Archival Report

Computational Modeling Applied to the Dot-Probe Task Yields Improved Reliability and Mechanistic Insights

Rebecca B. Price, Vanessa Brown, and Greg J. Siegle

ABSTRACT

BACKGROUND: Biased patterns of attention are implicated as key mechanisms across many forms of psychopathology and have given rise to automated mechanistic interventions designed to modify such attentional preferences. However, progress is substantially hindered by limitations in widely used methods to quantify attention, bias leading to imprecision of measurement.

METHODS: In a sample of patients who were clinically anxious ($n = 70$), we applied a well-validated form of computational modeling (drift-diffusion model) to trial-level reaction time data from a two-choice "dot-probe task"—the dominant paradigm used in hundreds of attention bias studies to date—in order to model distinct components of task performance.

RESULTS: While drift-diffusion model–derived attention bias indices exhibited convergent validity with previous approaches (e.g., conventional bias scores, eye tracking), our novel analytic approach yielded substantially improved split-half reliability, modestly improved test-retest reliability, and revealed novel mechanistic insights regarding neural substrates of attention bias and the impact of an automated attention retraining procedure.

CONCLUSIONS: Computational modeling of attention bias task data may represent a new way forward to improve precision.

Keywords: Attention bias, Attention bias modification, Anxiety, Computational modeling, Computational psychiatry, Drift-diffusion model

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Computational psychiatry aims to apply computational methods to observational data in psychiatric populations in the hopes of more precisely quantifying underlying mental processes, which may then track with observations at other levels of analysis (e.g., clinical symptoms, neural substrates) (1–3). Many psychiatric conditions are characterized by alterations in attention, a fundamental building block of cognition that dictates which stimuli are preferentially selected from within a dynamic environment and promoted for further processing (4). A prominent example comes from clinical anxiety, a prevalent and disabling condition (5,6), in which individuals demonstrate selective attentional preference (henceforth referred to as attention bias) in response to threat-relevant stimuli (7). Attention bias modification (ABM) procedures, a fully automated, computer-based, mechanistic intervention designed to target vigilance to threat, have shown some promise in reducing emotional vulnerability and/or alleviating clinical anxiety symptoms (8,9), supporting the theory that attention bias may play a causal role in anxiety. Though there are well-replicated behavioral findings regarding both the existence of attention bias across a wide range of anxious phenotypes (7) and the ability of ABM procedures to effectively modify attention (8,9), this literature has suffered from widely

acknowledged psychometric issues (10–12), including 1) the predominant use of tasks and analysis procedures that conflate numerous components of task performance and 2) a lack of sufficient test-retest stability to facilitate addressing key, clinically relevant questions related to individual differences (e.g., relationships between change in mechanism and change in symptoms, personalized treatment outcome prediction).

One form of computational modeling, drift-diffusion modeling (DDM) (13), has been strongly validated and widely used in both simulated and empirical datasets as a method of dissecting and modeling diverse components of trial-level behavioral data in the context of two-choice decision tasks (14). The dominant task paradigm used to quantify attention bias in hundreds of anxiety studies to date (7), the dot-probe task (15), is a two-choice decision task that is appropriate for application of DDM, though DDM has not been previously applied within the dot-probe literature, and rarely (16–22) has it been applied in affective psychopathology research. Briefly, DDM utilizes each individual's distribution of reaction times and errors across task trials to quantify a set of parameters that together produce the optimal fit to the individual's actual distribution of responses. Most relevant to the study of attentional

bias is the capacity to separate out two parameters, "drift" and "extradecisional time," effectively enabling the response process to be divided into 1) a measure of performance related to the response decision itself (represented by the drift parameter), which, in the case of the dot-probe, is an incidental decision task that is irrelevant to affective processing (e.g., does a probe cue display as an "E" or an "F"), and 2) the extradecisional components that occur before and after a probe decision is made. Though DDM analysis often focuses on decision-related parameters (e.g., drift, decisional threshold), in the case of the dot-probe task, it is this latter, extradecisional component that encompasses the attentional processes of theoretical interest (as well as more extraneous components such as response preparation and execution—e.g., pressing the correct button). More precisely, the extradecisional component includes the time an individual takes to orient attention to the probe location (which must occur before a decision about the probe can commence), which can then be compared for trials in which the probe location follows either an affective (e.g., threat-related) or neutral cue, providing an index of attentional preference. By separately modeling and thereby removing some irrelevant features of task performance (parameters related to the incidental probe decision), DDM could produce a purer behavioral measure of the attentional patterns of interest and might yield more precise and/or psychometrically sound estimates, enabling potential reanalysis of response data from many hundreds of studies that have previously utilized the dot-probe task in the study of psychopathology.

To test this thesis, we applied DDM to dot-probe behavioral data collected from a transdiagnostic sample of patients who were clinically anxious in the context of a mechanistic intervention study, in which participants were randomized to complete ABM procedures intended to modify attentional patterns or a sham control condition. We aimed to 1) explore the viability of DDM to achieve good model fits and/or superior reliability when applied to response data from a fairly typical dot-probe paradigm; 2) assess convergence regarding how novel attention bias scores derived via DDM relate to other variables, including conventional dot-probe attention bias scores, eye movements, and neural correlates; and 3) assess whether use of DDM enabled more sensitive detection of mechanistic shifts in attention over the course of the randomized controlled trial that were not observable when applying conventional analyses to task data.

METHODS AND MATERIALS

Full methods and primary clinical findings from the randomized controlled trial (clinicaltrials.gov: NCT02303691) have been reported previously (23). In brief, 70 unmedicated patients reporting clinically elevated levels of trait anxiety and associated clinician-rated disability were randomized to receive active ABM ($n = 49$) or a sham control variant ($n = 21$). See Supplemental Table S1 for sample characteristics.

Dot-Probe Task

The dot-probe assessment task was completed at baseline, at acute posttreatment, and at 1-month follow-up. At baseline, 10 idiographic threat words were selected collaboratively by the

participant and clinical interviewer and ideographically matched (on familiarity and word length) to 10 neutral words; these idiographic lists were supplemented by 20 threat words and 20 neutral words from a normative corpus used previously in ABM research [e.g., (24)]. Word pairs (80% threat-neutral; 20% neutral-neutral) were presented vertically for either 500 ms (50% of trials) or 1500 ms (50% of trials), followed by a probe ("E" or "F") in either the upper or lower word location. Participants responded via button press to indicate the probe letter displayed. A total of 300 trials were given. The present analyses focused on two conditions of shorter (500-ms) duration trials, composed of 60 trials each, which were randomly interspersed over the course of the experiment: "congruent" trials (in which the probe appeared in the previous location of the threat word) and "incongruent" trials (in which the probe replaced the neutral word). Given that the ABM intervention specifically trained attention using 500-ms stimulus presentations (see details below), we specifically hypothesized that intervention effects would be evident on these trials. The remaining task trials, composed of congruent and incongruent trials of longer (1500-ms) duration and neutral-neutral word pairs of both short and long duration, were exploratory and not included in the present analyses. To provide a direct measure of overt eye movements, a RK-768 eye tracker (ISCAN, Inc., Woburn, MA) concurrently measured eye gaze during the task (see Supplemental Analyses for details).

In a separate functional magnetic resonance imaging (fMRI) session prior to the onset of treatment, the same dot-probe task was administered, with minor modifications (e.g., only 500-ms duration word pairs were included; randomly jittered intertrial intervals of 0–8 seconds). Blood oxygen level–dependent data were acquired simultaneously on a 3T Siemens Trio scanner (Siemens, Washington, DC) (repetition time, 2000 ms; echo time, 28 ms; flip angle, 73°; 38 slices; field of view, 200×200 mm^2; voxel size, $3.125 \times 3.125 \times 3.2$ mm). Standard preprocessing steps were applied in AFNI software (National Institute of Mental Health, Bethesda). Of the 70 randomized participants, 68 had usable data ($n = 1$ excluded for excessive motion; $n = 1$ did not complete scan). Whole-brain analyses were conducted to identify regions robustly linked to DDM-derived attention bias scores across individuals [voxel threshold: $p < .005$; mapwise $p < .05$ via 3dClustSim with AFNI's spatial autocorrelation function, which provides accurate type I error control under our conditions (25)]. See Supplemental Methods and Materials for full details of fMRI data acquisition and analysis.

DDM Analysis

Analyses were completed using Fast-dm software [(26); see Supplemental Methods and Materials for software commands used and for preliminary model comparison steps that led to our adopted approach]. A distribution of reaction times and correctness (1 = correct; 0 = incorrect) values of each trial response was compiled for each individual, at each assessment point, for each of the two trial types described above. Each of these discrete distributions was then modeled using the Kolmogorov-Smirnov method to search through the parameter space and identify the optimal combination of the following parameters: extradecisional time (t_0),

drift (v), differences in speed of response execution for correct/incorrect responses (d), decisional threshold separation (a), variability in t_0, variability in v, and intertrial variability in starting point (sz). Consistent with recommendations when applying DDM to correct/incorrect response distributions with a similar number of trials (14), a priori decisional bias (zr) was set to 0.5 (representing no starting bias toward correct/incorrect responding) and percentage of contaminants (p) was set to 0. Simulations (see Supplemental Analyses) verified that the DDM methods could accurately identify model parameter shifts in extradecisional time, as distinct from shifts in other relevant parameters (e.g., drift rates), for datasets with the current number of trials per condition and similar reaction time and error rate distributions.

Bias Scores

The extradecisional time parameters from each of the two conditions were used to generate an attention bias score for each participant and time point as follows: extradecisional_bias = t_0_incongruent – t_0_congruent. Likewise, conventional attention bias scores were generated from mean reaction time values from each trial type, after applying data handling and cleaning recommendations to optimize reliability (10). Across all bias scores, larger scores indicate greater degree of vigilance to threat.

ABM and Sham Interventions

The ABM and sham conditions were modeled after prior studies [e.g., (24)] and have been described in a previous report that focused on fMRI indices, collected during a distinct task, predicting clinical outcomes [see (23) and Supplemental Methods and Materials for details]. Briefly, participants in both groups completed eight twice-weekly sessions in the laboratory, using an abbreviated version of the dot-probe task as described above, with a few modifications. In all trials during training, word pairs were presented for 500 ms. The only distinction between the ABM and control conditions was in the relationship between the probe location and the threat word in each word pair. In ABM, for 100% of threat-neutral trials (80% of all trials), the probe replaced the neutral word, thereby shaping attention away from threatening cues through practice. In the sham condition, the distribution of trials was the same as in the assessment dot-probe, with the probe replacing either the threat or neutral word with equal likelihood.

RESULTS

Model Fit

DDM models were a good fit for every participant's datasets (for each assessment point and trial type) according to Kolmogorov-Smirnov tests, which assess the probability that empirical and predicted data distributions differ (all $p \geq$ .59; mean p = .983; SD = .017). Model fits did not differ by trial type, time point, or group (ABM vs. control) ($p \geq$ .18). Figure 1 illustrates the model fit for the empirical data distribution in a representative subject. See Supplemental Table S3 for descriptive statistics for all model parameters.

Incongruent Trials

--- Empirical CDF
--- Model-predicted CDF

Kolmogorov-Smirnov p = .915

Congruent Trials

--- Empirical CDF
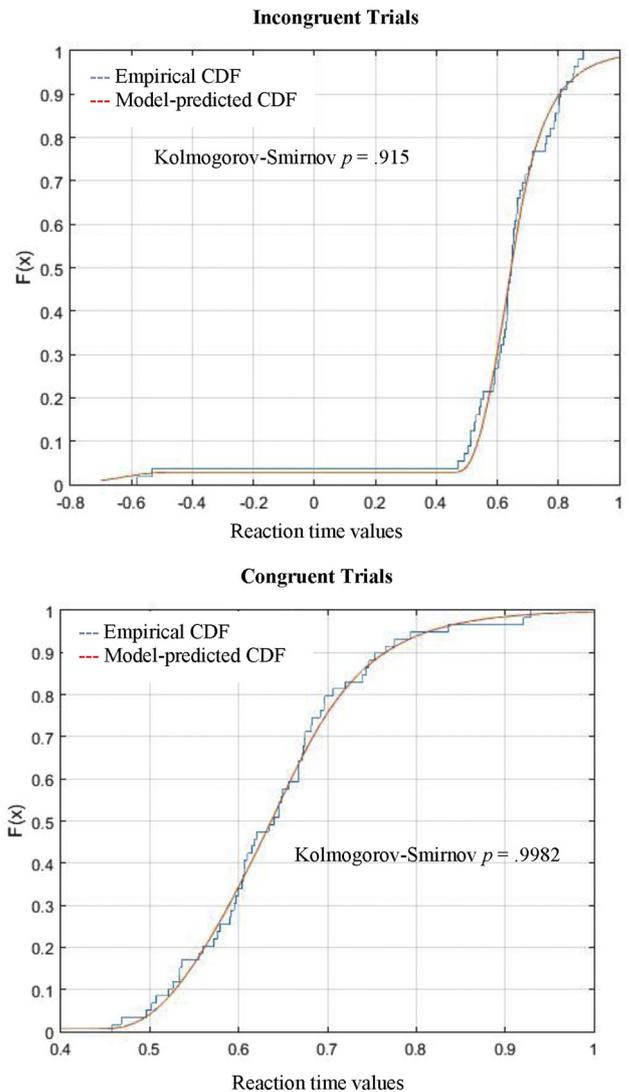--- Model-predicted CDF

Kolmogorov-Smirnov p = .9982

Figure 1. Representative empirical and model-predicted cumulative distribution functions (CDFs) of trial-level behavioral performance on the dot-probe task, constructed from a single individual at baseline. For graphical purposes only, error trials (present in the top panel only) are represented as negative values reflecting the inverse of observed reaction time.

Reliability

Test-retest reliability of attention bias scores was examined across baseline, posttreatment, and 1-month follow-up assessments in the sham control group only, as test-retest stability would not be expected among individuals who received active ABM specifically intended to alter attention bias. By conventional psychometric standards, intraclass correlation coefficient (ICC) values ≤ 0 indicate no reliability, while values that are statistically significant (relative to 0) but < 0.5 indicate low reliability (27). Extradecisional bias scores were significantly reliable across the three sessions (baseline, posttreatment, 1-month follow-up) spanning a roughly 2-month period, though the reliability coefficient was low (ICC = 0.25; p = .037). Reliability was particularly strong across the first two (baseline and posttreatment) assessments (r = .63; p = .003). By

contrast, conventional bias scores showed no reliability (ICC = 0.001; $p = .48$; maximum pairwise $r = .20$, not significant), even when using only trials with probes appearing on the bottom of the screen, as recommended previously (10) to improve dot-probe reliability (ICC = -0.14; $p = .82$; maximum pairwise $r = .27$, not significant).

To assess split-half reliability, DDM models were recalculated allowing the t_0 parameter to vary as a function of odd versus even trials (see Supplemental Analyses for alternative split-half reliability results when allowing additional model parameters to vary as a function of odd versus even trials). Extradecisional bias scores were derived separately from odd versus even trials and correlated with one another, and a Spearman-Brown prediction formula was applied to estimate reliability. Split-half reliability was adequate at each assessment point (baseline: Spearman-Brown reliability = 0.85, $r = .732$, $p < .001$; posttreatment: reliability = 0.52, $r = .355$, $p < .001$; follow-up: reliability = 0.83, $r = .716$, $p < .001$). By contrast, the split-half reliability for conventional bias scores was uniformly unacceptable (nonsignificant and near or below 0; r: $-.185$ to $.187$, $p \leq .15$), both when analyzing all relevant trials and for dot-on-bottom trials only.

Correlates of Extradecisional Time

Age. For both trial types at baseline, extradecisional time was correlated with participant age ($r \geq .44$; $p < .001$), while drift rates were not ($|r| < .09$; $p > .45$). This replicates a very well-established pattern within the DDM literature when applied to other two-choice tasks (28), suggesting the parameters derived from the dot-probe task in this sample conformed to established expectations.

Eye Movements. For both trial types at baseline, extradecisional time was moderately correlated with the percentage of trials in which overt eye fixations on one or both of the words in the word pair were registered by the eye tracker ($r \geq .35$; $p < .004$), while drift rates were not related to eye fixations

($|r| < .05$, $p > .71$) (see Supplemental Analyses for eye-tracking details). This further supports the DDM's ability to accurately separate extradecisional components of task performance, which include overt attentional shifts in eye gaze (which would be expected to increase extradecisional time). However, unlike eye movement data, the extradecisional time component preserves the ability to capture important covert extradecisional processes (e.g., covert/mental shifts in attention) (29) not reflected in overt eye movements.

Conventional Bias Scores. Extradecisional bias scores were moderately correlated with conventional bias scores at two of the three assessment points (baseline: $r = .34$; $p = .005$; posttreatment: $r = .20$; $p = .113$; follow-up: $r = .27$; $p = .039$), suggesting that the novel DDM-derived indices track with conventional methods, but are not fully collinear with them.

Neural Correlates. In whole-brain analyses, extradecisional bias scores from the baseline assessment were negatively correlated with fMRI contrast values (incongruent-minus-congruent trial responses) across several regions implicated in emotional and attentional regulation of salient stimuli, including left temporoparietal junction, ventral anterior cingulate, and dorsomedial prefrontal cortex (Figure 2). This pattern may implicate decreased regulatory control as a neural substrate linked to increased vigilance to threat (indexed by extradecisional bias) across individuals (30,31). When using conventional attention bias scores in an identical whole-brain search, no significant clusters tracking with degree of bias across individuals were identified.

Intervention Effects

Intent-to-treat mixed-models regression with extradecisional bias as the dependent measure, training group (ABM or control) as a between-subjects factor, subject as a random factor, and time point (baseline, acute posttreatment, 1-month follow-up) as a within-subject factor revealed a significant effect of
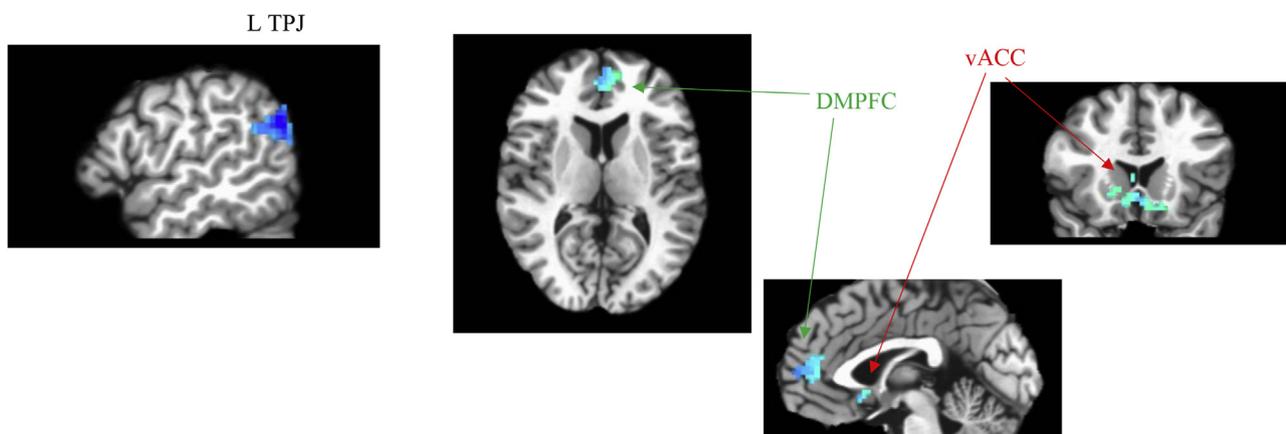

Figure 2. Clusters where incongruent-minus-congruent functional magnetic resonance imaging contrast values negatively correlate with drift-diffusion model–derived extradecisional bias scores across individuals (from whole-brain analysis with mapwise $p < .05$; voxelwise $p < .005$). From left to right, panels display the following clusters from Results text: left temporoparietal junction ([L TPJ]; $n = 121$ voxels; peak voxel: $x = -46$, $y = -69$, $z = 38$; $R^2 = .28$); dorsomedial prefrontal cortex ([DMPFC]; $n = 93$ voxels; peak voxel: $x = -1$, $y = 45$, $z = 14$; $R^2 = .20$); ventral anterior cingulate cortex ([vACC]; $n = 96$ voxels; peak voxel: $x = 5$, $y = 15$, $z = -3$; $R^2 = .21$). No significant clusters exhibiting positive correlations were found.

training condition on the slope of extradecisional bias over time, indicating that the trajectory of scores over time differed across training conditions: $t_{68} = -3.41$, $p = .001$, $r_{effect\ size} = .38$ [a large effect (32)]. As shown in Figure 3, extradecisional bias decreased steadily over the course of the assessment points in the ABM group, such that individuals in this group became less biased toward threat over the course of the baseline, acute posttreatment, and 1-month follow-up (within-group effect of time: $t_{48} = -2.71$, $p = .009$, $r_{effect\ size} = .36$), while extradecisional bias increased over time in the control training group ($t_{20} = 2.15$, $p = .044$, $r_{effect\ size} = .43$). These findings were maintained in models that included participant gender and age as covariates.

Conversely, identical mixed-models regression analyses with conventional bias scores as the dependent measure revealed no evidence of intervention effects. Specifically, there were no effects of group on either the slope or the intercept of attention bias over the three assessment points (group effect on slope of attention bias: $p > .46$; $r_{effect\ size} \leq .09$). There were also no effects of time on conventional attention bias scores when considering the ABM group alone ($p \geq .40$, $r_{effect\ size} \leq .12$).

Exploratory Analysis: Relationship to Clinical Outcomes

We explored whether change in extradecisional bias (delta score: posttreatment − baseline) was related to change in our primary clinical outcomes (clinician-rated hypervigilance; Mood and Anxiety Symptom Questionnaire–Anxious Arousal and General Distress subscales; see Supplemental Methods and Materials for details), in either the ABM or sham training groups or across the full sample. No significant relationships were found ($|r| < .15$; $p > .31$).

DISCUSSION

The dot-probe task has been used in many hundreds of studies of affective conditions, spanning both internalizing [e.g., anxiety (7), depression (33), trauma (34), suicidality (35)] and externalizing [e.g., substance use (36), unhealthy eating (37)] conditions. The task assesses the clinically relevant construct of attention bias—or preferential allocation of attention to disorder-relevant stimuli—which is a feature of information processing believed to have wide-reaching effects on the generation and/or maintenance of a range of psychopathological symptoms. In this first, proof-of-principle application of a well-validated computational modeling approach to dissect behavioral data collected during the dot-probe task, we introduce a novel analytic approach for dot-probe data and show that good model fits were readily achievable using publicly available software. We further demonstrate that split-half reliability of resulting DDM-derived attention bias indices was strong—a necessary precondition for evaluating individual differences (38)—and test-retest reliability, though still modest, clearly outperformed conventional attention bias scores, where widely acknowledged problems with reliability threaten to stall progress (10,11). With respect to convergent validity, the DDM-derived extradecisional parameters tracked as expected with participant age, eye movements measured concurrently during the task, and conventional bias scores, and with altered salience network activation during a dot-probe task performed in the fMRI scanner (Figure 3). Finally, the novel extradecisional bias scores appeared more sensitive to treatment change—when using these indices, hypothesized mechanistic intervention effects were unveiled that were not detectable using conventional bias quantification methods.

The advantages of computational modeling include the ability to make full use of trial-level data to obtain more fine-grained detail about cognitive processes (3). In the context of anxiety research, computational modeling approaches have previously revealed novel insights including altered learning mechanisms (e.g., increased threat expectations, decreased ability to leverage causal statistics to accurately predict outcomes) (39,40), which may contribute to the development of affective biases such as attention bias (41); dynamic processes of task performance such as an increased tendency to apply caution in response to errors (19); and effects of threatening content on memory performance that were not detectable using traditional memory bias indices (17,18). In an effort to encourage replications and extensions of the current work, we used computational modeling methods that are freely available for download, making the enormous corpus of previously
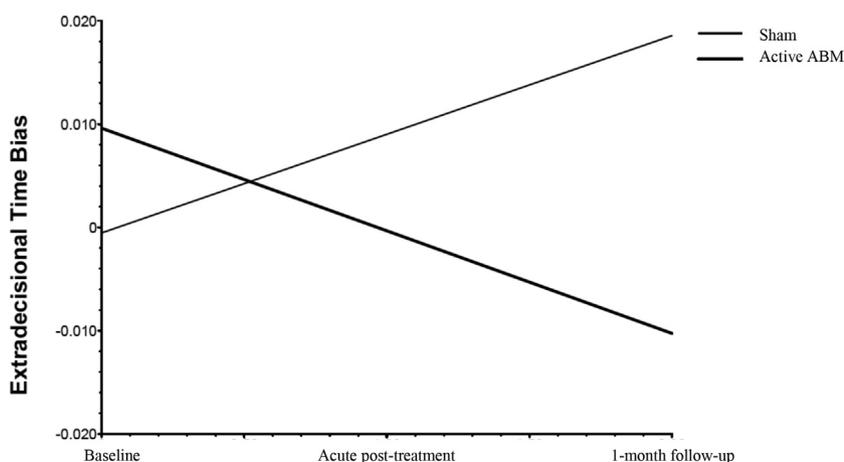

Figure 3. Hierarchical linear regression equation plots depicting changes (slope) in extradecisional bias as a function of training group. ABM, attention bias modification.

collected dot-probe data—which has produced replicable (7) yet notoriously mixed and unreliable (11) findings using conventional analysis techniques—ripe for the picking. Our results suggest the potential benefits may include improved reliability, interpretability, and sensitivity of attention bias indices.

Our fMRI analyses suggest the DDM-derived index could also be readily traced backward to neural substrates, while conventional bias scores could not. Findings implicated decreased recruitment of attentional and emotional control regions that regulate responses to salient stimuli (30,31) in those individuals showing the largest degree of extradecisional bias. While this finding may be consistent with the hope that computational psychiatry will assist in establishing linkages across levels of analysis, we were unable to further link extradecisional bias forward to clinical symptoms in the current sample. Specifically, in exploratory analyses we found no evidence that shifts in extradecisional bias over time mediated acute improvements in clinical symptoms (following either ABM or sham training). These analyses were limited by the relatively small sample sizes in the two arms, the (still suboptimal) test-retest reliability of the DDM indices, and by the fact that robust between-group differences in clinical outcomes were not observed in the current study (23). Larger or more clinically homogeneous samples may be required to adequately test for such linkages. Given the prevalent usage of the dot-probe task across numerous ABM studies conducted to date, reanalysis of existing datasets may present an accessible opportunity to address these questions in sufficiently powered samples.

Limitations

The DDM extradecisional time parameter conflates both cognitive processes of theoretical interest (e.g., time taken to orient attention to the probe location) and those of less interest (response preparation/execution). Although good model fits to the empirical data were obtained in the present analyses, computational modeling necessarily involves assumptions that may vary in their applicability across participants and/or studies, and model fits, though uniformly adequate, did vary to some degree across individual datasets. With respect to test-retest reliability, the DDM-derived bias scores surpassed that of conventional bias scores in the current dataset, as well as exceeding the maximum reliability achieved in previous exhaustive analyses of conventional bias scores conducted across multiple datasets (maximum ICC = 0.19) (10); yet test-retest reliability still remained suboptimal, which may be particularly problematic if correlational analyses of individual differences in trajectories over time within a group (e.g., mediation analyses) are desired. This may be partly due to inherent (mathematically determined) challenges in obtaining good reliability whenever a bias score is computed as a difference score between two task conditions that are themselves highly correlated across individuals (11), or may be a natural by-product of state (rather than trait-like) influences on performance. Unexpectedly, extradecisional bias increased over repeated assessments within the sham training group, which could be linked to the aforementioned factors limiting stability of bias scores over time, coupled with the relatively small control group sample, or could suggest that the control

training had an unanticipated (and potentially unwanted) effect in this sample. The dot-probe task has been critiqued for conflating other features of attention that DDM cannot separate—such as initial engagement with threat versus disengagement from threat, and overt and covert aspects of attention (29,42). While the current findings may inform improved analysis strategies applicable to a large volume of existing data, future work should aim to develop and refine new assessment methods [e.g., (40)], ideally with an explicit eye toward task features that will maximize the ability to apply computational analytic methods and precisely quantify cognitive components most relevant to the attentional mechanisms of interest. Finally, the current dataset was suboptimal for examining key clinically relevant questions (e.g., mediation of clinical effects), particularly given small within-treatment sample sizes and the lack of robust group differences in clinical outcomes.

Conclusions

The present analyses suggest that a well-validated computational modeling method (DDM) is appropriate for modeling of the dot-probe task in clinically anxious samples and represents an improved analytic technique that can yield novel insights. Widespread interest in quantifying and mechanistically targeting attention bias in clinical populations has led to widespread use of the dot-probe task. However, efforts to better understand the nature, role, and neurobiological substrates of attentional patterns are stymied by recent recognition of the limitations of conventional analytic methods. Our results introduce one possible method of extracting more reliable, precise, and sensitive attention bias metrics from existing behavioral dot-probe datasets—which likely span tens of thousands of participants—and could therefore improve the potential to translate this fundamental, transdiagnostic mechanism, both backward to neural substrates and forward to clinical applications.

ARTICLE INFORMATION

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