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Computational modelling of attentional selectivity in depression reveals perceptual deficits

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Original Article

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Abstract

Background. Depression is associated with broad deficits in cognitive control, including in visual selective attention tasks such as the flanker task. Previous computational modelling of depression and flanker task performance showed reduced pre-potent response bias and reduced executive control efficiency in depression. In the current study, we applied two computational models that account for the full dynamics of attentional selectivity.

Method. Across three large-scale online experiments (one exploratory experiment followed by two confirmatory – and pre-registered – experiments; total $N = 923$), we measured attentional selectivity via the flanker task and obtained measures of depression symptomology as well as anhedonia. We then fit two computational models that account for the dynamics of attentional selectivity: The dual-stage two-phase model, and the shrinking spotlight (SSP) model.

Results. No behavioural measures were related to depression symptomology or anhedonia. However, a parameter of the SSP model that indexes the strength of perceptual input was consistently negatively associated with the magnitude of depression symptomatology.

Conclusions. The findings provide evidence for deficits in perceptual representations in depression. We discuss the implications of this in relation to the hypothesis that perceptual deficits potentially exacerbate control deficits in depression.

It is an established finding that depression is associated with deficits in cognitive function (Burt, Zembar, & Niederehe, 1995; McDermott & Ebmeier, 2009; Rock, Roiser, Riedel, & Blackwell, 2014; Snyder, 2013) and executive function (EF) (Snyder, 2013). EFs refer to the set of high-level cognitive processes that control ongoing behaviour to allow a goal-directed action (Miyake et al., 2000; Norman & Shallice, 1986) by regulating subordinate cognitive processes (see e.g. Logan & Gordon, 2001). The finding that EFs are impaired in depression is perhaps not surprising given that the prefrontal cortex – an essential region for efficient executive functioning (Stuss & Knight, 2002) – has been shown to function hypoactively in depressed individuals (Levin, Heller, Mohanty, Herrington, & Miller, 2007).

Assessing the effects of clinical disorders on executive functioning is complicated by the fact that EFs themselves are not directly observable; as they are higher-order processes that act on lower-order processes (e.g., such as perceptual processes), one can only infer the influence and efficacy of EFs by observing changes in manifest variables, such as response time (RT; Logan & Gordon, 2001; Miyake et al., 2000). Importantly, though, changes in EF and subordinate processes can independently influence manifest variables. This complicates matters because a clinical disorder that negatively affects a subordinate process may lead to prolonged RT in a clinical group in comparison to a control group; the impaired RT could mistakenly be taken as evidence of impaired EFs in the clinical group.

One solution to this *task impurity problem* (Miyake et al., 2000) is to fit computational cognitive models to data from clinical and control groups (Farrell & Lewandowsky, 2010; Lewandowsky & Farrell, 2010). Such models of EF will have parameters that reflect higher-order processes (such as control processes) and lower-order processes (such as the strength of perceptual representations), allowing one to distinguish between effects on EFs and subordinate processes, and how these processes change across conditions and clinical groups.

Modelling the effects of depression on flanker task performance

One popular measure of a component of EF – visual selective attention – is the Eriksen flanker task (Eriksen & Eriksen, 1974). In this task, participants are presented with a series of arrows (for example) and must respond to the direction of the central arrow (left *v.* right). On some trials, the central arrow is flanked by arrows that point in the opposite direction to that of the target (*incongruent trials*; e.g. >><>>), and on other trials the central arrow is flanked by arrows pointing in the same direction (*congruent trials*; e.g. <<<<<). It is a well replicated

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finding that incongruent trials are responded to more slowly and with poorer accuracy than congruent trials; this *congruency* effect is thought to reflect the interference caused by the flankers during response selection in the incongruent condition, and the time taken to overcome such interference. The magnitude of the flanker effect can thus be used to assess the efficacy of visual selective attention, with smaller values suggesting better selective attention.

Dillon et al. (2015) recently utilised the flanker task to assess visual selective attention in individuals with major depressive disorder (MDD) compared to a control group. In the behavioural data, Dillon et al. (2015) found those with MDD performed more slowly *but also more accurately* than control participants on incongruent trials. Such speed–accuracy trade-offs are notoriously difficult to interpret (see e.g. Wagenmakers, van der Maas, & Grassman, 2007; Wickelgren, 1977): slower RTs suggest *poorer* performance, but better accuracy suggests *better* performance.

Dillon et al. (2015) fitted a computational model of flanker task performance – the Linear Approach to Threshold with Ergodic Rate (LATER) model (Noorani & Carpenter, 2013) – to correct RTs for both groups. This model has parameters reflecting three core cognitive processes: pre-potent response bias (the degree to which the participant is influenced by distracting flankers); response inhibition (required to resist early responding); and executive control (required to overcome the pre-potent response and respond accordingly to the central target). The results of the modelling showed reduced pre-potent response bias and slower executive control in the depressed group. Within the depressed group, there was a significant negative correlation between the speed of executive control and a questionnaire measure of anhedonia.

Modelling attentional selectivity

Given the striking speed–accuracy trade-off reported by Dillon et al., 2015, it is imperative to take into account both accuracy and response speed when modelling the effects of depression. It has been shown that accuracy data provides essential information – and hence, essential constraints on theoretical modelling – about the dynamics of attentional selectivity in the flanker task. Gratton, Coles, Sirevaag, and Eriksen (1998) used *conditional accuracy functions* (CAFs) to examine the dynamics of attentional selectivity in the flanker task. CAFs are constructed by ordering a participant's RTs for each condition (e.g. congruent trials and incongruent trials separately) from fastest to slowest, and then dividing this data into equally-sized bins. The accuracy for each bin is then plotted against the mean RT for each bin to show how accuracy changes across the RT distribution.

Gratton et al. (1998) used CAFs of flanker task performance to show that attentional selectivity improves with processing time: They reported a large congruency effect in accuracy for the fastest RT bins, but this congruency effect in accuracy reduced as RT increased. This finding is consistent with theoretical accounts of flanker task performance that assume attentional selectivity is relatively poor at early stages of processing, leading to uncertain response selection on incongruent trials as it is heavily influenced by the flanker stimuli; as processing time increases, attentional selectivity improves leading to a reduction of the influence of flanker stimuli on response selection. Note that this theoretical insight could not be established if accuracy data were not accounted for.

The current study

The purpose of the present study was to revisit the effect of depression on flanker task performance, but to fit the data two models – the dual-stage two-phase (DSTP) model of Hübner, Steinhauser, and Lehle (2010) and the shrinking spotlight (SSP) model of White, Ratcliff, and Starns (2011) – that were explicitly designed to jointly account for RT and accuracy performance, and thus could model the full dynamics of attentional selectivity.

Overview of the models

Both the DSTP and the SSP model successfully capture the improvement of attentional selectivity with processing time, but with different theoretical accounts. Figure 1 provides an overview of the main theoretical difference between the two models. A more detailed computational account of the two models is provided in online Supplementary material Appendix A; a brief description of the main parameters in each model is provided in Table 1.

Both models assume that response selection proceeds according to a drift-diffusion process: After perceptual encoding of the stimulus, the cognitive system accumulates (noisy) evidence over time toward one of two response boundaries (one representing a correct response, and the other representing an error response). The boundary that is reached by the diffusion process determines the model's response accuracy, and the time taken for the boundary to be reached the RT.

Both models assume early stages of response selection are influenced by both the flankers and the central target, but at later stages of processing, response selection is primarily driven by attention to the central target. The two models, however, have different assumptions as to how attentional selectivity increases over time, and how this influences response selection. The DSTP model assumes two phases to response selection: In a first phase, attentional selectivity is poor and response selection is influenced by the whole stimulus display; at a discrete point in time, the attentional system selects the central target for more-detailed processing, leading to the second phase of response selection which is influenced solely by the central target. The time taken for the system to select which stimulus to process further is also modelled by a parallel diffusion process (see Fig. 1). The SSP model also assumes that early stages of response selection are influenced by the whole stimulus display, but that attentional selectivity improves gradually over time (i.e. the attentional spotlight gradually reduces its diameter), meaning that later stages of response selection are influenced less by the flankers. The contribution of each element in the stimulus display (i.e. the central target and the flankers) is a multiplicative combination of the strength of perceptual input of the stimulus items (represented by model parameter p) and the area of the attentional spotlight currently over the stimulus items.

General method

We conducted one exploratory experiment, followed by two confirmatory (pre-registered) experiments. In this section, we provide an overview of the general method shared by all three experiments. Where relevant, we also highlight the minor differences between each experiment. All experiments were programmed and delivered using the online behavioural science platform Gorilla™ (https://gorilla.sc; Anwyl-Irvine, Massonnié, Flitton, Kirkham, & Evershed, 2020). Participants were recruited using Prolific

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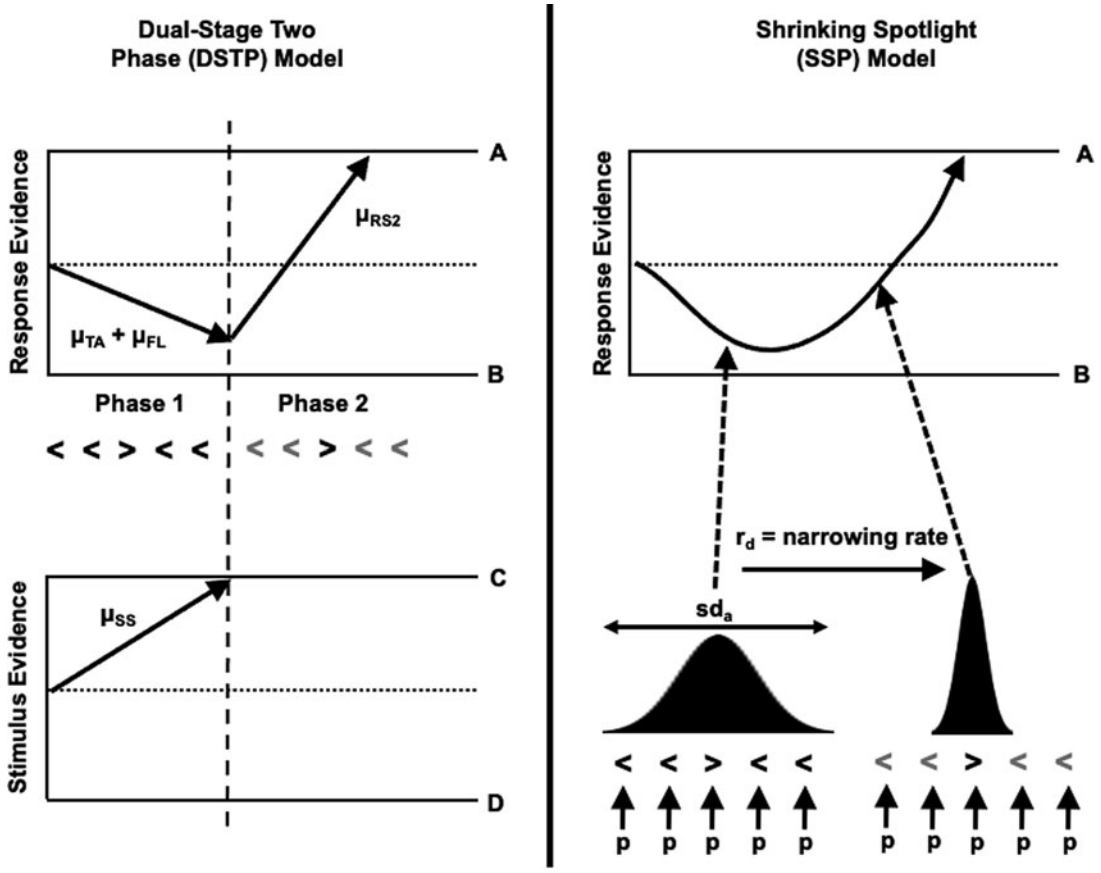


Fig. 1. Schematic overview of the response selection processes in both models. **DSTP Model:** The upper panel depicts the diffusion process for response selection, and the lower panel depicts the diffusion process for stimulus selection. The point in time that a stimulus is selected for further processing is depicted by the dashed vertical line. The diffusion process before this point represents the first stage of response selection, and after this point represents the second – more selective – stage of response selection. **SSP Model:** The upper panel depicts the diffusion process for response selection, the drift rate of which is determined by the perceptual input of stimuli that fill within the area of the attentional spotlight, depicted in the lower panel. As time progresses, the attentional spotlight becomes more focussed around the central target, meaning perceptual information from the flankers contribute less to the drift rate of response selection as time increases. Figure available at https://flickr.com/photos/150716232@N04/48957578602 under CC license https://creativecommons.org/licenses/by/2.0/.

Academic (https://prolific.ac). This study received full ethical clearance from the Ethics Panel run by the School of Psychology at Keele University, UK (application number PS–190046). The methods and analytical strategy were pre-registered for Experiments 2 and 3 at https://aspredicted.org (see https://aspredicted.org/3hr8j.pdf and https://aspredicted.org/8eg68.pdf, respectively).

Participants

Using pre-screening tools in Prolific Academic, we limited our sample to participants residing in the UK or the USA aged between 18 and 60. Participants were screened so that they could only use a laptop or desktop machine (i.e. no mobile devices or tablet). After exclusion criteria were applied (see later section in the General Method), the final sample sizes for Experiments 1–3 were 294, 311, and 318, respectively. The demographic information of the final samples across all three experiments is shown in Table 2.

Materials and flanker task

Demographics questionnaire

Participants completed a brief questionnaire to measure some demographic information. Participants were asked to: enter their date of birth; select their gender (male–female–other); enter how many years of post-16 education they had; select whether they had a clinical diagnosis of depression (i.e. from a health professional; yes–no); if they did have depression, select whether they were currently taking medication for depression (yes–no); select whether they were taking medication for another mental health problem (yes–no; if yes, participants were asked to indicate what the mental health problem was); enter how many episodes of depression the participant had experienced over the past 2 weeks, regardless of whether they had a formal diagnosis or not[1].

Quick inventory of depressive symptomatology–self-report (QIDS–SR)

The QIDS–SR (Rush et al., 2003) is a 16-item self-report questionnaire assessing severity of depression symptoms experienced by respondents over the past 7 days. Each item relates to a particular symptom (e.g. feeling sad), and requires the participant to select one response from four options that best describes them (e.g. 'I almost always feel sad'). The scale shows very good internal consistency and sensitivity to symptom changes (Rush et al., 2003). Scores on the quick inventory of depressive symptomatology (QIDS) range from 0 to 27 (low to high depressive symptomatology).

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Table 1. List and brief description of model parameters in the DSTP model and the SSP model

Model	Parameter	Description
DSTP	*A*/*B*	Height of the boundary for the response selection diffusion process
	C/*D*	Height of the boundary for the stimulus selection diffusion process
	μ_{TA}	Drift rate for central target during response selection phase 1
	μ_{FL}	Drift rate for flankers during response selection phase 1
	μ_{SS}	Drift rate for stimulus selection
	μ_{RS2}	Drift rate for phase 2 of response selection
	ter	Non-decision time (time taken for perceptual encoding of stimuli and motoric response speed).
SSP	*A*/*B*	Height of the boundary for the response selection diffusion process
	ter	Non-decision time (time taken for perceptual encoding of stimuli and motoric response speed)
	p	Perceptual input strength of elements of stimulus display (+*p* for target and congruent flankers; −*p* for incongruent flankers).
	rd	Rate of attentional distribution reduction
	sd_a	Initial width of attentional distribution

Snaith–Hamilton pleasure scale (SHPS)

The SHPS (Snaith et al., 1995) is a 14-item self-report questionnaire that probes the participant's ability to experience pleasure; the questionnaire asks participants to consider their response in relation to how they have felt in the last few days. Each item requires participants to read a statement (e.g. ' I would find pleasure in my hobbies and pastimes'), and to then select a response to indicate their agreement with the statement (e.g. 'Definitely Agree, Agree, Disagree, Definitely Disagree'). We used the scoring method recommended by Franken, Rassin, and Muris (2007) (Definitely Agree = 1, Agree = 2, Disagree = 3, Definitely Disagree = 4). In Experiment 1, the response options were always ordered: Definitely Disagree, Disagree, Agree, Definitely Agree. In Experiments 2 and 3, the response options were changed to match exactly the order and wording presented by Snaith et al. (1995) (e.g. sometimes 'Strongly' was used instead of 'Definitely'; sometime 'Strongly Agree' was the first option, etc.).

Attention checks

In Experiments 2 and 3, we wanted to exclude participants who were demonstrably not paying attention to the questionnaire items. Thus, we used an attention check embedded within the SHPS questionnaire. Specifically, the final item on the SHPS read, 'It is important that you pay attention to this study. Please select *Disagree*' [2]. Participants who failed to select this response option were excluded from the final sample.

Flanker tasks

We used the same trial timings for all trials (practice and main blocks) for all experiments. On each trial, a black fixation cross was presented on the centre of the screen for 500 ms; this was immediately followed by a presentation of the flanker stimulus, which was displayed until the participant made a response. After a response was registered, the fixation cross for the next trial was presented. The flanker stimuli used in Experiments 1 and 2 were arrows, presented in black font. The central target could face either left or right. This central target was flanked by two arrows on either side; these flankers all faced the same direction as each other. On *congruent* trials, the flankers faced the same direction as the target (e.g. <<<<<); on *incongruent* trials, the flankers faced the opposite direction as the target (e.g. >><>>). The participants' task was to make a spatially-congruent response as to the direction of the central target, pressing the 'Z' key for a left response, and the 'M' key for the right response. In Experiment 3, we used the letters 'K' and 'A' as stimuli (e.g. a congruent trial would be KKKKK, and an incongruent trial would be AAKAA). The participants' task was to judge the identity of the central letter by pressing the 'A' key if the letter was A, and the 'K' key if the letter was K. In all experiments, the stimulus from each trial was selected randomly from the total set of four possible stimuli, with the constraint that all stimuli occurred equally often in each block. Participants were asked to respond as quickly and as accurately as possible as soon as the stimulus appeared, using the index finger of each hand for their responses.

In all experiments, participants took part in 16 practice trials before commencing the main flanker blocks. The number and duration of the flanker blocks differed across experiments: in Experiment 1, there were 6 blocks of 60 trials; in Experiments 2 and 3 there were 8 blocks of 60 trials. Participants were provided feedback on their accuracy in the practice blocks: on correct trials, a green tick would overlay the central target; on incorrect responses, a red cross would overlay the central target.

Procedure

The same procedure occurred in all three experiments. Upon entering the study online, participants were presented with an information screen that provided general information about the study so they could decide whether they wished to take part, at which point participants were presented with a screen on which they provided informed consent.

Participants then completed the brief demographics questionnaire. At this point, the experimental software randomised the participant to one of four presentation orders, which counterbalanced the order of presentation of the questionnaires and the flanker task: (1) flanker task – QIDS – SHPS; (2) flanker task – SHPS – QIDS; (3) QIDS – SHPS – flanker task; (4) SHPS – QIDS – flanker task.

Before completing the flanker task, participants were presented with a full instruction screen that provided complete instructions for how to complete the flanker task. This was followed by a brief practice block before moving on to the main blocks. After each block, participants were invited to take a short (self-paced) break. The QIDS questionnaire was presented on four consecutive screens, with four questions per screen. Participants indicated their response to each item by selecting the relevant response clicking a radio button with their mouse; participants could change their response freely until they proceeded to the next screen. The SHPS questionnaire was presented across four screens, with four items on the first three screens, and two items on the last screen. Responses were again indicated via radio buttons. Once participants had completed all elements of

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Table 2. Demographics data for the sample from all experiments

Item		Experiment 1	Experiment 2	Experiment 3
Final sample size		294	311	318
Age: mean years (s.e.)		31.30 (0.65)	33.11 (0.64)	35.19 (0.66)
Gender:	*n* Male (%)	126 (42.86)	106 (34.08)	108 (33.96)
	n Female (%)	159 (54.08)	198 (63.67)	210 (66.04)
	n Other (%)	9 (3.06)	7 (2.25)	0 (0.00)
Education: mean years (s.e.)		5.00 (0.15)	5.05 (0.16)	4.78 (0.21)
Depression diagnosis:	*n* Yes (%)	91 (30.95)	72 (23.15)	74 (14.78)
	n No (%)	203 (69.05)	239 (76.85)	244 (85.22)
Depression medication"	*n* Yes (%)	58 (63.74)	47 (65.28)	46 (62.16)
	n No (%)	33 (36.26)	25 (34.72)	28 (37.84)
Other medication:	*n* Yes (%)	29 (9.86)	25 (8.04)	37 (11.64)
	n No (%)	265 (90.14)	265 (91.96)	281 (88.36)
Number of depressive episodes:	0 (%)	106 (36.05)	145 (46.62)	165 (51.26)
	1–3 (%)	113 (38.44)	125 (40.19)	113 (35.53)
	4–7 (%)	49 (16.67)	34 (10.93)	30 (9.43)
	8 + (%)	26 (8.84)	7 (2.25)	12 (3.77)

Note: s.e., standard error of the mean; *n*, number.

the study, they were presented with a debrief screen, which provided detailed information about the nature of the experiment.

Quality checks and data exclusion

Before analysing the data, we conducted some quality checks on the data and removed some participants with reference to predefined (and pre-registered in Experiments 2 and 3) exclusion criteria. In Experiments 2 and 3, individuals who failed the attention check embedded within the SHPS questionnaire were removed. Responses to the questionnaires were also examined for 'straight-lining' (e.g. only selecting the left-most response to all items); participants who showed straight-lining to all questions for both questionnaires were removed.

For the behavioural data, we removed participants who had a mean accuracy lower than 80%. For the RT analysis, error trials were removed; RTs were trimmed by removing RTs shorter than 250 ms and longer than 1500 ms. In cases where trimming removed more than 25% of an individual's data, that participant was removed.

Results

Analytical strategy

All inferential analyses utilised a Bayesian regression approach using the brms package (Bürkner, 2017) in R (R Core Team, 2017). Default regularising priors from the brms package were used throughout. Unless otherwise stated, the response variable in the regressions was modelled as being distributed normally. Predictor variables were considered to contribute meaningfully if their 95% credible intervals (CI) did not include zero[3]. Each statistical model was fit using brms by running four chains of the 'no U-turn' sampling (NUTS) of the posterior distribution for each parameter, with 4000 samples per chain (the first 2000 samples of which counting as 'burn-in'); we inspected the chains to ensure convergence, and all $\hat{R}$ were close to 1.

Questionnaire scores

There were good variability and ranges of scores across all three experiments for both the QIDS (Experiment 1: range = 0–25, M = 11.27, s.d. = 6.12; Experiment 2: range = 0–24, mean = 9.27, s.d. = 5.26; Experiment 3: range = 0–24, mean = 9.15, s.d. = 5.31) and the SHPS scores (Experiment 1: range = 14–50, mean = 27.91, s.d. = 7.69; Experiment 2: range = 14–44, mean = 28.02, s.d. = 6.25; Experiment 3: range = 14–51, mean = 27.08, s.d. = 6.76). Bayesian regressions showed that QIDS scores were positively predicted by SHPS scores across all three experiments, indicating good convergence of the measures [Experiment 1: $\beta_{\text{Intercept}} = 7.63$, 95% CI(6.82, 8.43), $\beta_{\text{SHPS}} = 1.11$ (0.95, 1.28); Experiment 2: $\beta_{\text{Intercept}} = -5.29$ (−7.37, −3.16), $\beta_{\text{SHPS}} = 0.52$ (0.44, 0.59); Experiment 3: $\beta_{\text{Intercept}} = -4.22$ (−6.08, −2.33), $\beta_{\text{SHPS}} = 0.49$ (0.43, 0.56)][4].

In the study of Dillon et al. (2015), participants were included in the 'depressed' condition if they had – together with meeting other diagnostic criteria – a QIDS score of 14 or more (which reflects moderate depression); inclusion in the control group required a QIDS score lower than 8. In our samples, there were 109, 67, and 70 who scored above 14 in the QIDS in Experiments 1–3, respectively; these numbers were 88, 122, and 137 for those scoring below 8. Also, our sample contained a reasonable proportion of participants who self-declared a clinical diagnosis of depression (see Table 2). Thus our samples contained a good spread of depression symptomology.

Behavioural results

Before presenting the results of the computational modelling, we provide an overview of the behavioural results to explore the

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magnitude of the flanker effect in both RT and error, as well as the relationship between these outcomes and questionnaire scores.

Flanker effect in RT and accuracy

For the RT analysis, a Bayesian regression was conducted with trial-level RT as the outcome variable and *congruency* as the predictor variable; the outcome variable was modelled as an ex-Gaussian distribution[5]. There was a large flanker effect in RT in all three experiments [Experiment 1: $\beta_{incongruent} = 48$ (37, 59); Experiment 2: $\beta_{incongruent} = 53$ (44, 63); Experiment 3: $\beta_{incongruent} = 30$ (21, 39)]. The accuracy analysis utilised a similar Bayesian regression, but the outcome variable (proportion correct) was modelled as a skewed normal distribution. Again, there was a large flanker effect in all three experiments [Experiment 1: $\beta_{incongruent} = -0.01$ (−0.014, −0.006); Experiment 2: $\beta_{incongruent} = -0.01$ (−0.014, −0.007); Experiment 3: $\beta_{incongruent} = -0.01$ (−0.015, −0.008)].

Predicting behavioural data from QIDS and SHPS

We performed a series of Bayesian regressions to explore whether the behavioural flanker effect was predicted by scores on the QIDS and SHPS. Results showed that the RT flanker effect was not predicted by QIDS scores [Experiment 1: $\beta_{QIDS} = 0.02$ (−0.53, 0.58); Experiment 2: $\beta_{QIDS} = 0.23$ (−0.41, 0.89); Experiment 3: $\beta_{QIDS} = 0.11$ (−0.22, 0.44)] or SHPS scores [Experiment 1: $\beta_{SHPS} = -0.65$ (−1.67, 0.40); Experiment 2: $\beta_{SHPS} = -0.17$ (−0.71, 0.38); Experiment 3: $\beta_{SHPS} = -0.04$ (−0.29, 0.21)]. The accuracy flanker effect was also not predicted by either QIDS [Experiment 1: βQIDS = −0.0003 (−0.0010, 0.0005); Experiment 2: $\beta_{QIDS} = -0.0003$ (−0.0009, 0.0003); Experiment 3: $\beta_{QIDS} = 0.0001$ (−0.0004, 0.0007)] or SHPS scores [Experiment 1: $\beta_{SHPS} = -0.0003$ (−0.0015, 0.0009); Experiment 2: $\beta_{SHPS} = 0.0000$ (−0.0005, 0.0004); Experiment 3: $\beta_{SHPS} = 0.0002$ (−0.0001, 0.0006)]. See online Supplementary material Appendix C for more details.

Modelling results

We fit the DSTP and SSP models to individual participant data using the flanker package (Grange, 2016). The models were fitted to trial-level RT and accuracy data. Full details of the fit routine and assessment of the goodness of fits (which were good) for both models can be found in online Supplementary material Appendix D. We also report in Supplementary material Appendix D formal model comparison tests of whether one model provided superior fits over the other. We found that the SSP model was superior for Experiments 1 and 2, and the DSTP model was superior for Experiment 3.

To assess whether model parameters were predicted by QIDS and SHPS scores, a series of Bayesian regressions were conducted; the outcome variables in all regressions were modelled as a skewed normal distribution. For ease of exposition, we present the regression coefficients for all models and all experiments in Table 3; plots of all Bayesian regressions can be found in the online Supplementary material Appendix E.

DSTP model

No DSTP parameter was consistently predicted by depression scores (QIDS) across the three experiments. Although the parameter μ_{TA} was negatively associated with depression symptoms in Experiment 1, this did not replicate in Experiment 2 or 3. Likewise, although the parameter μ_{SS} was negatively associated with depression in Experiment 3, we did not find this to be the case in the first two experiments. However, this parameter was negatively associated with anhedonia (SHPS) in Experiments 2 and 3, but this was not evident in Experiment 1. This suggests that the time is taken for the cognitive system to select the central target for further processing – in the model, reflected by the drift rate shown in the lower panel of the DSTP schematic shown in Fig. 1 – is longer for those with higher levels of anhedonia. Parameter μ_{FL} was negatively associated with anhedonia in Experiment 2, but not in Experiment 1 or 3.

SSP model

We found that the SSP model parameter p was consistently (negatively) predicted by depression (QIDS) across all three experiments [the 95%CI for this regression coefficient in Experiment 1 only just included zero, βQIDS = −0.002 (−0.0043, 0.0001)]. This relationship is plotted in Fig. 2. This parameter – which reflects the perceptual input strength of each element of the encoded flanker stimulus – was lower in individuals with higher levels of depression symptoms. This parameter was also negatively predicted by measures of anhedonia in Experiments 2 and 3, but not in Experiment 1. No other SSP parameters were predicted by QIDS or SHPS scores.

General discussion

The current study aimed to extend the findings of Dillon et al. (2015) by fitting two computational models able to account jointly for accuracy and RT performance, as well as the ubiquitous improvement of attentional selectivity with time found in the flanker task. Specifically, we fit the DSTP model (Hübner et al., 2010) and the SSP model (White et al., 2011) to data from three large-scale online experiments where self-reported measures of depression symptomology (as measured by the QIDS) and anhedonia (as measured by the SHPS) were recorded.

In terms of behavioural data, we did not find any relationship between depression symptomology or anhedonia on any of the primary dependent variables at the mean level, in contrast to the findings of Dillon et al. (2015). However, in the supplementary analysis (see online Supplementary material Appendix F) where we grouped participants into high-QIDS (a score of 14 or above) and low-QIDS (a score below 8), group differences emerged in the conditional accuracy functions, with high-QIDS participants showing poorer attentional selectivity at faster responses. As the DSTP and SSP models are fitted to conditional accuracy functions (combining RT and accuracy) and cumulative distribution functions (which describe the whole of the correct RT distribution), this analysis suggests that there were effects of depression that the modelling could be useful to describe.

No DSTP model parameter was consistently associated with depression or anhedonia across any of the three experiments. In contrast, however, the SSP model parameter p was consistently negatively associated with depression (and anhedonia in Experiments 2 and 3). This model parameter reflects the strength of the perceptual input of each item in the stimulus display (see Supplementary material Appendix A for more details), suggesting this input strength is weaker in those with higher levels of depression. In an experimental validation of the SSP model, the p parameter has been shown to vary systematically with the intensity and contrast of presented visual stimuli (Servant, Montagnini, & Burle, 2014), suggesting it can index perceptual index strength accurately.

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Table 3. Bayesian regression coefficients (with 95% CIs) predicting DSTP and SSP model parameters from QIDS and SHPS questionnaire scores across all experiments

			QIDS		SHPS	
Experiment	Model	Parameter	$\beta_{Intercept}$	β_{QIDS}	$\beta_{Intercept}$	β_{SHPS}
E1	DSTP	*A*	0.105 [0.097, 0.112]	−0.0001 [−0.0006, 0.0004]	0.106 [0.094, 0.117]	−0.0001 [−0.0005, 0.0003]
		C	0.088 [0.081, 0.096]	0.0004 [−0.0002, 0.0009]	0.087 [0.074, 0.100]	0.0002 [−0.0002, 0.0006]
		μ_{TA}	0.159 [0.144, 0.174]	**−0.0013 [−0.0025, −0.0002]**	0.155 [0.128, 0.181]	−0.0004 [−0.0013, 0.0005]
		μ_{FL}	0.200 [0.179, 0.222]	−0.0007 [−0.0022, 0.0008]	0.212 [0.176, 0.247]	−0.0007 [−0.0019, 0.0005]
		μ_{SS}	0.539 [0.508, 0.570]	−0.0010 [−0.0034, 0.0013]	0.529 [0.472, 0.586]	0.0000 [−0.0020, 0.0019]
		μ_{RS2}	1.240 [1.178, 1.301]	0.0008 [−0.0039, 0.0054]	1.210 [1.102, 1.321]	0.0014 [−0.0025, 0.0051]
		ter	0.288 [0.277, 0.299]	0.0000 [−0.0008, 0.0009]	0.297 [0.277, 0.316]	−0.0003 [−0.0010, 0.0004]
	SSP	*A*	0.071 [0.067, 0.075]	−0.0001 [−0.0004, 0.0002]	0.072 [0.065, 0.078]	−0.0001 [−0.0003, 0.0002]
		ter	0.345 [0.333, 0.357]	0.0001 [−0.0009, 0.0010]	0.356 [0.334, 0.378]	−0.0004 [−0.0011, 0.0004]
		p	0.502 [0.474, 0.530]	−0.0021 [−0.0043, 0.0001]	0.489 [0.439, 0.539]	−0.0004 [−0.0021, 0.0013]
		rd	0.036 [0.033, 0.040]	−0.0002 [−0.0004, 0.0000]	0.037 [0.031, 0.042]	−0.0001 [−0.0003, 0.0001]
		sda	1.771 [1.692, 1.849]	−0.0023 [−0.0083, 0.0038]	1.807 [1.666, 1.947]	−0.0022 [−0.0069, 0.0026]
E2	DSTP	*A*	0.104 [0.098, 0.110]	−0.0004 [−0.0009, 0.0000]	0.109 [0.098, 0.120]	−0.0003 [−0.0007, 0.0001]
		C	0.088 [0.081, 0.096]	0.0003 [−0.0002, 0.0008]	0.089 [0.076, 0.101]	0.0001 [−0.0004, 0.0005]
		μ_{TA}	0.148 [0.132, 0.164]	0.0002 [−0.0013, 0.0017]	0.165 [0.131, 0.199]	−0.0005, [−0.0017, 0.0007]
		μ_{FL}	0.206 [0.187, 0.223]	−0.0014 [−0.0031, 0.0003]	0.248 [0.203, 0.291]	**−0.0020 [−0.0035, −0.0004]**
		μ_{SS}	0.539 [0.508, 0.570]	−0.0024 [−0.0052, 0.0004]	0.587 [0.520, 0.654]	**−0.0025 [−0.0049, −0.0002]**
		μ_{RS2}	1.207 [1.151, 1.263]	0.0040 [−0.0013, 0.0093]	1.185 [1.060, 1.313]	0.0021 [−0.0024, 0.0064]
		ter	0.293 [0.285, 0.301]	−0.0003 [−0.0011, 0.0005]	0.290 [0.271, 0.308]	0.0000 [−0.0006, 0.0007]
	SSP	A	0.072 [0.069, 0.076]	−0.0002 [−0.0005, 0.0001]	0.072 [0.065, 0.079]	−0.0001 [−0.0003, 0.0002]
		ter	0.352 [0.344, 0.360]	**−0.0008 [−0.0016, −0.0001]**	0.354 [0.335, 0.373]	−0.0003 [−0.0010, 0.0003]
		p	0.496 [0.473, 0.520]	**−0.0027 [−0.0049, −0.0006]**	0.545 [0.491, 0.601]	**−0.0026 [−0.0045, −0.0008]**
		rd	0.030 [0.027, 0.033]	−0.0001 [−0.0004, 0.0001]	0.030 [0.025, 0.035]	0.0000 [−0.0002, 0.0001]
		sda	1.731 [1.654, 1.806]	0.0012 [−0.0059, 0.0083]	1.736 [1.569, 1.909]	0.0002 [−0.0058, 0.0060]
E3	DSTP	A	0.098 [0.092, 0.104]	−0.0004 [−0.0008, 0.0001]	0.097 [0.084, 0.109]	−0.0001 [−0.0005, 0.0004]
		C	0.082 [0.077, 0.088]	0.0004 [−0.0001, 0.0009]	0.093 [0.082, 0.104]	−0.0003 [−0.0007, 0.0001]
		μ_{TA}	0.120 [0.108, 0.131]	−0.0005 [−0.0015, 0.0004]	0.119 [0.095, 0.140]	−0.0001, [−0.0009, 0.0007]
		μ_{FL}	0.117 [0.104, 0.129]	−0.0006 [−0.0017, 0.0005]	0.133 [0.108, 0.158]	−0.0008 [−0.0017, 0.0001]
		μ_{SS}	0.508 [0.487, 0.529]	**−0.0020 [−0.0040, −0.0001]**	0.546 [0.501, 0.589]	**−0.0021 [−0.0037, −0.0005]**
		μ_{RS2}	1.261 [1.206, 1.313]	−0.0001 [−0.0052, 0.0051]	1.326 [1.214, 1.436]	−0.0025 [−0.0064, 0.0016]
		ter	0.288 [0.279, 0.296]	−0.0003 [−0.0011, 0.0006]	0.281 [0.263, 0.300]	0.0001 [−0.0005, 0.0008]
	SSP	*A*	0.066 [0.0630, 0.069]	−0.0002 [−0.0005, 0.0001]	0.069 [0.062, 0.075]	−0.0002 [−0.0004, 0.0001]
		ter	0.344 [0.3352, 0.352]	0.0000 [−0.0008, 0.0008]	0.330 [0.312, 0.349]	0.0005 [−0.0002, 0.0012]
		p	0.437 [0.4176, 0.456]	**−0.0026 [−0.0044, −0.0008]**	0.453 [0.415, 0.492]	**−0.0015 [−0.0029, −0.0001]**
		rd	0.052 [0.0473, 0.057]	−0.0003 [−0.0007, 0.0001]	0.052 [0.042, 0.062]	−0.0001 [−0.0005, 0.0003]
		sda	1.802 [1.7212, 1.880]	−0.0030 [−0.0105, 0.0047]	1.794 [1.632, 1.958]	−0.0007 [−0.0067, 0.0052]

Do perceptual deficits exacerbate control problems in depression?

Although some evidence exists from psychophysical experiments that depression is associated with deficits in perceptual processing (e.g. Bubl, Kern, Ebert, Bach, & van Elst, 2010; Bubl, van Elst, Gondan, Ebert, & Greenle, 2009; Normann, Schmitz, Furmaier, Doing, & Bach, 2007) – and that depression can lead to poorer visual search times (Maekawa, Anderson, de Brecht, & Yamagishi, 2018) – to our knowledge our findings are the first to report perceptual deficits in depression captured by a computational model of higher-order cognition. This finding is of significance because the models capture how perceptual information and higher-order attentional processes interact to produce successful performance. Indeed, this is one of the many advantages of utilising computational models of cognition to probe clinical disorders (see e.g. White, Ratcliff, Vasey, & McKoon, 2010) because we can tease apart the effects of depression on higher-order processes and lower-order, subordinate, processes. The findings from the current study are striking as they suggest that depression symptomology is not negatively affecting attentional processes *per se*, but instead suggests depressed participants show deficits in a lower-order, subordinate, process of perceptual representation[6].

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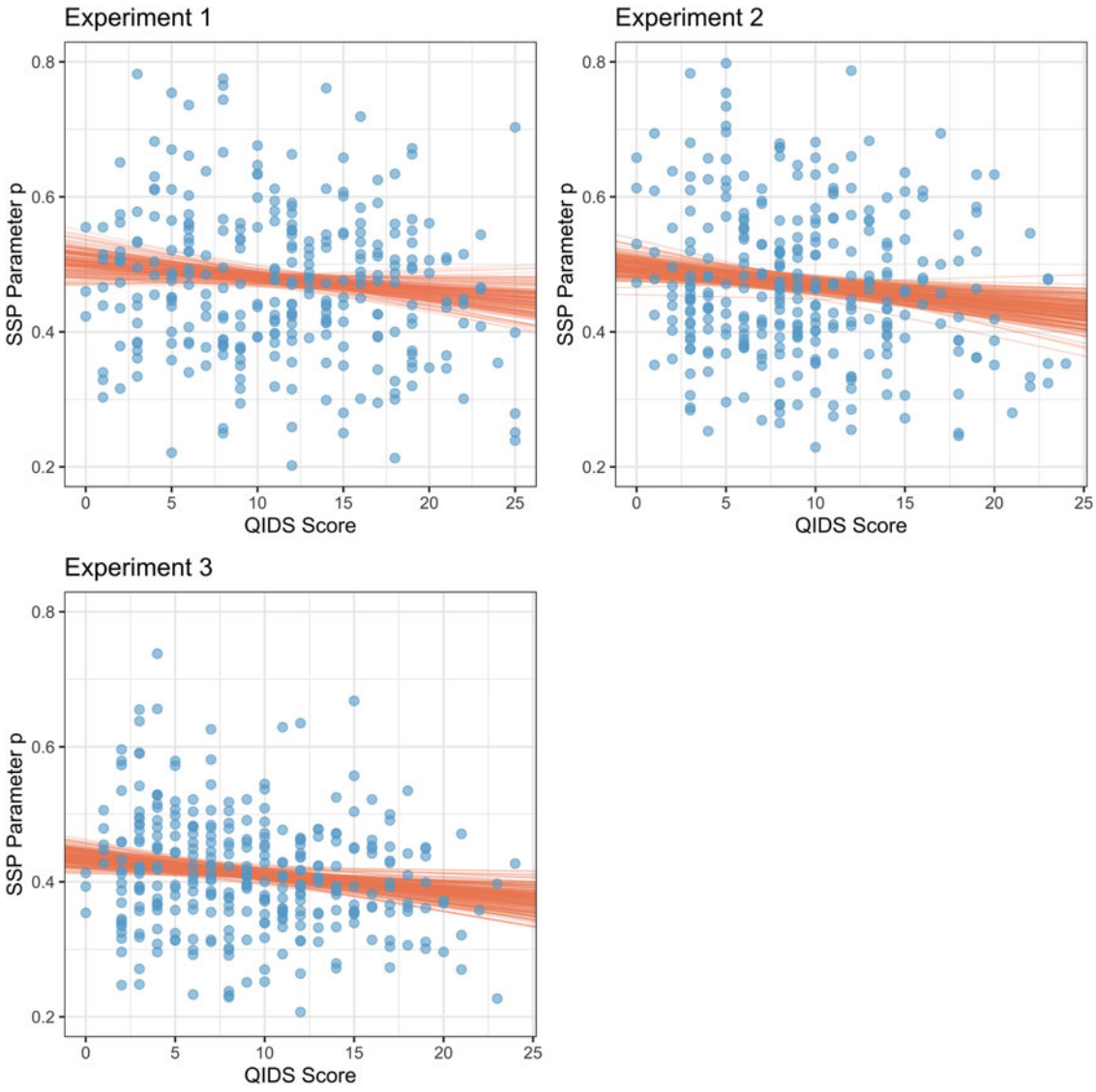


Fig. 2. Relationship between the SSP model parameter *p* and measure of depression from the QIDS questionnaire for Experiments 1–3. Points represent participant data; the lines represent 200 draws from the posterior distribution for the statistical models Experiments 1–3.

This raises the intriguing hypothesis – which should be the subject of future work – that the cognitive control deficits in depression found in recent studies (Burt et al., 1995; McDermott & Ebmeier, 2009; Rock et al., 2014; Snyder, 2013) are problems that are exacerbated by perceptual deficits: If individuals with depression have weaker perceptual representations, then the cognitive system has weaker information with which to work when cognitive control is required, leading to less efficient control.

Indeed, this hypothesis is not inconsistent with the findings of Dillon et al. (2015), who found significantly reduced pre-potent response bias in the depressed group. This parameter reflects the negative influence of flankers on incongruent trials, which push the cognitive system towards an error response. Finding a reduction of this parameter in depressed participants could be interpreted as a weaker perceptual representation of the flankers, which would mean they influenced behaviour less than in control participants. In the extreme version of this hypothesis, perceptual deficits might exclusively explain control problems in depression.

Future work should combine computational modelling with experimental manipulation of perceptual properties of stimulus displays to test this hypothesis further. In addition, the emotional nature of the stimuli should be considered in future work. We used emotionally neutral stimuli. A substantial body of literature demonstrates that patients with depression show mood-congruent emotion processing bias; specifically, negative stimuli (e.g. negative faces) are processed more rapidly and deeply, whilst processing of positive stimuli seems to be impaired (e.g. Gotlib, Krasnoperova, Yue, & Joormann, 2004; Stuhrmann, Suslow, & Dannlowski, 2011). Furthermore, evidence indicates that these impairments in emotion processing can be reversed with psychotropic treatment (Fu et al., 2007). Future work should thus explore whether our general pattern of results replicates using emotional stimuli.

Limitations

The study has several limitations that should be considered. Firstly, due to the many model parameters, our analyses – and thus our conclusions – rest on the outcome of multiple comparisons, so we should be cautious of our Type-1 error rate. Whilst a

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valid concern, we believe that our main finding of reduced SSP model parameter *p* with depression severity is robust. It replicated across (pre-registered) experiments, across depressive symptom measures, and was also evident in the group analysis based on extreme QIDS scores (Supplementary material Appendix F).

Secondly, we used an online sample rather than using lab-condition testing. However, there is good evidence that online recruitment can provide quality data for cognitive tasks (Crump, McDonnell, & Gureckis, 2013). Our behavioural data quality was also very high (see online Supplementary material Appendix C), suggesting that this potential limitation has not impacted on our conclusions.

Finally, we did not recruit a clinical sample; however, we had many participants in all three Experiments who scored above 14 on the QIDS, which Dillon et al. (2015) used as an inclusion criterion in their 'depressed' group. Therefore, although not from a clinical sample, we had a significant subset in each experiment that exhibited moderate depression on the QIDS. As we show in online Supplementary analysis Appendix F, when we compare this high-QIDS group with a low-QIDS group (QIDS score lower than 8 Dillon et al., 2015), our main conclusions of lower *p* SSP parameter values in higher depression stands. However, when we grouped participants into those who declared a clinical diagnosis of depression and those who declared no such diagnosis, we found no consistent group differences. Although there are many advantages to conducting research on a large non-clinical sample (see e.g. the Research Domain Criteria set out by the NIMH: https://www.nimh.nih.gov/research/research-funded-by-nimh/rdoc/index.shtml), further tests of the 'perceptual-hypothesis' should be conducted on individuals with diagnosed MDD. Computational modelling will be essential to address this hypothesis.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S0033291720002652.

Data. All raw data, analysis scripts, and computer code for the modelling can be downloaded from https://osf.io/rufp9/. The experimental materials for Experiment 1 can be downloaded from https://gorilla.sc/openmaterials/43291, for Experiment 2 from https://gorilla.sc/openmaterials/55094, and for Experiment 3 from https://gorilla.sc/openmaterials/55095.

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Conflict of interest. None.

Ethical standards. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

Notes

1 The exact wording of this question was '*Regardless of whether you have a diagnosis or not, how many episodes of depression have you had in the past two weeks?*'. We meant this to mean how many discrete times have you felt depressed over the past 2 weeks, rather than the formal diagnostic definition of the word 'episode' (i.e. one episode being equivalent to two weeks' duration of depression.).

2 This wording is recommended by Prolific Academic: http://tiny.cc/AttentionChecks.

3 Note that Bayesian credible intervals are not to be conflated with frequentist confidence intervals. Unlike the CI, we can make probabilistic statements about the true population value for the predictor variable. If a 95% credible interval does not contain zero, we can state there is a 95% probability that the true population predictor value is not zero.

4 See online Supplementary Material Appendix B for plots of these regressions.

5 Response times are not normally distributed (i.e. they are non-Gaussian), and instead are positively skewed. Ex-Gaussian distributions are convolutions of a Gaussian distribution and an exponential distribution (which – together – produce positively skewed distributions), and have been shown to capture response time distributions well.

6 A reviewer noted – quite rightly – that these results may also be compatible with the view that, in depression, an altered attentional process (e.g. increased attention to depressive ruminations versus external stimuli) may reduce the effectiveness of external perceptual stimuli globally. We are not able to resolve this issue with our data. However, we note that 'attentional' parameters in both models (e.g. μSS in the DSTP model and *rd* in the SSP model) were not found to be associated with depression severity.

References

Anwyl-Irvine, A. L., Massonnié, J., Flitton, A., Kirkham, N., & Evershed, J. K. (2020). Gorilla in our midst: An online behavioral experiment builder. *Behavior Research Methods*, *52*, 388–407. 10.3758/s13428-019-01237-x..

Bubl, E., Kern, E., Ebert, D., Bach, M., & van Elst, L. T. (2010). Seeing gray when feeling blue? Depression can be measured in the eye of the diseased. *Biological Psychiatry*, *68*, 205–208. doi:10.1016/j.biopsych.2010.02.009.

Bubl, E., van Elst, L. T., Gondan, M., Ebert, D., & Greenle, M. W. (2009). Vision in depressive disorder. *The World Journal of Biological Psychiatry*, *10*, 377–384. doi:10.3109/15622970701513756.

Bürkner, P.-C. (2017). Brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. doi:10.18637/jss.v080.i01

Burt, D. B., Zembar, M. J., & Niederehe, G. (1995). Depression and memory impairment: A meta-analysis of the association, its pattern, and specificity. *Psychological Bulletin*, *117*, 285–305. doi:10.1037/0033-2909.117.2.285.

Crump, M. J. C., McDonnell, J. V., & Gureckis, T. M. (2013). Evaluating Amazon's Mechanical Turk as a tool for experimental behavioral research. *PLoS One*, *8*, e57410. doi:10.1371/journal.pone.0057410.

Dillon, D. G., Wiecki, R., Pechtel, P., Webb, C., Goer, F., Murray, L., … Pizzagalli, D. (2015). A computational analysis of flanker interference in depression. *Psychological Medicine*, *45*, 2333–2344. doi:10.1017/S0033291715000276.

Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics*, *16*, 143–149. doi:10.3758/BF03203267.

Farrell, S., & Lewandowsky, S. (2010). Computational models as aids to better reasoning in psychology. *Current Directions in Psychological Science*, *19*, 329–335. doi:10.1177/0963721410386677.

Franken, I. H. A., Rassin, E., & Muris, P. (2007). The assessment of anhedonia in clinical and non-clinical populations: Further validation of the Snaith–Hamilton Pleasure Scale (SHAPS). *Journal of Affective Disorders*, *99*, 83–89. doi:10.1016/j.jad.2006.08.020.

Fu, C. H. Y., Williams, S. C. R., Brammer, M. J., Suckling, J., Kim, J., Cleare, A. J., … Bullmore, E. T. (2007). Neural responses to happy facial expressions in major depression following antidepressant treatment. *American Journal of Psychiatry*, *164*, 599–607.

Gotlib, I. H., Krasnoperova, E., Yue, D. N., & Joormann, J. (2004). Attentional biases for negative interpersonal stimuli in clinical depression. *Journal of Abnormal Psychology*, *113*, 127–135. doi:10.1037/0021-843X.113.1.121.

Grange, J. A. (2016). Flankr: An R package implementing computational models of attentional selectivity. *Behavior Research Methods*, *48*, 528–541. doi:10.3758/s13428-015-0615-y.

Gratton, G., Coles, M. G. H., Sirevaag, E. J., & Eriksen, C. W. (1998). Pre- and poststimulus activation of response channels: A psychophysiological analysis. *Journal of Experimental Psychology: Human Perception & Performance*, *14*, 331–344. doi:10.1037//0096-1523.14.3.331.

Hübner, R., Steinhauser, M., & Lehle, C. (2010). A dual-stage two-phase model of selective attention. *Psychological Review*, *117*, 759–784. doi:10.1037/a0019471.

https://doi.org/10.1017/S0033291720002652 Published online by Cambridge University Press

Levin, R. L., Heller, W., Mohanty, A., Herrington, J. D., & Miller, G. A. (2007). Cognitive deficits in depression and functional specificity of regional brain activity. *Cognitive Therapy & Research*, *31*, 211–233. doi:10.1007/s10608-007-9128-z.

Lewandowsky, S., & Farrell, S. (2010). *Computational modeling in cognition: Principles and practice*. Sage: Thousand Oaks, CA.

Logan, G. D., & Gordon, R. D. (2001). Executive control of visual attention in dual-task situations. *Psychological Review*, *108*, 393–434. doi:10.1037/0033-295X.108.2.393.

Maekawa, T., Anderson, S. J., de Brecht, M., & Yamagishi, N. (2018). The effect of mood state on visual search times for detecting a target in noise: An application of smartphone technology. *PLoS One*, *13*, e0195865. doi:10.1371/journal.pone.0195865.

McDermott, L. M., & Ebmeier, K. P. (2009). A meta-analysis of depression severity and cognitive function. *Journal of Affective Disorders*, *119*, 1–8. doi:10.1016/j.jad.2009.04.022.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzkia, A. H., Howertera, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology*, *41*, 49–100. doi:10.1006/cogp.1999.0734.

Noorani, I., & Carpenter, R. H. S. (2013). Antisaccades as decisions: LATER model predicts latency distributions and error responses. *European Journal of Neuroscience*, *37*, 330–338. doi:10.1111/ejn.12025.

Norman, D. A., & Shallice, T. (1986). Attention to action: Willed and automatic control of behavior. In R. J. Davidson, G. E. Schwartz, & D. Shapiro (Eds.), *Consciousness and self-regulation: Advances in research and theory* (pp. 1–18). New York: Plenum.

Normann, C., Schmitz, D., Furmaier, A., Doing, C., & Bach, M. (2007). Long-term plasticity of visually evoked potentials in humans is altered in major depression. *Biological Psychiatry*, *62*, 373–380. doi:10.1016/j.biopsych.2006.10.006.

R Core Team (2017). *R: A language and environment for statistical computing [computer software manual]*. Vienna, Austria: R Core Team. Retrieved from https://www.R-project.org/.

Rock, P. L., Roiser, J. P., Riedel, W. J., & Blackwell, A. D. (2014). Cognitive impairment in depression: A systematic review and meta-analysis. *Psychological Medicine*, *44*, 2029–2040. doi:10.1017/S0033291713002535.

Rush, A. J., Trivedi, M. H., Ibrahim, H. M., Carmody, T. J., Arnow, B., Klein, D. N., … Keller, M. B. (2003). The 16-item Quick Inventory of Depressive Symptomatology (QIDS) clinician rating (qids-c) and self-report (qids-sr): A psychometric evaluation in patients with chronic major depression. *Biological Psychiatry*, *54*, 573–583.

Servant, M., Montagnini, A., & Burle, B. (2014). Conflict tasks and the diffusion framework: Insight in model constraints based on psychological laws. *Cognitive Psychology*, *72*, 162–195. doi:10.1016/j.cogpsych.2014.03.002.

Snaith, R. P., Hamildon, M., Morley, S., Humayan, A., Hargreaves, D., & Trigwell, P. (1995). A scale for the assessment of hedonic tone: The Snaith–Hamilton pleasure scale. *British Journal of Psychiatry*, *167*, 99–103. doi:10.1192/bjp.167.1.99.

Snyder, H. R. (2013). Major depressive disorder is associated with broad impairments on neuropsychological measures of executive function: A meta-analysis and review. *Psychological Bulletin*, *139*, 81–132. doi:10.1037/a0028727.

Stuhrmann, A., Suslow, T., & Dannlowski, U. (2011). Facial emotion processing in major depression: A systematic review of neuroimaging findings. *Biology of Mood and Anxiety Disorders*, *1*, 10. doi:10.1186/2045-5380-1-10.

Stuss, D. T., & Knight, R. T. (Eds.), (2002). *Principles of frontal lobe function*. New York, NY, USA: Oxford University Press.

Wagenmakers, E.-J., van der Maas, H. L. J., & Grassman, R. P. P. P. (2007). An EZ-diffusion model for response time and accuracy. *Psychonomic Bulletin & Review*, *14*, 3–22. doi:10.3758/BF03194023.

White, C. N., Ratcliff, R., & Starns, J. J. (2011). Diffusion models of the flanker task: Discrete versus gradual attentional selection. *Cognitive Psychology*, *63*, 210–238. doi:10.1016/j.cogpsych.2011.08.001.

White, C. N., Ratcliff, R., Vasey, M. W., & McKoon, G. (2010). Using diffusion models to understand clinical disorders. *Journal of Mathematical Psychology*, *54*, 39–52. doi:10.1016/j.jmp.2010.01.004.

Wickelgren, W. A. (1977). Speed–accuracy trade-off and information processing dynamics. *Acta Psychologica*, *41*, 67–85. doi:10.1016/0001-6918(77)90012-9.

https://doi.org/10.1017/S0033291720002652 Published online by Cambridge University Press