of threatening meanings, which is certainly plausible. This last point remains an open possibility worthy of further investigation.

General Discussion

The most important finding from this study was that individuals with high trait anxiety had a processing advantage for threatening words in single-string lexical decision. A processing advantage for threatening words in anxious participants has been shown numerous times before, but as far as we know it has never been demonstrated in a nonclinical sample using a task that does not involve competition among multiple inputs. Although Vythilingam et al. (2007) reported enhanced processing of threat cues in patients with PTSD using such a task, the present study makes it clear that this effect is not specific to patients with PTSD, but rather characterizes high levels of anxiety more generally. Thus input competition for processing priority is not essential to explanations of threat advantage in anxiety.

This finding allows for more parsimonious models of anxiety that no longer need to account for why threat bias only manifests with processing competition. Instead, tasks with input competition can be considered one type of situation in which more general underlying processes lead to biased threat processing in individuals with high anxiety. The other interesting result from the present study is that there were no anxiety-related differences in response criteria or nondecision time, even when blocks of trials contained a higher proportion of threatening words. We expected that the blocking manipulation would produce differences in response caution or bias, but the results did not support our hypothesis. However, because anxiety-related differences in response bias have been shown elsewhere (e.g., Windmann & Kruger, 1998), and the decisions in the present study were based on the lexicality, not the threat value of the words, the failure to find response bias in the present study should not be taken to challenge previous findings of bias.

It is important to note that differences in threat bias between participants with high and low anxiety were not significant in comparisons of RTs or accuracy, though the differences were in the expected direction. We attribute this to the insensitivity of the behavioral measures coupled with relatively small effects. In fact, our results suggest that we might find a significant threat bias in RTs if we replicated the experiment with very large samples. Fortunately, the diffusion model provided a substantial increase in sensitivity without recourse to very large samples, which are particularly unlikely to be feasible when studying clinical populations. This can best be shown by assessing the relative diagnostic utility of each measure (see Wenger, Negash, Petersen, & Petersen, 2010). Figure 3 shows the relevant values for accuracy, mean RTs, median RTs, and drift rates. The values in the figure were calculated as follows: Threat bias was calculated for each measure (e.g., threat_accuracy – nonthreat_accuracy) for all 126 participants. Then a discriminant function analysis (DFA, e.g., Rao, 1973;

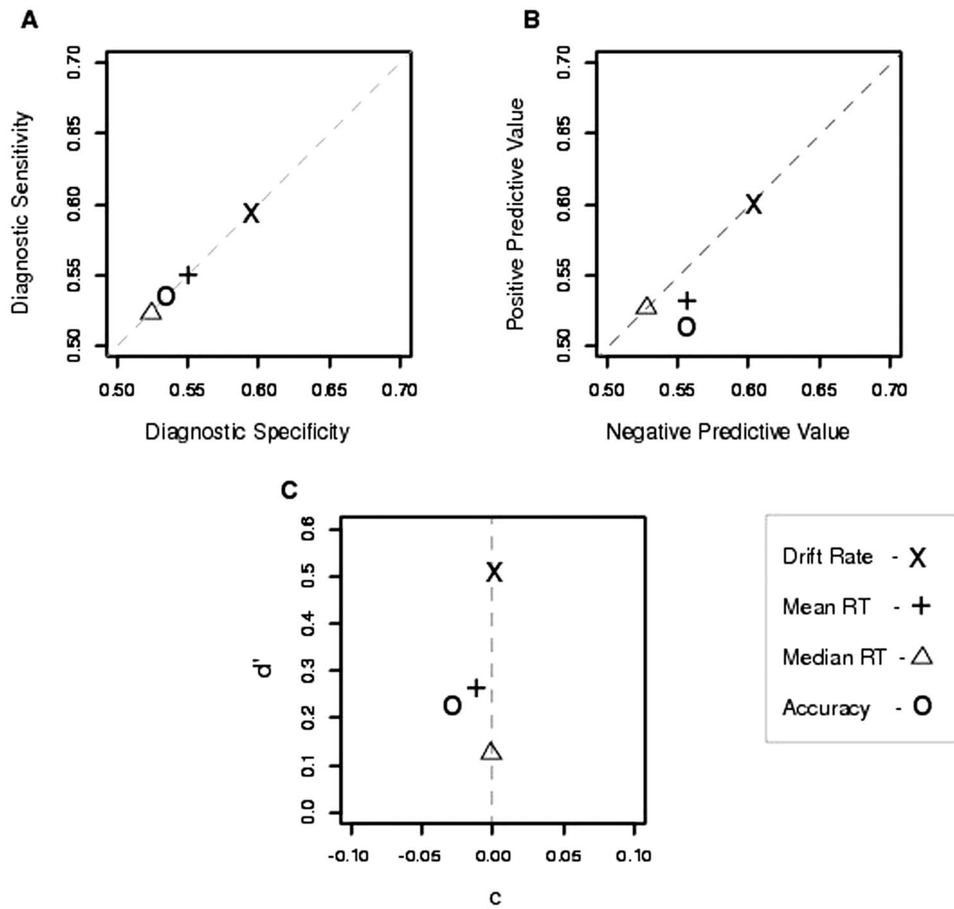

Figure 3. Diagnostic utility for each dependent measure, derived from the discriminant function analysis. Results were derived from all participants across the three experiments. RT = reaction time.

Wenger et al., 2010) was performed to determine how well each measure could classify participants as either high or low anxiety. With only one predictor variable for each function analysis, this amounted to a linear regression with the coefficients used to group the participants.

Figure 3 is meant to illustrate the relative diagnostic utility of each measure. Effect sizes from this and related studies are sufficiently small that they do not provide practical diagnostic utility, but the relationship among the different measures can still provide insight into their relative utility in other circumstances. Panel A of Figure 3 shows the sensitivity and specificity of each measure. Drift rates produce the highest sensitivity and specificity, and show no apparent bias. Panel B shows the positive and negative predictive value of each measure, again with drift rates showing better positive and negative predictive power than the other measures. Finally, Panel C shows that drift rates provide the highest discriminability with minimal bias.

The threat bias found in this study challenges the null results from previous studies (e.g., Ferraro et al., 2006; Hill & Kemp-Wheeler, 1989; MacLeod & Mathews, 1991; Mogg et al., 1991), but there are reasons to believe that such a bias is present for anxious individuals. The methodology employed in the present study was specifically designed to increase the sensitivity of the analyses. Both priming and sequential effects were reduced by presenting the threatening words sporadically and always after an unrelated high frequency word (Experiment 1). Further, the diffusion model analysis utilized all of the data and separated out variability related to each of the response components, providing a more sensitive measure of lexical processing, as shown in Figure 3.

Although the results of the present study provide evidence that processing competition is not necessary for a threat bias to emerge, there is little doubt that processing priority (or selective attention) plays an important role in threat bias. In fact, there is reason to believe that threat bias should be larger in tasks with competition compared to those without, which could explain why RTs were sensitive enough to show a threat bias in the double-string but not the single-string lexical-decision task (MacLeod & Mathews, 1991; Mogg et al., 1991). For both versions of the lexical-decision task, enhanced processing of threatening words relative to nonthreatening words (e.g., due to increased activity of the amygdala) would produce stronger evidence for threatening words, and thus an advantage over nonthreatening words. A further advantage would arise in the double-string version because of preferential attention to the threatening word. As a reminder, in the double-string task the word response should be given if one or both of the letter-strings is a word. If we assumed that the two letter strings were processed serially, then on critical trials in which a threatening word is presented with a nonword, anxious individuals should attend to the threatening word before the nonword (because it wins the input competition) and thus would have sufficient evidence for the word response without needing to check the other letter-string. Conversely, on critical trials with a nonthreatening word and a nonword, the nonword will be attended to first on some proportion of trials. Because the nonword response is only correct if both letter-strings are nonwords, RTs will be slower on these trials because the other letter-string would need to be inspected before a decision could be made. Thus threat bias in the double-string version reflects the benefit of attending to the word first and enhanced lexical processing of threatening words, whereas the single-string version reflects only the latter. This extra benefit in the double-string version can account for the fact that RT comparisons were sensitive enough to detect the bias in only the double-string version (MacLeod & Mathews, 1991; Mogg et al., 1991).

Although the advantage for threatening words in the double-string task has been discussed within a serial-processing framework, there would be a similar advantage for threatening words if we assumed that both strings were processed in parallel in a system with limited capacity (e.g., Neufeld & McCarty, 1994; Neufeld, Townsend, & Jette, 2007). Suppose the double-string stimulus was processed as a single target and that for individuals who are anxious, processing of threatening words is facilitated. Facilitated processing of threatening words would lead to a smaller reduction in capacity. Thus for participants who are anxious, trials with neutral words would reduce processing capacity more than trials with threatening words, leading to faster RTs for threat trials. Such a reduction in capacity might not produce as large of behavioral effects when only one letter-string is being processed, potentially accounting for the larger effects of threat bias in double-string lexical decision.

Engagement and Disengagement

There have been several studies investigating whether threat bias is due to facilitated engagement or delayed disengagement. Results from probe tasks suggest that individuals who are anxious have difficulty disengaging their attention from threatening stimuli (Amir et al., 2003; Fox, Russo, & Dutton, 2002). It has been argued that the probe task is not well suited to assess facilitated engagement (see Koster, Crombez, Verschuere, & De Houwer, 2004), but there is still evidence that facilitated engagement contributes meaningfully to threat bias (Bannon, Gonsalvez, & Croft, 2008; Koster et al., 2006).

The results from the present study and previous work involving lexical decision support the role of facilitated engagement in threat bias as well, as it is unclear how delayed disengagement would improve responding in either single- or double-string lexical decision tasks. Enhanced processing of threatening words in lexical decision could result from two different processes. As mentioned above, the advantage for threatening words could reflect an attentional boost to those words from the amygdala. That is, early processing in the amygdala identifies threatening words as salient, and thus more resources are directed toward further processing that is required to determine the lexicality of the words. Conversely, threatening words might be more frequently encountered for individuals who are anxious, and thus they are better represented internally and provide a stronger lexical match. In this regard, lexical decision might not reflect attentional processes, but rather simply the strength of the lexical representation.

Regardless of the underlying cause, enhanced lexical processing of threatening words supports the role of facilitated engagement of threat in anxiety. Combined with the results from dot-probe tasks, it seems that both facilitated engagement and delayed disengagement are involved in threat bias in anxiety. Indeed, the combination of these phenomena would be much more detrimental than either alone.

Conclusions

The present study demonstrated a reliable threat bias for participants with high-trait anxiety in a task that does not involve processing competition among multiple inputs. This indicates that input competition is not required for enhanced processing of threat. Consequently, models of anxiety can posit a more general account of threat bias that is not restricted to situations with multiple-competing inputs. The diffusion model proved to be a valuable asset for data analysis in this study, and we recommend that future research involving two-choice tasks consider the model as an alternative to comparisons of RTs and accuracy. Quantitative models like the diffusion model can improve analyses of behavioral data by explicitly formulating the relationship between the data and the underlying processes. We suggest that null results should be interpreted cautiously as they might reflect an underpowered design rather than a true lack of differences, especially when there are a limited number of participants and/or stimuli. The diffusion model provides a practical approach to increase the power of the design without needing to add participants or critical stimuli, making it a promising analytical tool for future exploration of processing differences associated with psychopathology.

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Appendix

Quality of Fit

The diffusion model predicts both the accuracy values and the RT distribution shapes for correct and error responses, which are compared against the behavioral data to assess fit quality. The RT distribution is typically represented by the .1, .3, .5 (median), .7, and .9 quantile RTs, which provide a good approximation of the distribution shape. The five quantiles divide the correct and error RT distributions into six bins each, resulting in 11 (12 – 1) degrees of freedom from the data for each condition (see Ratcliff, Thapar, & McKoon, 2009; Ratcliff & Tuerlinckx, 2002). The total degrees of freedom for the chi-square are given as $(K * 11) - M$, where K is the number of conditions in the experiment and M is the number of model parameters.

The quality of model fits can be assessed qualitatively in addition to the quantitative assessment described above. We can plot the actual and predicted values to determine if there are any systematic misses. Figure A1 shows the actual data plotted against the predicted values produced by the diffusion model parameters (collapsed across all conditions). For simplicity, only the accuracy and RT quantiles for correct responses are shown from Experiment 1, though similar results were found for all of the fits. The diagonal line in each of the plots represents perfect correspondence between actual and predicted values. As the figure shows, all of the values fall on or near the line, showing good fits to the data. Further, though not shown here, the residuals are normally distributed around 0, indicating that there are no systematic biases in the model predictions. The diffusion model captures the accuracy values and RT distribution shapes across a number of conditions, which is a powerful constraint for the model that supports confidence in the extracted parameter values.

(*Appendix continues*)

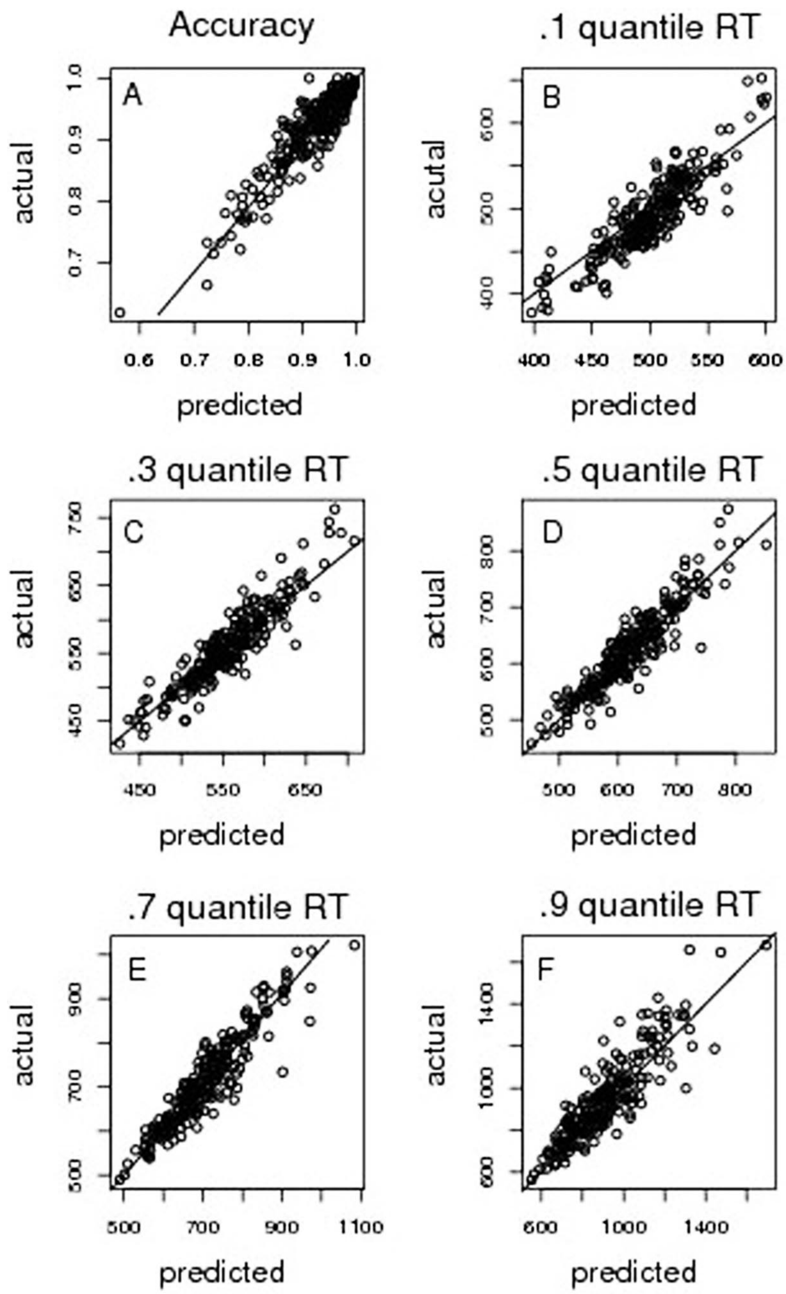

Figure A1. Goodness-of-fit plots from Experiment 1. The real values are plotted against the predicted values from the diffusion model for accuracy (A), and the reaction times (RTs) for the .1 (B), .3 (C), .5 (D), .7 (E), and .9 (F) quantiles of the RT distribution. See text for details.

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