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A Diffusion Model Account of the Relationship Between the Emotional Flanker Task and Rumination and Depression

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Although there exists a consensus that depression is characterized by preferential processing of negative information, empirical findings to support the association between depression and rumination on the one hand and selective attention for negative stimuli on the other hand have been elusive. We argue that one of the reasons for the inconsistent findings may be the use of aggregate measures of response times and accuracies to measure attentional bias. Diffusion model analysis allows to partial out the information processing component from other components that comprise the decision-making process. In this study, we applied a diffusion model to an emotional flanker task. Results revealed that when focusing on a negative target, both rumination and depression were associated with facilitated processing due to negative distracters, whereas only rumination was associated with less interference by positive distracters. After controlling for depression scores, rumination still predicted attentional bias for negative information, but depression scores were no longer predictive after controlling for rumination. Consistent with elusive findings in the literature, we did not find this pattern of results when using accuracy scores or mean response times. Our results suggest that rumination accounts for the attentional bias for negative information found in depression.

Keywords: information processing, cognitive psychometrics, attentional bias, Bayesian, mathematical model

That depression is characterized by biased processing of emotional material is a consensus among many cognitive theories of depression. This bias is hypothesized as a preferential processing of negative information, which as a result, tends to promote or maintain the negative emotional state found in depression (Disner, Beevers, Haigh, & Beck, 2011; Gotlib & Joormann, 2010; Koster, De Lissnyder, Derakhshan, & De Raedt, 2011; Mathews & MacLeod, 2005). Despite the appeal of a straightforward theory, findings on the relationship between depression and various cognitive processes, particularly on selective attention, have been less clear-cut (Gotlib & Joormann, 2010; Mathews & MacLeod, 1994, 2005).

One of the ways to investigate selective attention in depression is through interference tasks, in which participants perform a central task while ignoring emotional distracters (Mathews & MacLeod, 1994, 2005). Two experimental paradigms that are often used in the cognition literature to capture interference during selective attention are the Stroop and Flanker tasks (Hübner, Steinhauser, & Lehle, 2010). Although the modified emotional Stroop task has been one of the main paradigms in examining selective attention in depression, its validity as a way of measuring interference during selective attention remains a controversy (Mathews & MacLeod, 2005).

Only recently have researchers started to use the emotional flanker task in depression research. Using faces (e.g., Fenske & Eastwood, 2003; Horstmann, Borgstedt, & Heumann, 2006) or words (Zetsche, D'Avanzato & Joormann, 2012; Zetsche & Joormann, 2011) as stimuli, the emotional flanker task has shown effects similar to the classical flanker task (Eriksen & Eriksen, 1974). In this task, participants identify the valence of a target stimulus while attempting to ignore flanking distracters. In relation to the target stimulus, flankers may be congruent (flankers are of similar valence and have the same response as the target stimulus), incongruent (flankers are of opposite valence and of different response as the as the target stimulus), or neutral (flankers are of

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neutral valence and have no response required; Fenske & Eastwood, 2003; Horstmann et al. 2006). It is assumed that participants are generally unable to completely ignore the flankers, resulting in slower responses in incongruent trials (interference effect), and faster responses in congruent trials (facilitation effect), compared with neutral trials (Eriksen & Eriksen, 1974; Flowers, 1990; Mattler, 2005; Sanders & Lamers, 2002).

However, recent studies on the relationship between depression and selective attention for negative information, as captured by the emotional flanker task, show only weak evidence for such a link (Zetsche et al., 2012; Zetsche & Joormann, 2011). That is, although Zetsche et al. (2012) found that depressed participants (vs. control participants) experienced greater interference from irrelevant negative words given a positive target, they found no such association in another study (Zetsche & Joormann, 2011).

In a similar vein, Zetsche and colleagues also examined whether attentional bias for negative information relates to rumination. Rumination is defined as a maladaptive emotion regulation strategy characterized by repetitively thinking about negative events and their possible causes, meanings and consequences and is considered to be a core element in the development and maintenance of depressive symptoms (Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008). Although it has been postulated that attentional control would also be associated with rumination (Koster et al., 2011), Zetsche and colleagues found this relationship to be elusive when using the emotional flanker task. In one study, Zetsche et al. (2012) found no relationship between attentional bias for negative words and rumination, whereas in another study, Zetsche and Joormann (2011) found the counterintuitive result that rumination was associated with *less* interference from negative word distracters.

According to Zetsche and Joormann (2011), one possible explanation for this weak link is that alternative comparison conditions in the emotional flanker task have not been used. In the two studies, Zetsche and colleagues measured interference from negative distracters when there was a positive target. However, studies using the dot-probe task have revealed that depressed individuals' preferential processing for negative information do not apply throughout all aspects of selective attention (Gotlib & Joormann, 2010; Joormann & Siemer, 2011; Mathews & MacLeod, 2005). Consistent findings using the dot-probe task have only been found in studies in which emotional stimuli were presented for longer durations (e.g., Donaldson, Lam, & Mathews, 2007; Gotlib, Krasnoperova, Yue, & Joormann, 2004). This led researchers to conclude that depressed individuals do not necessarily direct their attention toward negative stimuli, but once the negative stimuli captures their attention, they have difficulty disengaging from it (Gotlib & Joormann, 2010; Joormann & Siemer, 2011; Koster et al., 2011; Mathews & MacLeod, 2005). In addition, the prolonged processing of negative information that defines depressive rumination is also associated with this inability to disengage attention from negative information (Koster et al., 2011).

These studies inform us that the selective attention for negative information observed among ruminators and depressed participants mostly occurs when the negative material has already captured their attention. We therefore expect that in the emotional flanker task, the effect of distracters would primarily emerge when the target stimulus—the focus of attention at the onset of a trial—is negative. We hypothesize that depression and rumination will be associated with more facilitated processing due to negative distracters and less interference by positive distracters when there is a negative target.

The Diffusion Model for Two-Choice Response Times

A possible explanation for the unclear findings is that traditional data analysis methods are not sensitive enough to the subtleties of the attention tasks. The analysis of flanker effects (as most other effects in this domain of study) typically involves comparisons of accuracies and mean response times (RTs). However, cognitive models of reaction time (RT) or choice response time (CRT) have convincingly argued that RT and CRT are highly complex aggregate measures that result from the combination of different ongoing processes underlying response decisions (see, e.g., Luce, 1986). For example, in Ratcliff's (1978) diffusion model, RT is governed by several independent parameters, among which are speed of information processing, response conservativeness, a priori bias, and stimulus encoding and response execution. Slow responses can come about due to an impaired rate of information processing, a high level of response conservativeness, bias against the correct response, or slow encoding or response execution.

Clearly, aggregate measures like mean RT are not sensitive to this complexity, and using such insensitive measures as a basis to find relationships with depression or rumination may obscure any relationship with the crucial processes that are actually at play during the execution of these tasks. To fully understand the processes involved in a task like the emotional flanker task and their relationships with depression and rumination, a cognitive modeling approach, such as diffusion model analysis, is called for.

The diffusion model for two-choice response times (Ratcliff, 1978) has been shown to capture the processes at play in a variety of psychological phenomena, including attention (e.g., Dutilh et al., 2012), emotion (White, Ratcliff, Vasey, & McKoon, 2009, 2010a), and psychopathology (White, Ratcliff, Vasey, & McKoon, 2010b).

The central notion in diffusion model analysis is that speeded binary decisions come about after a process of *sequential accumulation of information*. A participant is assumed to sample information from a stimulus until some critical level of evidence toward one or the other response is reached. Four basic parameters determine the response process. The process parameter that captures the rate of information accumulation—or the speed of information processing—is known as the *drift rate*. The amount of information needed—or the caution of the participant—is called the *boundary separation*. The information already present before the accumulation starts is called the *starting point* of the accumulation process. Finally, a fourth parameter captures the residual response time that is not used by the decision process; this parameter is known as the *nondecision time.* Figure 1 gives a graphical presentation of the diffusion model. In practical applications of the diffusion model, it may additionally be assumed that some of the basic parameters vary from trial to trial.

A diffusion model provides a simultaneous account of RT and accuracy scores in a single model and is hence not affected by the statistical entanglement of these two dependent variables. A critical advantage of diffusion model analysis in the present context is that it allows us to zoom in on the drift rate parameter (denoted δ below). This parameter captures the *effi-*

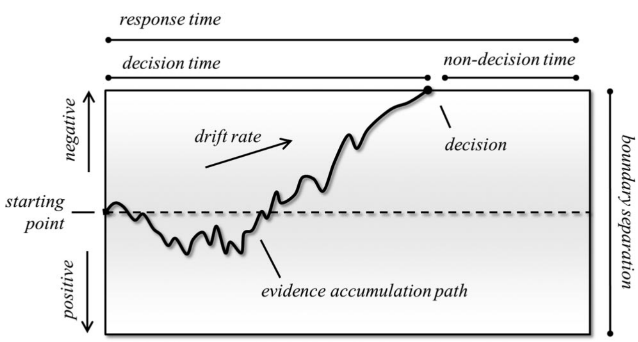

Figure 1. A graphical depiction of the diffusion model for two-choice response times. The horizontal axis is the time dimension, and the vertical axis is the evidence dimension. The jagged line is an example evidence accumulation process, initiating at a starting point, evolving with an average increase (drift rate), and terminating at the upper boundary to yield a "negative" decision. The decision time is added to the nondecision time to obtain the total RT.

ciency of information processing in the decision making process, which is expected to decrease or increase by the addition of incongruent or congruent flankers, respectively. Here, we will go one step further and apply a *hierarchical diffusion model* (HDM; Vandekerckhove, Tuerlinckx, & Lee, 2011). HDM analysis has the additional advantage of being able to (a) take into account between-person differences in the process parameters and (b) use external covariates to explain the observed variability in parameters, like rumination or depression (e.g., Vandekerckhove, Verheyen, & Tuerlinckx, 2010).

The Present Study

The aim of the present study is twofold: First, we aim to examine the relationship between depression and rumination on the one hand and attentional bias for emotional information as measured in the emotional flanker task on the other hand. We hypothesize that the selective attention for negative material that is found in depression and rumination would mainly occur when the target word is negative, which is consistent with the impaired disengagement hypothesis (Koster et al., 2011). Specifically, we hypothesize that when the target word is negative, rumination and depression would be associated with a facilitated processing of negative distracters and a lack of interference by positive distracters. This is informed by studies that use the dot-probe task to measure attentional bias in depression: Selective attention in depression and rumination occurs when the negative material has already captured the attention of the participants.

Second, by using a more sophisticated approach in analyzing CRT data, we hope to find the missing evidence for a relationship between depression, rumination, and attentional bias in the emotional flanker task. With the diffusion modeling approach, we are able to single out the information-processing component (as captured by the drift rate parameter) that is assumed to be a more precise measure of the facilitation and interference effects found in the emotional flanker task.

Method

Participants

One hundred participants were preselected from a pool of 439 first-year undergraduates from University of Leuven based on their scores on the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977). We selected from the pool a sample with a wide and balanced range of depression scores (range = 0–50, M = 19.27, SD = 12.53). One participant withdrew early leaving a final sample of 99 participants (62 women, 37 men, M_{age} = 19.05, SD_{age} = 1.27). Participants were paid €70 for participation in a study that involved the below tasks along with other tasks not relevant for the present purpose.

Materials

Self-report measures. The CES-D was used to measure level of depressive symptomatology. Participants responded to questions about how often they felt a certain depressive symptom in the past week, ranging from 0 (*rarely or none of the time*) to 3 (*most or all of the time*). Participants were also asked to complete the Ruminative Response Scale (Treynor, Gonzales, & Nolen-Hoeksema, 2003) as a measure of their tendency to ruminate. Ranging from 1 (*almost never*) to 4 (*almost always*), participants rate how often they respond in a certain way when they feel sad or depressed.

Emotional flanker task. We adapted the emotional flanker task from Fenske and Eastwood (2003) using affective words instead of schematic faces as stimuli and positioning the flankers above and below the target word, instead of adjacent to it. Stimuli were Dutch translations of 14 affective words (five negative, M = 2.28, SD = 0.84; four neutral, M = 5.71, SD = 0.18; and five positive, M = 7.66, SD = 0.81) taken from the Affective Norms of English Words list (Bradley & Lang, 1999). The words were selected to be exactly four letters long and monosyllabic. Valenced words were matched for arousal ratings.

The task was divided into one practice block comprising 20 trials (not scored) and 120 actual trials separated into four blocks. Each trial began with a blank screen of 1000 ms, followed by a fixation cross displayed on the center of the screen for 500 ms. The fixation cross was then replaced by a target word with two flankers (distracters) located above and below the target word, which remained on the screen until the participant responded. Participants were then asked to indicate, as quickly and accurately as possible, whether or not the target word was positively or negatively valenced. Using the computer keyboard, participants pressed "1" if the answer was "positive" and "2" if the answer was "negative."

The trials varied in target valence (negative and positive) and flanker condition (congruent, neutral, and incongruent). A congruent condition refers to a trial where the flankers are of the same valence and elicit a similar response to the target word; an incongruent condition refers to a trial where flankers are of the opposite valence and elicit an opposite response to the target word; and a neutral condition refers to a trial where the flankers are of neutral valence and do not elicit either response. Following Friedman and Miyake's (2004) procedure, these trial types were randomized, with the constraint that there were no negative priming trials and that no same condition occurred on more than three successive trials.

The focus of our analyses will be the behavioral differences between the incongruent and neutral flanker conditions (interference effect) on the one hand and those between the neutral and congruent flanker conditions (facilitation effect) for each target valence (positive, negative).

Results

We subdivide this section into *Classical Analysis*, where we process and analyze our data using the standard method, and *Diffusion Model Analysis*, where we apply a cognitive process model.

Classical Analysis

Data preprocessing. RT and accuracy scores for interference and facilitation effects were calculated separately for both the positive-target condition (PTC) and the negative-target condition (NTC). For each flanker condition of every target valence, we applied the data preparation procedure of Friedman and Miyake (2004) for RT measures. Only correct trials were included in the RT analyses (M = 92%, SD = 5%). Upper and lower criteria were determined through visual inspection of the overall RT distributions; values under 200 ms and over 1500 ms were eliminated. For each participant, RTs more than 3 SD from the participant's mean for each condition were replaced with values that were 3 SD from the participant's mean for that condition. Between-subjects RT distributions were then examined for each condition, and scores above or below 3 SD from the group mean were replaced with values that were plus or minus 3 SD from the mean, respectively.

Calculation of effects. To describe results, we will recode our data into effects and contrasts expressing the magnitude of the facilitation and interference effects. For example, if $RT_{+,+,i}$ is participant i's mean RT in the congruent flanker PTC, and $RT_{\times,+,i}$ is their mean RT in the neutral flanker PTC, then the magnitude of their facilitation effect in the PTC was calculated as $RT_{\times,+,i} - RT_{+,+,i}$. Similarly, the magnitude of the facilitation effect in the NTC is given by $RT_{\times,-,i} - RT_{-,-,i}$. In the same vein, the magnitude of the interference effect was computed as $RT_{-,+,i} - RT_{\times,+,i}$ in the PTC and $RT_{+,-,i} - RT_{\times,-,i}$ in the NTC. Note that the interference effect in the PTC is *interference due to the negative flanker*, and interference in the NTC is *interference due to the positive flanker* (in both cases, because they are contrasted with a neutral-flanker condition). We computed similar contrasts for the accuracy scores. Columns two and three of Table 1 present the exact difference formulas used.

Flanker effect. Using a 2 (target condition: negative, positive) × 3 (flanker condition: congruent, neutral, incongruent) repeated-measures ANOVA, we first analyzed accuracy and mean RTs to examine the flanker effect. For accuracy scores, we found main effects for both target, $F(1, 98) = 37.28$, $p < .01$, partial $\eta^2 = .28$, and flanker conditions, $F(2, 97) = 42.73$, $p < .01$, partial $\eta^2 = .47$. Overall, participants performed better in the PTC relative to the NTC. In addition, they performed worse in the incongruent condition relative to the neutral and congruent conditions. These main effects were qualified by a significant Target × Flanker interaction, $F(2, 97) = 14.07$, $p < .01$, partial $\eta^2 = .23$. The interaction is reflected in participants performing worse in the congruent relative to the neutral condition in the PTC, $t(98) = -2.75$, $p = .01$, $d = -.28$,[1] but performing better in the congruent relative to the neutral condition in the NTC, $t(98) = 3.41$, $p < .01$, $d = .38$. The pattern of interaction is depicted in the left panel of Figure 2.

We did the same analysis for the mean correct RTs and found similar results for the accuracy scores. We found main effects for both target, $F(1, 98) = 141.67$, $p < .01$, partial $\eta^2 = .59$, and flanker conditions, $F(2, 97) = 72.69$, $p < .01$, partial $\eta^2 = .60$. In general, participants were faster to respond in the PTC relative to the NTC. In addition, they were slower in the incongruent condition relative to the neutral and congruent conditions. These main effects were also qualified by a significant Target × Flanker interaction, $F(2, 97) = 32.15$, $p < .01$, partial $\eta^2 = .40$. Similar to the trend found in the accuracy scores, the interaction effect is reflected in participants responding slower in the congruent relative to the neutral condition in the PTC, $t(98) = -4.82$, $p < .01$, $d = -.21$, but responding faster in the congruent relative to the neutral condition in the NTC, $t(98) = 5.05$, $p < .01$, $d = .25$. Means and standard deviations for the accuracies and RTs of the different flanker conditions by target valence are presented in Figure 2.

Relationships with rumination and depression. Statistics from univariate regressions using measures of depression and rumination to predict interference and facilitation effects are presented in Table 2. Only for accuracy scores did rumination significantly predict the facilitation effect in the NTC and PTC: The higher the rumination score, the stronger the facilitation effect of negative distracters in the NTC and the weaker the facilitation effect of positive distracters in the PTC. No other significant relationships were found. For the RTs, we found no significant relationships between the conditions of the emotional flanker task and rumination or depression.

To control for the correlation between rumination and depression ($r = .65$, $p < .01$), we ran a series of bivariate regression analyses using depression and rumination as simultaneous predictors of the various interference and facilitation effects (see Table 2). After controlling for depression, the relationship between rumination and the facilitation effect (computed from accuracy scores) in the NTC remained. No other relationships were found for both accuracy and RT scores.

Diffusion Model Analysis

In order to investigate the relationships among depression, rumination, interference and facilitation effects more closely, we now apply an HDM to the emotional flanker task data, focusing our analysis on effects on the drift rate parameter.

Data preprocessing. Data preprocessing for the classical analysis is slightly different from that for a diffusion model analysis, as both correct and error responses are simultaneously needed for the latter. Apart from this restriction, we used the same data preprocessing and conventions for outlier censoring as in the classical analysis, described above.

Model details. The specific assumptions of the diffusion model were as follows. Each trial's CRT was assumed to be an independent realization of a diffusion process with the parameters described in the Diffusion Model section, above. The boundary

[1] Cohen's d for paired t-tests was computed as $d = t\sqrt{2(1-r)/n}$ (Dunlap, Cortina, Vaslow, & Burke, 1996).

Table 1
Formulas for the Facilitation and Interference Contrasts, by Target Valence Condition

	Response time	Accuracy	Drift rate
Facilitation, positive target	$RT_{\times,+,i} - RT_{+,+,i}$	$AC_{+,+,i} - AC_{\times,+,i}$	$\delta_{\times,+,i} - \delta_{+,+,i}$
Facilitation, negative target	$RT_{\times,-,i} - RT_{-,-,i}$	$AC_{-,-,i} - AC_{\times,-,i}$	$\delta_{-,-,i} - \delta_{\times,-,i}$
Interference, positive target	$RT_{-,+,i} - RT_{\times,+,i}$	$AC_{\times,+,i} - AC_{-,+,i}$	$\delta_{-,+,i} - \delta_{\times,+,i}$
Interference, negative target	$RT_{+,-,i} - RT_{\times,-,i}$	$AC_{\times,-,i} - AC_{+,-,i}$	$\delta_{\times,-,i} - \delta_{+,-,i}$

Note. The classical "flanker effect" is the sum of the interference and facilitation effects.

separation and starting point parameters were assumed to be constant for each participant (i.e., independent of condition) and were treated as random effects across participants. The nondecision time parameter was allowed to differ between conditions to allow for encoding differences and was assumed to vary from trial to trial according to a truncated normal distribution with a person-specific variance.

Most importantly, the drift rate parameters[2] were subjected to regression equations of the form $\delta_{-,-,i} = \delta_{\times,-,i} + \phi_{-,i} + \beta_1 R_i + \beta_2 C_i$, where $\delta_{-,-,i}$ is the congruent flanker NTC drift rate for person i, $\delta_{\times,-,i}$ is the neutral-flanker (reference) NTC drift rate for person i, $\phi_{-,i}$ is the person-specific random intercept of the facilitation effect, R_i and C_i are the standardized rumination and depression scores for person i, respectively, and the β-s are the corresponding regression weights. Similar equations were constructed for the drift rates in the congruent-positive, incongruent-negative, and incongruent-positive conditions using the contrasts given in Table 1. Drift rates for the neutral-flanker conditions were considered free parameters. We ran a series of three models, differing only in the assumptions regarding the βs. In the rumination-only model, $\beta_2 = 0$. In the depression-only model, $\beta_1 = 0$. In the bivariate model, both βs are freely estimated.

We applied the hierarchical diffusion model in a Bayesian statistical context using customized software (see Vandekerckhove et al., 2008, 2010). Full introductions to Bayesian statistical inference can be found in Gelman, Carlin, Stern, and Rubin (2004) or Kruschke (2010). For brevity, we do not report extensive algorithm or model fit checks, except to note that the Markov chain Monte Carlo procedure converged rapidly and that posterior predictive checks indicated satisfactory model fit to the data. Details regarding convergence, model fit, and the complete specification of the model are available via http://supp.cidlab.com/PVK13.

Statistical inference for the hierarchical diffusion model. The "drift rate" rows of Table 2 contain results from the HDM analysis, with estimates computed as posterior means and standard errors as posterior standard deviations. To carry out inference on the parameters, we compute a posterior statistic p that is equal to twice the parameter's posterior mass below 0 if the mean of the posterior was positive and equal to twice the mass above 0 if the mean was negative. One interpretation of this statistic is that it is the mass of the smallest symmetric tail area that includes 0. If this "Bayesian p value" is very low—say, less than .05—we conclude that there is strong evidence that the parameter differs from 0 in the direction indicated by its posterior mean.

Flanker effect. First, we analyzed the effect of the experimental manipulations on the drift rate parameter to confirm that the flanker effect is indeed captured by this parameter. Figure 3, left panel, shows sample mean drift rates for the six conditions. It is clear from the figure that the drift rate is strongly affected by the flanker condition manipulation. On average, drift rates are lower in the incongruent flanker conditions than in the neutral and congruent flanker conditions. With negative targets, the congruent condition has higher drift rates than the neutral flanker condition, but with positive targets the means differ less convincingly. The side panels show the distribution in the population of the magnitude of the facilitation and interference effects, by flanker valence (see Table 1 for definitions). They show considerable variability among participants.

Relationships with rumination and depression. We applied three HDMs, two with univariate regression analyses, using rumination and depression to explain the observed variability in the interference and facilitation parameters (as defined in Table 1), and one with a bivariate regression. Results are presented in Table 2.

As expected, depression was positively related to the facilitation effect in the NTC: The higher the depression score, the greater the facilitation by negative distracters in the NTC. There was no evidence of any relationship between depression and other effects. Also in the NTC, rumination was positively related to the facilitation effect and negatively related to the interference effect. That is, the higher the rumination score, the greater the facilitation due to the negative distracters and the weaker the interference due to positive distracters in the NTC. The relationship between rumination and the negative-flanker PTC was marginal, with a Bayesian p value just in excess of .05. No relationships were found between rumination and the facilitation effect in the PTC.

The goal of the bivariate model was to control for the correlation between rumination and depression by using them as simultaneous predictors of the various interference and facilitation parameters. After controlling for depression, the effect of rumination on the facilitation and interference contrasts in the NTC persisted. Conversely, controlling for the effect of rumination eliminated the effect of depression on facilitation in the NTC.

Discussion

The present study was designed for two purposes: First, we wanted to examine whether depression and rumination were associated with attentional bias for negative information as measured in the emotional flanker task. Learning from studies on the dot-

[2] Previous studies applying process models to flanker tasks (Liu, Holmes, & Cohen, 2008; White, Ratcliff, & Starns, 2011) have proposed diffusion model variants with a variable drift rate to account for below-chance performance among fast responses on incongruent trials. However, our data do not exhibit this feature, and we were able to account for all the major characteristics of our data with a simpler model.

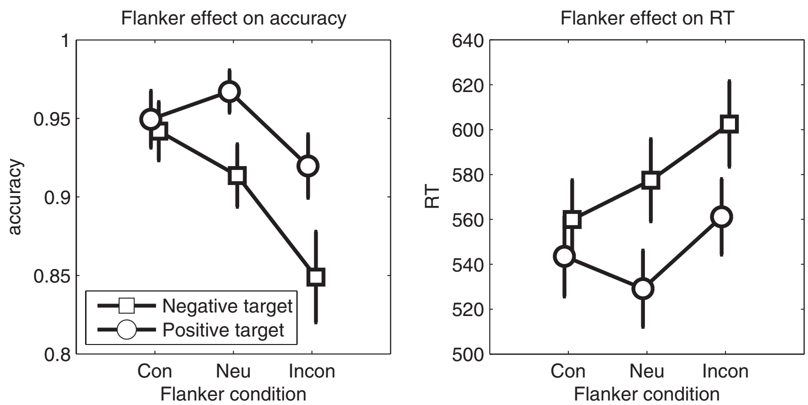

Figure 2. The flanker effect on the accuracies (left panel) and RTs (right panel) by target valence. Error bars are 99% confidence intervals. In general, participants performed worse and were slower in the incongruent conditions compared with the congruent and neutral conditions. The interaction is reflected in the faster and better performance in the congruent (vs. the neutral) condition when there is a negative-valence target, but a slower and worse performance in the congruent (vs. the neutral) condition when there is a positive-valence target.

probe task, we hypothesized that biased processing of distracter information would occur when the negative stimulus is the target and is therefore the focus of attention. Second, we wanted to present the utility of using a diffusion modeling approach in attentional bias in depression and rumination. We argued that the elusive findings commonly found in the literature might be due to a lack of sensitivity of the traditional data analysis approach. With diffusion models, we take into account the different ongoing processes underlying response decisions and so can isolate the information-processing component (drift rate parameter) that is of particular relevance to the study.

Using mean correct RTs, the standard approach for analyzing attentional bias, we replicated the weak relationships found in the literature between the flanker effects on the one hand and rumination and depression on the other hand. Specifically, our results are in line with those obtained from two studies concerning the relationship between the emotional flanker task, and rumination and depression. In the first study, Zetsche et al. (2012) found that depression, and not rumination, was related to greater interference from negative distracter words when there was a positive target, whereas in the second study, Zetsche and Joormann (2011) found that rumination was associated with less interference from irrelevant negative words (which was counterintuitive), whereas depression did not reveal any significant relationships.

Using parameter estimates from a diffusion modeling approach, which combines RTs and accuracy scores in one model, we were

Table 2
Descriptives and Regression Analyses of Rumination and Depression Predicting The Various Flanker Conditions

			Univariate regression						Bivariate regression					
			Rumination			Depression			Rumination			Depression		
Flanker conditions	*M*	*SD*	β	*SE*	*p*	β	*SE*	*p*	β	*SE*	*p*	β	*SE*	*p*
Interference effect (negative target)														
Accuracy	.06	.10	0.02	0.02	.34	0.02	0.02	.30	0.01	0.03	.73	0.02	0.03	.57
RT	25.06	36.37	−7.56	7.74	.33	−5.88	7.53	.44	−6.31	10.29	.54	−1.87	9.99	.85
Drift rate[ab]	7.75	1.04	**−2.49**	**0.92**	**<.01**	−0.09	1.01	.94	**−2.73**	**1.23**	**.02**	0.49	1.33	.70
Facilitation effect (negative target)														
Accuracy	.03	.08	**0.06**	**0.02**	**<.01**	0.03	0.02	.10	**0.07**	**0.02**	**<.01**	−0.02	0.02	.45
RT	17.49	34.46	6.94	7.34	.35	9.75	7.09	.17	0.66	9.70	.95	9.33	9.42	.32
Drift rate[ab]	4.96	1.14	**3.34**	**1.01**	**<.01**	**3.05**	**1.15**	**<.01**	**2.78**	**1.34**	**.03**	0.92	1.49	.55
Interference effect (positive target)														
Accuracy	.05	.08	0.02	0.02	.26	0.00	0.02	.86	0.03	0.02	.18	−0.02	0.02	.46
RT	32.00	35.80	−1.94	7.65	.80	−1.64	7.43	.83	−1.45	10.17	.89	−0.72	9.88	.94
Drift rate[ab]	9.93	1.20	**2.13**	**1.10**	**.05**	1.00	1.21	.41	2.45	1.51	.11	−0.62	1.59	.68
Facilitation effect (positive target)														
Accuracy	−.02	.06	**−0.03**	**0.01**	**.03**	−0.03	0.01	.06	−0.02	0.02	.19	−0.01	0.02	.57
RT	−14.44	29.83	3.23	6.37	.61	2.25	6.19	.72	3.01	8.47	.72	0.33	8.23	.97
Drift rate[ab]	−3.49	1.24	−1.01	1.14	.37	−0.79	1.25	.54	−0.86	1.53	.57	−0.27	1.64	.88

Note. Rumination (M = 2.08, SD = 0.47) and Depression (M = 0.73, SD = 0.49). RT = Reaction time. Regression components with *p*-values less than .05 have been bolded.
[a] Drift rates and difference scores were multiplied by 100. [b] See section on Diffusion Model Analysis for the computation of the Bayesian *p*-value in this row.

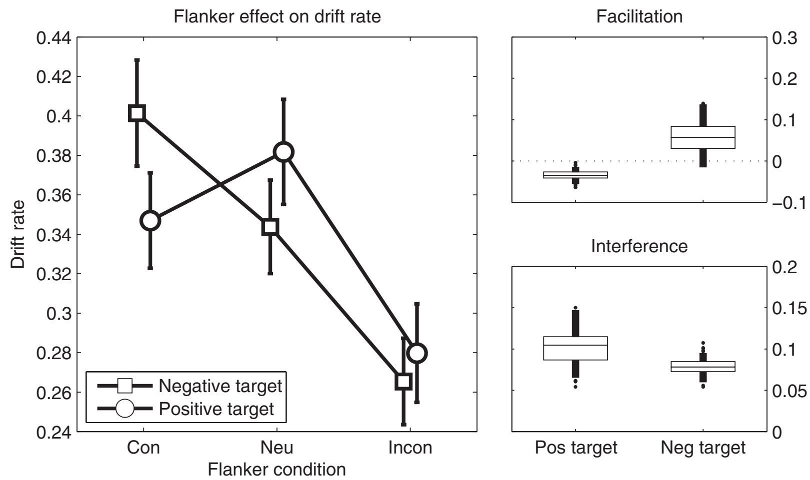

Figure 3. The flanker effect on the drift rate parameter by target valence. Error bars indicate 99% Bayesian credibility intervals. In the left panel, similar to the accuracies and RTs, participants performed worse in the incongruent conditions compared with the congruent and neutral conditions. The interaction is reflected in the better performance in the congruent (vs. the neutral) condition when there is a negative-valence target, but a worse performance in the congruent (vs. the neutral) condition when there is a positive-valence target. The side panels show the between-participant distributions of the magnitudes of facilitation and interference effects. Boxes indicate the interquartile range (IQR) and whiskers end at 1.5 times the IQR. The horizontal line marks the median. There are significant interindividual differences in the magnitudes.

able to observe the relationships hypothesized in the literature. We found that in the NTC, both rumination and depression were positively related to facilitation of negative distracters and that rumination (but not depression) was negatively related to interference by positive distracters. In addition, after controlling for the effects of depression, only the relationships found between rumination and the facilitation and interference effects in the NTC persisted. This implies that the attentional bias we found in the NTC particularly taps into the ruminative aspect of depression.

Overall, our findings demonstrate that by using the drift rate parameter from the diffusion model, we were able to reveal relationships that would have otherwise been masked by the use of accuracy scores and RTs. Specifically, the drift rate parameter was able to capture (a) the negative relationship between rumination and interference by positive distracters in the NTC, (b) the positive relationship between rumination and facilitation by negative distracters in the NTC, and (c) the positive relationship between depression and facilitation by negative distracters in the NTC (which did not persist after controlling for Effect b of rumination).

We write this article with three cautionary notes in mind. With regards to methodology, we have two important limitations: First, the matching of the stimuli on valence and arousal was based on Affective Norms of English Words list (Bradley & Lang, 1999) and was not reassessed after being translated to Dutch. Second, we did not control for word frequency in selecting the stimuli. This was mainly due to the already ample constraints on the stimulus set (i.e., matching in nominal valence and arousal, same word length, monosyllabic words) and the lack of further flexibility in the available word set. Although these are limitations of the present study, we believe that the effect on our data would be in the form of decreased statistical power (increased Type II error), not an increased false alarm probability (Type I error). Moreover, we find the interference (incongruent relative to neutral trials) and flanker (incongruent relative to congruent trials) effects to be robust regardless of the valence of the distracters or the target word. The counterintuitive finding of interference due to the addition of positive-congruent flankers (i.e., neutral relative to congruent trials in the positive target condition) is not uncommon in the flanker literature (see Flowers & Wilcox, 1982, for a directed study of the phenomenon). Indeed, as noted by Flowers and Wilcox (1982), "evidence for both increased interference and facilitative priming can be found in situations in which subjects are required to recognize or respond to a target character surrounded by other identical characters" (p. 581). However, because we cannot say with confidence how this inverse effect relates to stimulus valence, we decided not to rely on it for our conclusions regarding the relationship with depression and rumination. Finally, in the present study we used a subclinical sample, and it is unclear if our results generalize to a sample with clinically significant depression.

Despite these limitations, the present study has several potential contributions for the field of emotion psychology. From a theoretical point of view, we support Joorman and Siemer's (2011) conclusion that bias for negative information found in depression does not function throughout all aspects of selective attention. Rather, this bias (i.e., processing of irrelevant negative information) seems to be apparent only when negative information is already the focus of attention of dysphoric individuals. We also provide evidence that attentional bias for negative information is a cognitive process that is associated with rumination. Similar to Joormann and Siemer's (2011) assertion regarding depression, attentional bias in rumination does not operate throughout all aspects of selective attention. Indeed, Nolen-Hoeksema (1991) emphasized that "the key characteristic in a ruminative response style is that people are focusing on their negative emotional state"

(p. 569). Similarly, Koster et al. (2011) postulated in their impaired disengagement hypothesis that rumination is characterized by the inability to disengage attention from negative thoughts and to focus attention on positive distracters. Our findings support this claim: When focusing on a negative target, trait ruminators processed irrelevant negative information more and ignored irrelevant positive information more. Finally, our findings show that the attentional bias found among dysphoric individuals can be explained by differences in rumination. This finding is not unique to our study. In fact, a recent study by Demeyer, De Lissnyder, Koster, and De Raedt (2012) found that the relationship between rumination and cognitive control remained significant even after controlling for depression scores. These findings suggest that dysphoric individuals' attentional bias for negative information is a result of their ruminative response style: When more irrelevant negative (and less positive) information enters working memory, this contributes to being "stuck" in a cycle of negative thought, which in turn contributes to the maintenance and development of depressive symptoms (Joormann, 2010; Koster et al., 2011).

From a more methodological point of view, we present a case study of using cognitive models as applied measurement tools—an approach sometimes referred to as *cognitive psychometrics* (e.g., Batchelder, 2010)—in the field of emotion psychology. By partitioning the behavioral process into meaningful constituents, cognitive psychometrical models are able to focus on effects in specific components of the response process. In the present case, we used a very generic process model—the diffusion model—as measurement model. Although this model was able to account for all major aspects of the data, future studies may require more intricate process assumptions. For example, in order to fully account for the data, nonemotional flanker tasks often require the assumption of systematic within-trial changes in drift rate (e.g., White, Ratcliff, & Starns, 2011). Other data may require trial-to-trial variability (as in Ratcliff, 1978; Vandekerckhove & Tuerlinckx, 2007) or decision boundaries that move inward within a trial (Zhang, Vandekerckhove, Wagenmakers, & Lee, 2012). The use of well-informed cognitive models as psychodiagnostic tools is a particularly attractive prospect.

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