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Cueing Effects in the Attentional Network Test: a Spotlight Diffusion Model Analysis

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Abstract

The attentional network test (ANT) uses flanker stimuli with different cue conditions to quantify differences in attentional processing. However, it is unclear precisely how the alerting and orienting cues in the task affect different decision processes. The present study leveraged computational modeling to identify the relationship between attentional cues and decision components. ANT data from a large sample of 156 participants were analyzed using the spotlight diffusion model, which quantifies decision components for response caution, motor/encoding time, perceptual processing, and attentional control. The spotlight analysis showed that the attentional cues had multiple effects on decision processing. Compared to the no cue condition, an alerting cue led to faster encoding/motor speed, improved perceptual processing, and increased attentional focusing. The orienting cue further led to a decrease in response caution and increased encoding/motor speed and attentional focusing to reduce interference from incompatible flankers. This analysis demonstrates that alerting and orienting cues have complex effects on decision processes that are not captured by simple differences in RTs, and that model-based analyses can delineate such effects to allow researchers to identify precisely how attentional processing varies across individuals or conditions in tasks like the ANT.

Keywords Attentional Networks Test · Drift Diffusion Model · Shrinking Spotlight Model

Introduction

The attentional network test (ANT) is commonly employed to investigate different attention processes and how they vary across individuals, conditions, or groups (Fan et al. 2002). The ANT, which involves flanker stimuli (e.g., >><>>) and different cueing conditions, has been shown to be a reliable test (Fan et al. 2002) and is comprehensive enough to be performed by adults (e.g., Jennings et al. 2007), children (e.g., Rueda et al. 2004), and monkeys (e.g., Saalmann et al. 2012). Typical ANT effects show that providing alerting and orienting cues improve response speed and reduce interference from irrelevant stimuli. However, it is currently unclear exactly how such cues affect the different decision components that drive performance in the task. The present study leverages computational modeling to decompose ANT data into different decision components and explore how they are affected by attentional cues. A shrinking spotlight diffusion model (White et al. 2011) was used to analyze ANT data from a large set of participants and test cueing effects on response caution, perceptual processing, encoding/motor time, and attentional focus. This principled decomposition of the ANT provides insight into how decisions are affected by the presence or absence of attentional cues.

The standard ANT involves flanker stimuli and requires participants to identify a central target that is flanked by stimuli that are either compatible (<<<<<) or incompatible (<<><<) with the target (Fig. 1). The ANT expands upon the standard flanker task by including different cueing conditions meant to target alerting, orienting, and executive attention networks. In this domain, the concept of "networks" is loosely defined and can best be understood as different attentional processes: alerting attention to when a stimulus will appear, orienting attention to when and where the stimulus will appear, and employing executive control to narrow attention on the target. In the task, the stimuli on each trial can appear

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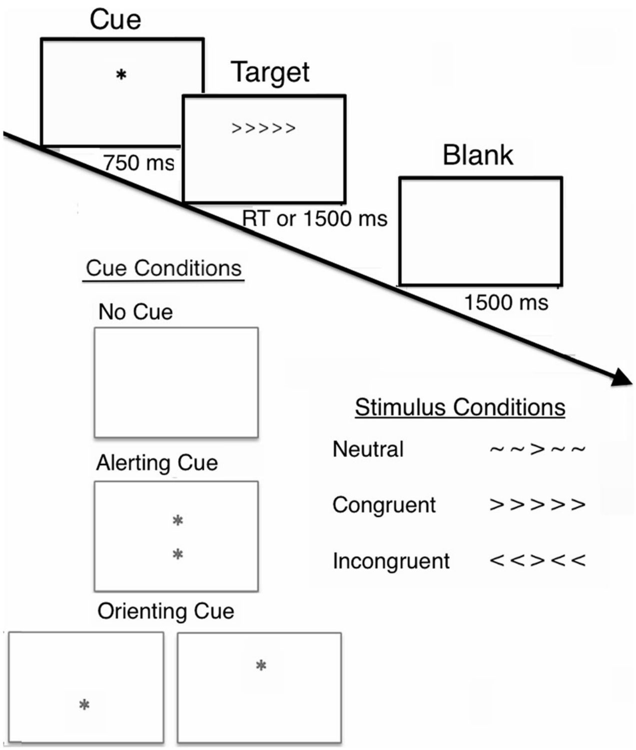

Fig. 1 Schematic of the attention network test and trial sequence for the experiment

either above or below the center of the screen. In the no cue condition, there is uncertainty as to when and where the stimuli will appear. In the alerting cue condition, a double cue is presented that alerts participants to when the stimulus will appear without providing information about which location it will appear. In the orienting cue condition, a single cue is presented that alerts participants to when and orients to where the stimulus will appear.

The ANT allows for quantification of three attentional networks or processes: the alerting network, the orienting network, and the executive attention network. These attentional networks are typically quantified by comparing response times (RTs) across the different cueing and stimulus conditions. The alerting network is assessed by comparing RTs from the alerting (double) cue condition to the no cue condition, the orienting network is assessed by comparing RTs from the orienting (single) cue condition to the alerting cue condition, and the executive attention network is assessed by comparing RTs for congruent and incongruent flanker stimuli. The ANT produces robust effects on processing; compared to the no cue condition, the alerting cue speeds responses and reduces flanker interference, and the orienting cue further speeds responses and reduces flanker interference compared to the alerting cue.

The present study seeks to better understand the cognitive effects of the attention cues by analyzing ANT data with the shrinking spotlight diffusion (SSP) model (White et al. 2011). The SSP was designed to account for processing in the flanker task and specifies how various decision components interact to drive performance in the task. The model is based on a drift-diffusion process in which noisy evidence is accumulated over time until a threshold amount is reached, at which point the decision is committed. In contrast to a standard drift-diffusion model (Ratcliff 1978), the SSP assumes that the decision evidence, known as the drift rate, can vary over time as a function of attentional focusing by the participant. Specifically, the model assumes that visual attention is represented by a spotlight over the stimulus that can be shrunk or focused on the target over time (Fig. 2). In the model, the spotlight is represented by a normal distribution of attention over the stimulus, and the drift rate is given by the summed contribution of each item in the display, weighted by how much attention is distributed to each item.

At the beginning of a trial, attention is diffuse and thus the flankers contribute heavily to the drift rate. But as the decision unfolds, participants can narrow the spotlight to focus on the target and reduce the influence of the flankers. For incompatible stimuli (<<><<), this results in decision evidence that favors the incorrect response early in the trial, but transitions to favor the correct response later in the trial as the spotlight is focused.

The SSP includes several parameters of processing that affect behavior for flanker stimuli. The boundary separation parameter, a, provides an index of response caution and the speed/accuracy trade-off: wide boundaries indicate a large amount of evidence required for the decision and lead to slow but accurate responses, whereas narrow boundaries lead to fast but error-prone responses. The perceptual strength parameter, p, provides an index of the perceptual contribution of each item in the stimulus display: a large value of p indicates strong perceptual processing and relatively easy ability to identify the arrows and map them onto the correct response. In standard application of the SSP, the values of p do not differ in magnitude across the items in the display, and take a positive or negative value depending on the direction of the arrow. In Fig. 2, negative values of p indicate evidence for the bottom boundary (right response) and vice versa for positive values of p. The nondecision parameter, Ter, provides an index of the residual time needed for encoding the stimulus and execution the motor response. The starting point parameter, z, provides an index of a priori response bias: if z is closer to the top boundary, it indicates the participant is biased toward that response before the trial begins. Finally, there are two parameters that govern attentional control: the spotlight width, sd_a, provides an index of the initial distribution of attention at stimulus onset, and the shrinking rate parameter, r_d, provides an index of the speed at which the spotlight can be focused on the target. As discussed below, the sd_a and r_d parameters combine to measure the attentional control for a participant in the task; strong attentional control is reflected by a narrower spotlight and/or rapid shrinking rate. Overall, the SSP assumes

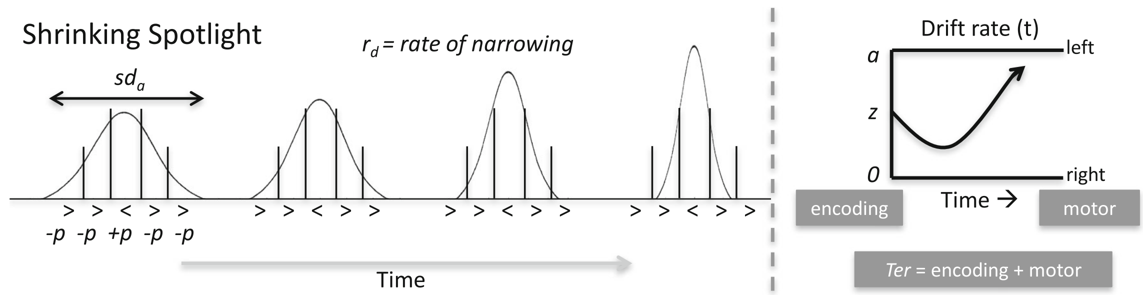

Fig. 2 Representation of the shrinking spotlight model. Left: attentional narrowing portion of the model. Right: drift rate (decision evidence) over time in a drift-diffusion model framework. See text for details

that performance in tasks with flanker stimuli is determined by the interaction of each of these parameters.

The SSP provides a theoretical account of processing for flanker stimuli and has been shown to account for data from flanker tasks (White et al. 2011). Other models exist that accomplish the same goal for flanker stimuli, including the dual-stage two-phase model (Hübner et al. 2010) and the diffusion model for conflict tasks (Ulrich et al. 2015). However, this study focuses on the spotlight model over the others because (1) it was designed specifically for visual attention tasks with flanker stimuli, and (2) it has been shown to provide better parameter estimation from behavioral data (White, Servant, and Logan 2018), which is elaborated upon later. Importantly for the present study, the SSP successfully accounts for effects of manipulations that are meant to target specific components of the model. For instance, speed/accuracy manipulations primarily affect the boundary separation parameter, whereas compatibility manipulations primarily affect the spotlight width and shrinking rate parameters (White et al. 2011). In this regard, the SSP can be used to analyze data from flanker tasks to determine which of the decision components are affected by different manipulations. For the ANT, which is the focus of this study, the SSP was used to investigate how the alerting and orienting cues affect decision processing beyond what can be learned from RT comparisons alone. This model-based analysis provides insight into how attentional cues improve processing speed and reduce interference in the ANT.

Methods

All of the data and codes for this project can be accessed at the following link (osf.io/qkube).

Procedure

A standard ANT was performed by a large set of participants, and the data were modeled with the SSP to relate the attentional networks to underlying decision components. In the task, a stimulus with five items was shown either 2 cm above or 2 cm below the middle of the screen, and participants were asked to determine whether the central (target) arrow faced left or right. Participants were seated approximately 25 in. from the screen (no chin rest was used) so that the stimulus subtended ~6° of visual angle. The stimulus remained on the screen until a response was given or 1.5 s had elapsed, after which the trial was coded as "no response." Responses were indicated by using the "z" or "/" keys for left and right targets, respectively.

The trial sequence is shown in Fig. 1 (top). There were three cueing conditions: no cue, alerting (double) cue, and orienting (single) cue. Note that the orienting cue was always valid such that the stimulus appeared in the same location as the single cue. There were also three stimulus conditions based on whether the flankers indicated the correct or incorrect response to the target: neutral, incompatible, and compatible. This resulted in a 3 × 3 design where each cue and stimulus combination was presented in random order. Participants completed 8 blocks of 72 trials with equal occurrence of each stimulus cue combination in a block. They were given the opportunity to rest after each block, and the entire experiment lasted approximately 45 min.

Participants

Participants were undergraduate students from Syracuse University who participated for course credit. All participants gave informed consent before the experiment. The goal was to obtain a large sample of participants to provide high statistical power for the comparisons below. There was a total of 175 participants in the experiment, but 19 were removed for either showing chance performance (i.e., just guessing) or failing to complete the entire experiment.

Shrinking Spotlight Analysis

The SSP was fitted to the RTs and accuracy data separately for each participant and cueing condition (no cue, alerting cue, orienting cue). Responses were collapsed across right/left targets and upper/lower stimulus location to result in correct or incorrect responses. Preliminary analysis showed that there were no significant differences between target location (top vs. bottom) or arrow direction (left vs. right), providing support for collapsing across these factors. All of the parameters were free to vary for each fit of the model with the exception of the starting point, z, and the spotlight width, sd_a. The starting point was fixed to be halfway between the top and bottom boundaries because right and left responses were collapsed for the analysis. The spotlight width was fixed at a standard value of 1.8, which distributes roughly equal attention to each item in the display at stimulus onset, because this parameter trades off with the shrinking rate (see White, Servant, and Logan 2018). An exploratory analysis was performed in which both the spotlight width and the shrinking rate were allowed to vary, and the results were nearly identical to the fits with the spotlight width fixed (due to the parameter tradeoff).

This resulted in separate estimates of boundary separation, perceptual strength, nondecision time, shrinking rate for each participant, and cueing condition. We also performed exploratory fits and model comparisons in which certain parameters, like boundary separation, were fixed across cueing conditions. The results favored using the more complex models, allowing each parameter to vary across cue condition. Further, analysis of the behavioral data (below) showed essentially no differences between congruent and neutral stimuli, so these conditions were combined to provide more observations for constraining the model fitting. Thus, for a given participant and cueing condition, SSP parameters were estimated that provided the best fit for both congruent/neutral and incompatible trials simultaneously (see White et al. 2011). We note that the SSP has never been fitted to neutral trials before, and there are a number of aspects of this type of stimuli that deserve further consideration. Appendix A presents a more detailed exploration of how the SSP would handle neutral trials, but for the primary focus of this paper, the neutral trials were combined with congruent trials and modeled in the same manner.

The model was fitted using the RT quantiles from the observed data in the following manner: each model fit used a X^2 minimization based on the proportion of correct responses for a condition and five quantiles of the RT distribution (.1, .3, .5, .7, .9). Because of the low number of errors, only the median RT for incorrect responses was used in the model fitting. A recent simulation-recovery study on the SSP showed that this approach provides accurate estimation of all of the parameters with the exception of the spotlight width (sd_a) and shrinking rate (r_d) (White, Servant, and Logan 2018). The simulation study showed that these two parameters cannot be estimated independently because they trade off with each other: a wide spotlight that shrinks rapidly can produce similar interference as a narrow spotlight that shrinks slowly. Consequently, as mentioned above, the spotlight width was fixed at 1.8 in the fitting process. This means that the SSP measure of attentional control, *interference time* (see "Results"), is driven by estimates of the shrinking rate. Readers who are interested in additional details about implementing and fitting the SSP are directed to Grange (2016), White et al. (2011), or White et al. (2018).

Results

Any responses faster than 250 ms were excluded from analysis (less than .8% of the data). As mentioned above, responses were collapsed across right/left target direction and upper/lower stimulus location. First, we present the standard behavioral analyses to show that typical ANT effects were observed. Then, we turn to the SSP parameters to investigate how the alerting and orienting cues affect the decision components. Traditional frequentist comparisons across conditions (e.g., within-participant t tests) were augmented with the Bayesian t test package of Rouder and colleagues to provide quantification of the magnitude of evidence for or against the null hypothesis for each comparison (Rouder et al. 2009). The scale (r) on effect size of .5 was used, which estimates evidence for/against the null hypothesis based on an expected effect size that is moderate to small. The resulting Bayes factors can be interpreted as the change in belief in favor of the alternative or null hypothesis given the data. Thus, a BF_a of 3 indicates we should be three times more likely to believe the alternative hypothesis (difference between conditions) over the null, and a BF_0 of 7 indicates we should be seven times more likely to believe the null hypothesis (no difference between conditions) over the alternative.

Behavioral Analyses

Comparisons across stimulus and cueing conditions were performed on median RTs and accuracy rates. Figure 3 shows the behavioral data averaged across subjects. One-way repeated measures ANOVA with three levels was performed for the cue comparisons (no cue, alerting cue, orienting cue) and for the stimulus comparisons (incongruent, congruent, neutral). Because of the large sample size and high statistical power, all of the ANOVAs revealed significant results with p's < .001. The following focuses on post hoc pairwise comparisons among the conditions.

The standard ANT effects were found for the effects of the cues. RTs were faster for the alerting cue compared to no cue (i.e., the alerting effect, $t(155) = 20.64$, $p < .001$, $BF_a >$ 10,000), and for the orienting cue compared to the alerting cue (i.e., the orienting effect, $t(155) = 23.18$, $p < .001$, $BF_a >$ 10,000). For the cue effects on accuracy, although the differences were small, accuracy was significantly higher for alerting cue compared to that for orienting cue ($t(155) = 2.11$, $p = .036$, $BF_a = 1.03$), but the Bayes factor did not favor belief in a difference. There were no differences in accuracy

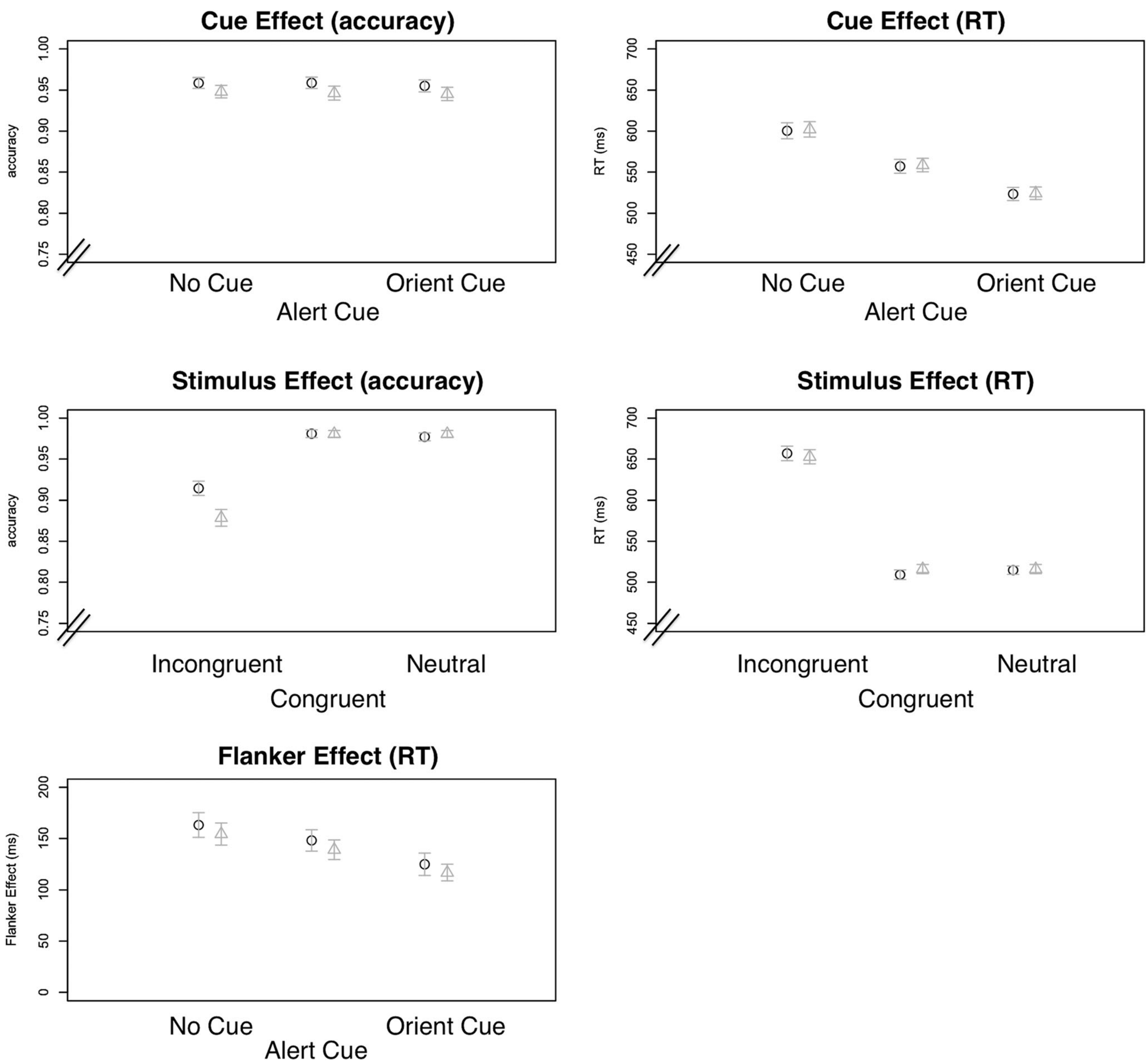

Fig. 3 Behavioral results from the ANT. Error bars reflect 95% confidence intervals across participants

between the no cue and alerting cue conditions ($t(155) = 0.11$, $p = .913$, $BF_0 = 7.97$), nor the no cue and orienting cue conditions ($t(155) = 1.82$, $p = .071$, $BF_0 = 1.66$). Overall, the cues had robust effects on RTs but not on accuracy.

For differences between the stimulus conditions, RTs were faster for compatible compared to incompatible stimuli ($t(155) = 26.27$, $p < .001$, $BF_a > 10{,}000$), and slightly faster for compatible compared to neutral stimuli ($t(155) = 3.42$, $p < .001$, $BF_0 = 28.54$). Accuracy rates followed the same pattern: accuracy was higher for compatible compared to incompatible ($t(155) = 12.02$, $p < .001$, $BF_a > 10{,}000$) and higher for compatible compared to neutral ($t(155) = 3.02$, $p = .002$, $BF_0 = 8.97$). Although congruent trials were slightly faster and more accurate than neutral trails, the differences were very small (~ 6 ms for RTs and .4% for accuracy). From here on out, the compatible and neutral conditions were combined to simplify the modeling and interpretation. We note that exploratory analyses and model fitting were performed without collapsing congruent and neutral trials, and the conclusions did not differ from the analyses presented below (see Appendix A).

The flanker effect, which gives a proxy for the executive attention network, was calculated by taking the difference in median RTs between compatible/neutral and incompatible stimuli. This provides a measure of the amount of interference from incompatible flankers, with larger values indicating greater interference and thus poorer attentional control. The flanker effect was smaller for the alerting (148 ms) compared to no cue (163 ms) condition ($t(155) = 4.51$, $p < .001$, BF_a = 1267.4), and smaller for the orienting (124 ms) compared to alerting cue condition ($t(155) = 8.25$, $p < .001$, $BF_a > 10{,}000$).

Overall, the results are broadly consistent with those of previous works using the ANT: incompatible flankers led to slower and less accurate responses, and the alerting and orienting cues sped overall responses and decreased interference from the incompatible flankers. Next, we turn to the SSP parameters to investigate how the different conditions affected the decision components.

Shrinking Spotlight Analyses

Before inferences can be made from the estimated SSP parameters, it is important to demonstrate that the model fit the data well and resulted in meaningful parameter estimates. This can be shown in two ways: by assessing the model fit to the data, and by demonstrating consistent parameters within individual participants. For the model fit, data were simulated from the best fitting parameters for each participant/condition and compared with the observed data. Figure 4 shows this comparison, which reveals that the model predictions closely align with the observed data. Note also that the predicted flanker effects for each cueing condition matched closely with the observed effects (Fig. 3), though predicted accuracy for incongruent trails was slightly lower than observed.

For the parameter consistency, within-participant correlations of the various parameters were assessed to determine whether they were stable across cueing conditions. Note that the SSP was fit separately to each cueing condition, resulting in three independently estimated sets of parameters for each participant. Thus, even though separate model fits were performed, one should expect that the parameter values are fairly stable across the conditions for each participant. That is, a participant who is highly cautious in the no cue condition should be expected to be highly cautious in the alerting and orienting cue conditions as well. Figure 5 shows a correlation matrix of the recovered parameters across individuals. In Fig. 5, interference time refers to the measure of attentional control derived from the spotlight width and shrinking rate. The figure shows robust parameter correlations within a given parameter (e.g., participants with strong perceptual strength, p, in one condition also had strong perceptual strength in the other conditions).

There were also significant negative correlations between different parameters (e.g., boundary separation and nondecision time) even for a single cue condition. Based on a recent simulation study that did not observe such correlations from synthetic data, we believe that these negative correlations stem from the participants and data rather than trade-offs in the model (see White, Servant, and Logan 2018). Note that the positive within-participant correlations were not guaranteed because the model was fitted separately to each condition; thus, the strong correlations across cueing conditions for each parameter suggest the model fitting captured meaningful trends in the data. Overall, Figs. 4 and 5 suggest the model fitting was successful and provides support for interpretation of the estimated parameters below.

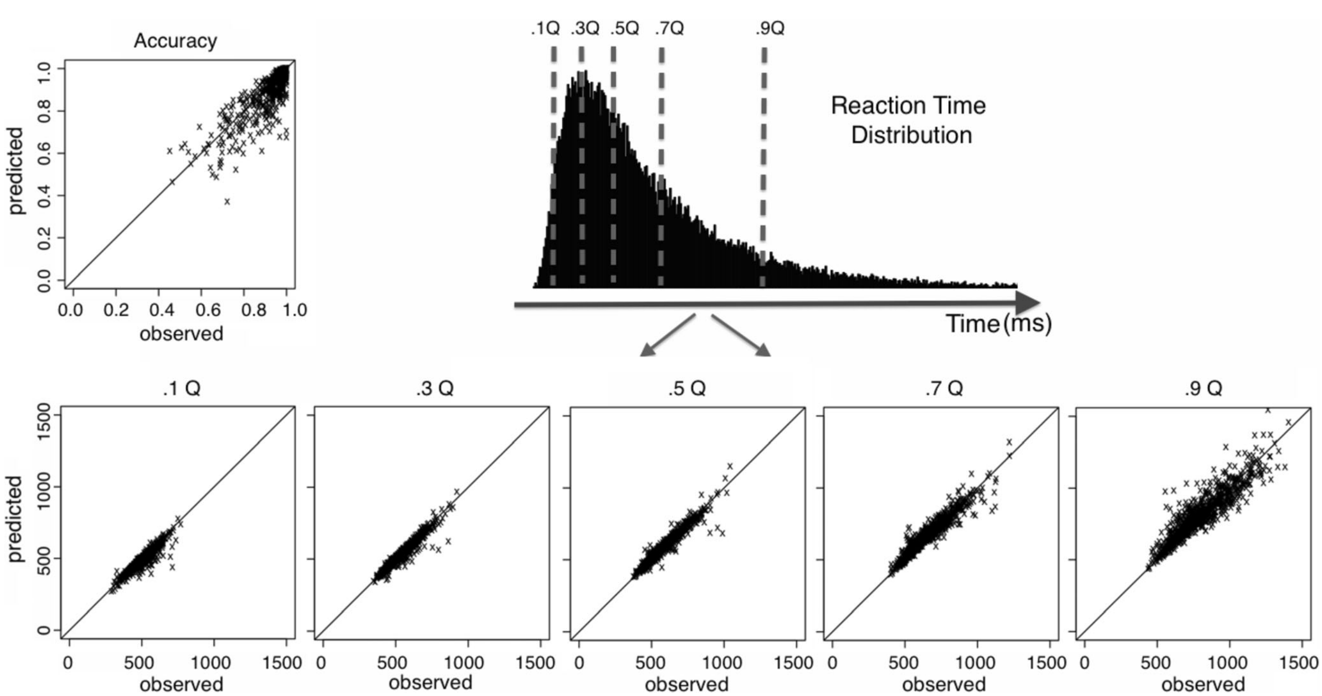

Fig. 4 Fit quality from the shrinking spotlight analysis. Observed responses are plotted against predicted responses from the best fitting SSP parameters for accuracy and the RT quantiles (Q) in ms

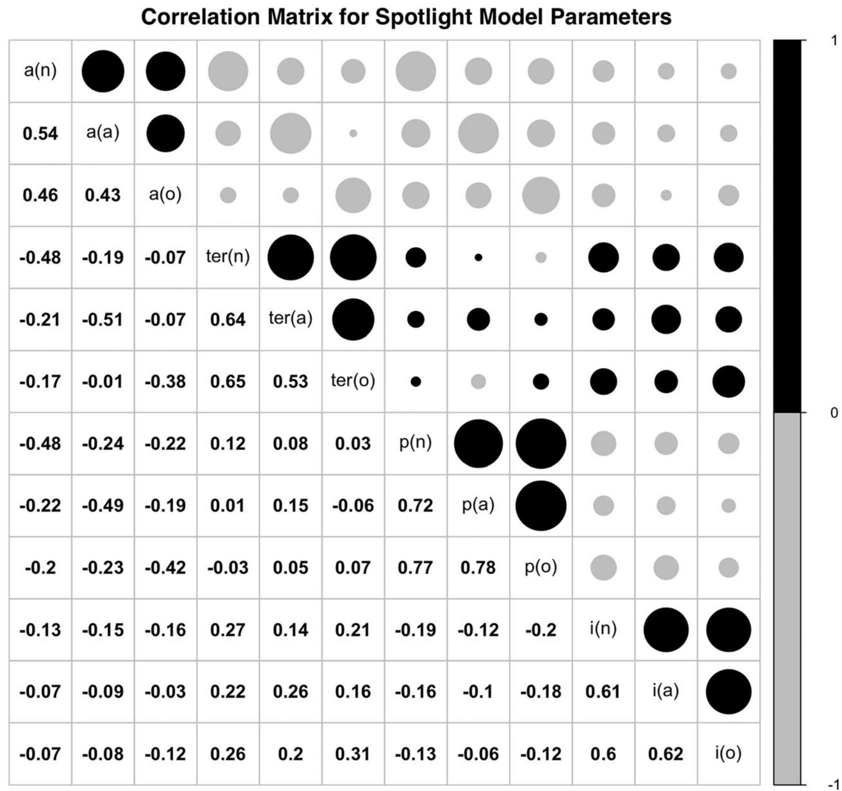

Fig. 5 Correlation matrix for parameters from the shrinking spotlight analysis. The size of each circle represents the strength of the correlation. Black circles, positive correlation; light gray circles, negative correlation. a, boundary separation; ter, nondecision time; i, interference time; p, perceptual strength. The letters in the parentheses denote the cueing condition (n, no cue; a, alerting cue; o, orienting cue). Values in the lower left portion of the figure indicate the *r* value for each correlation (values above .20 were significant at the $p < .05$ level)

As with the RT and accuracy data, one-way repeated measures ANOVAs were conducted on each of the parameters below. All of the ANOVAs showed highly significant effects of cueing condition (p's < .001), so the analyses below focus on post hoc comparisons between cueing conditions. The parameter values are shown in Fig. 6.

Boundary Separation

The boundary separation parameter, which reflects response caution (i.e., the speed/accuracy trade-off), was significantly affected by the orienting, but not the alerting cues. There was a small but significant difference in caution for the alerting compared to no cue condition ($t(155) = 2.13$, $p = .035$, $BF_a = 1.07$), though it should be noted that the Bayes factor essentially favored neither the null nor the alternative. Caution was also lower for the orienting compared to alerting (and no cue) condition ($t(155) = 3.43$, $p < .001$, $BF_a = 29.43$). This suggests that the presence of the cues, which reduces uncertainty about the timing and location of the stimulus, caused participants to decrease their caution for the upcoming response (see "Discussion"). This is consistent with work in task-switching that showed the predictability of an upcoming trial can lead to changes in response caution (Schmitz and Voss 2012). Further, this effect can be seen in the behavioral data as accuracy was slightly but significantly lower for the orienting cue condition (Fig. 3).

Nondecision Time

The nondecision time parameter, which reflects the duration of encoding and motor execution processes, was significantly affected by the attentional cues. Nondecision time was faster for the alerting compared to no cue condition ($t(155) = 2.70$, $p < .001$, $BF_a = 3.84$), though the Bayes factor only weakly favored a difference between conditions. Likewise, nondecision time was faster for the orienting compared to alerting cue condition ($t(155) = 4.37$, $p < .001$, $BF_a = 715$). Note that because this parameter combines encoding and motor execution processes, either factor could be driving the decreased nondecision time as a function of the attentional cues. However, we prefer the interpretation that these effects are driven by faster encoding time rather than faster motor execution, as the former is more likely to be affected by the preparation afforded by the cues (see Smith et al. 2004). Related work with task-switching paradigms is consistent with this finding, as nondecision time was shown to be faster when there was greater predictability for the upcoming trial (Schmitz and Voss 2014), which is the case when the alerting or orienting cues are presented.

Perceptual Strength

The perceptual strength parameter, *p*, which reflects the ease of differentiating right and left arrows in the stimulus, was significantly affected by the attentional cues. Perceptual

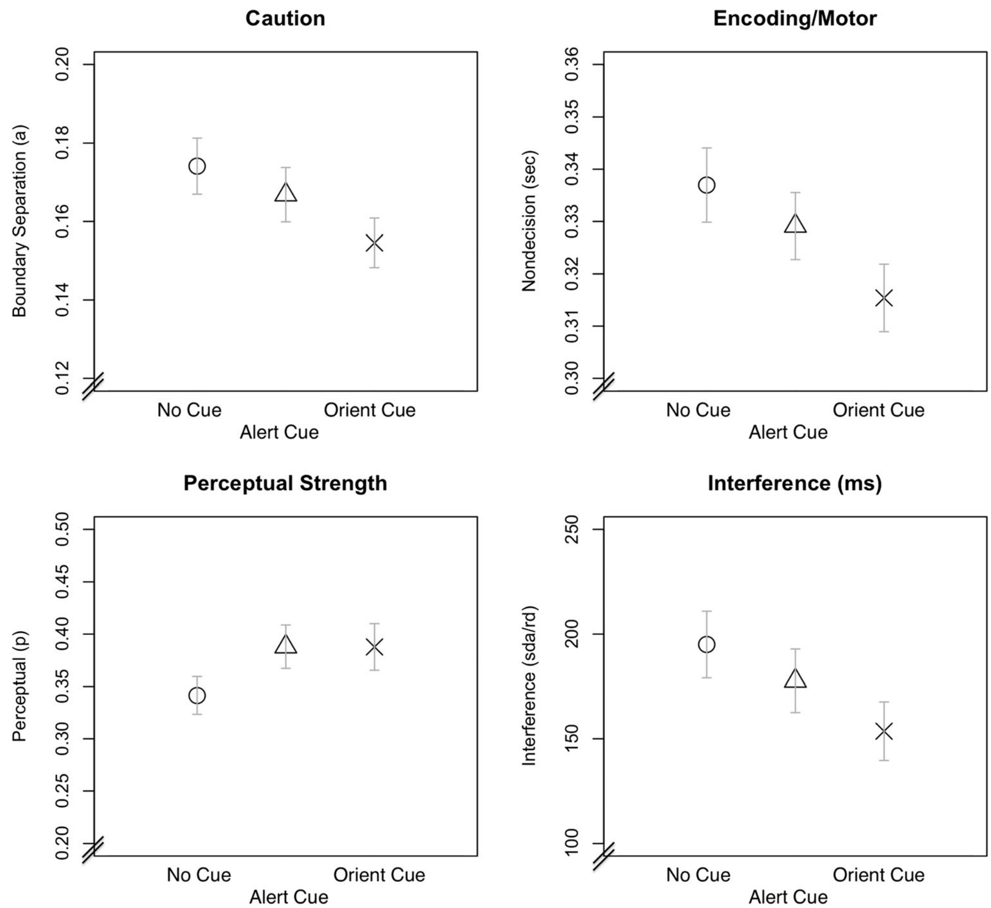

Fig. 6 Shrinking spotlight parameters for each cueing condition based on fits to the observed data. Error bars represent 95% confidence intervals across participants

strength was greater for alerting compared to no cue condition ($t(155) = 6.24$, $p < .001$, $BF_a > 10{,}000$), but did not differ between orienting and alerting cues ($t(155) = -.04$, $p = .971$, $BF_0 = 8.01$). Thus, perceptual processing was improved by the presence of a cue, but did not depend on whether the cue was alerting or orienting. This result is consistent with work in simple visual detection that demonstrated better perceptual processing for cued compared to uncued stimuli (Smith et al. 2004; Smith et al. 2010).

Attention Control and Interference

As mentioned above, the two parameters that govern attentional focusing in the SSP, spotlight width and shrinking rate, trade off with each other and thus should not be separately analyzed (see White, Servant, and Logan 2018). However, White et al. (2018) showed that the ratio of these parameters, sd_a/r_d, is accurately recovered from data and can be used to quantify flanker interference and attentional control. The resulting measure, which is referred to as interference time, reflects the amount of time needed to fully focus the spotlight on the target. Thus, smaller values of this measure indicate a better ability to engage selective attention (i.e., faster focusing) and reduce the interference from the flankers. This derived parameter is conceptually similar to the executive attention network measure that is typically obtained in the ANT. Because the spotlight width was fixed for the fitting process, interference time was calculated based on the shrinking rate (r_d) as $1.8/r_d$.

Attentional control, as indexed by the interference time parameter, was significantly affected by the attentional cues. Interference time was shorter for alerting compared to no cue conditions ($t(155) = 3.66$, $p < .001$, $BF_a = 61.02$), and for orienting compared to alerting cue conditions ($t(155) = 3.33$, $p = .001$, $BF_a = 21.71$). This indicates that the alerting and orienting cues improved participants' ability to narrow their attentional focus, and the orienting cue was more effective than the alerting cue. Note that the flanker effect predicted by the SSP parameters (mainly boundary separation, perceptual input strength, and spotlight width/shrinking rate) closely aligns with the observed effect (Fig. 3).

Discussion

The present study used computational modeling to understand how alerting and orienting cues affect decision components in the attentional network test. Data from a large set of participants were analyzed with the shrinking spotlight diffusion model to investigate which cognitive processes were affected by the attentional cues. Consistent with previous work, the behavioral data showed that the presence of alerting and orienting cues led to faster overall responses and reduced interference from incompatible flanking stimuli. The shrinking spotlight analysis showed that these effects were driven by changes in multiple components of the decision process. Compared to the no cue condition, the alerting cue, which provides information about when (but not where) the stimulus would appear, led to faster nondecision time (likely reflecting faster encoding), stronger perceptual processing, and stronger attentional focusing. Compared to the alerting cue, the orienting cue, which provides information about when *and* where the stimulus would appear, led to a reduction in response caution, even faster nondecision time, even stronger attentional focusing, but no change in perceptual processing. Thus, the facilitated processing that results from the presence of cues in the ANT is multifaceted.

Previous studies that have investigated the effects of trial cueing lend support to the present finding that the presence of cues enhances processing through multiple components of the decision process. Model-based analyses of task-switching data found that participants had smaller boundary separation (reduced caution) when presented with cues that reduced the uncertainty of the upcoming trial (Schmitz and Voss 2014). Likewise with the present data, the presence of the orienting cue (but not the alerting cue) led participants to decrease their caution on the upcoming trial.

Work in visual attention showed that the presence of a pretrial cue reduced nondecision time and improved visual processing (Smith et al. 2004). Likewise with the present data, nondecision time was faster when the orienting and alerting cues were present, which is likely due to faster encoding rather than faster motor execution. Similarly, the orienting and alerting cues led to enhanced perceptual processing of the visual stimulus, though there was no difference between the two cue types. Overall, the present results combined with previous work in different domains support the idea that attentional cues, which reduce uncertainty and allow preparation for the upcoming stimulus, can improve processing through multiple decision components.

Although this study focused on general cueing effects in the ANT with healthy adults, the shrinking spotlight analysis has promise for future studies interested in comparing ANT performance across individuals or groups. Hundreds of studies have been conducted to compare ANT data as a function of psychological disorder (e.g., Gooding et al. 2006; Leskin and White 2007; Posner et al. 2002), developmental stage (e.g., Konrad et al. 2005; Posner et al. 2006), and manipulations of stress (e.g., Anderson et al. 2007; Cavanagh and Allen 2008; Sato et al. 2012). These studies traditionally rely on comparisons of RTs to provide inferences about individual or group differences, and as such only scratch the surface for understanding precisely how these groups differ.

As an example of the potential limitation of relying solely on RT measures of ANT processing, a recent study used standard RT-based measures of ANT components to investigate effects of induced sad mood and moderate depression. The RT measures of attention showed that sad/depressed participants had stronger executive attentional control in the ANT than control participants, suggesting that mood influenced attentional control (Bellaera and von Mühlenen 2017). However, their data also showed that sad/depressed participants were faster than controls across all conditions, even simple congruent trials that do not require attentional control. This difference in general response speed suggests that negative mood was possibly related to decision components beyond the attentional networks indicated by the standard RT analysis. Sad/depressed participants in that study could have been less cautious, had faster nondecision time, and/or stronger perceptual processing. Unfortunately, these factors cannot be disentangled with analyses based on RTs alone, but application of models like the shrinking spotlight could unpack the underlying factors driving differences performance among individuals and groups.

Thus, in addition to elucidating the cognitive mechanisms driving improved performance in the presence of cues in the ANT, the results of the present study speak to the utility of cognitive modeling for assessing differences in processing from tasks like the ANT. Improvements in RTs can stem from multiple factors, so it is important to have a method to delineate these factors and determine which ones are driving differences in behavior. In this sense, behavioral measures like RTs are underdetermined because they provide no information about why performance improves in the presence of attentional cues. RT-based comparisons can tell us that participants are faster when given alerting and orienting cues, or that sad/depressed participants have faster responses than controls, but they do not tell us *why* they are faster.

Choice RT models like the shrinking spotlight model provide an elegant solution to this problem, as they can be used to delve deeper into the underlying source(s) of differences in behavioral performance. Such analysis with standard drift-diffusion models has been successfully employed to investigate performance across a range of tasks, including recognition memory (e.g., Ratcliff et al. 2004), numerosity judgments (Ratcliff et al. 1999), visual perception (e.g., Ratcliff and Rouder 1998), and task-switching (e.g., Schmitz and Voss 2012; Schmitz and Voss 2014). Newly developed conflict diffusion models, like the shrinking spotlight model, the dual-stage two-phase model, and the diffusion model for conflict tasks, can broaden the application of this approach to include tasks for which the standard diffusion model does not apply like the Stroop (Stroop 1935) and Simon (Simon 1969) tasks. In this regard, future work investigating differences in cognitive processing can benefit from the incorporation of model-based analyses to provide greater insight into the underlying factors that drive task performance.

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