The Thesis Committee for Mary Eileen McNamara
Certifies that this is the approved version of the following Thesis:

Evaluation of a Free-Viewing Task to Measure Distinct Negative and Positive Biases in Depression

APPROVED BY
SUPERVISING COMMITTEE:

Christopher Beevers, Supervisor

Jason Shumake

Evaluation of a Free-Viewing Task to Measure Distinct Negative and Positive Biases in Depression

by

Mary Eileen McNamara

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Abstract

Evaluation of a Free-Viewing Task to Measure Distinct Negative and Positive Biases in Depression

Mary Eileen McNamara, MA

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Supervisor: Christopher Beevers

Attentional bias has traditionally been inferred through the measurement of reaction-time-based tasks. Eye-tracking offers a way to measure attention bias directly, and free-viewing tasks with intricate stimuli presentations may capture the complexities and dynamics of attention bias in ways previous modalities have not. The present study developed a free-viewing task using a data-driven stimuli selection process. Two free-viewing tasks were created using sad and neutral stimuli, and happy and neutral stimuli to tease apart the distinct effects of negative and positive bias. In this study, eye tracking data was collected and analyzed from n = 130 participants using mixed-effect and generalized linear models. Results revealed the interaction term (depression severity and stimuli valence) influenced dwell time on emotional stimuli, such that with an increase of 1 SD in depression severity (7.87 points on the Beck Depression Inventory-II), participants spent less 60 ms less time viewing sad stimuli and 25 ms less viewing happy

stimuli. A significant interaction of depression severity and valence also influenced participant's latency to first fixation. Increased depression severity (1 SD) was associated with increased odds of being slower to fixate on stimuli when it was sad (OR = 1.10) and when it was happy (OR = 1.03). There was no effect of depression severity or stimuli valence on latency to first fixation, nor an effect of depression severity on the proportion of trials where the first fixation was emotional or proportion of trials where dwell time for emotional areas of interest (AOIs) exceeded neutral. Internal consistency for emotional dwell time was high for both tasks (omega = .95 and .94 for the sad and happy versions, respectively), and split-half reliability for the outcomes was overall strong. Findings suggest depressed individuals may interact with stimuli differently at various levels of depression severity. Implications for future research are discussed.

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Introduction

Major depressive disorder (MDD) is the leading cause of disability worldwide (World Health Organization, n.d.), with high rates of relapse (Kessler et al., 1997), and multiple lifetime episodes of depression are the norm, rather than the exception (Boland et al., 2009). Despite the global burden of depression, current treatment outcomes have frustrated researchers, practitioners, and clients alike. In a multi-site study comparing the efficacy of cognitive therapy to antidepressant medication, less than half of patients achieved remission over the course of 16 weeks (DeRubeis et al., 2005). Furthermore, approximately two-thirds of patients who undergo cognitive therapy for depression either do not respond or relapse within a year of treatment (Dobson et al., 2008). In light of the fact that the majority of patients strongly prefer psychotherapy over medication, these findings provide cogent evidence for the need to elucidate mechanisms of depression and identify malleable treatment targets to improve cognitive-based therapies (van Schaik et al., 2004).

Information processing biases on the levels of attention, interpretation, and memory are central mechanisms of Beck's cognitive model of depression, making them attractive targets for intervention (Beck, 2008). Of particular interest are attentional biases posited to be implicated in both the etiology and maintenance of depressive episodes (Disner et al., 2011). Adults with depression demonstrate a pattern of bias toward negative stimuli not seen in adults without depression (Gotlib et al., 1988, 2004). In fact, adults without depression typically exhibit patterns of attention toward positive stimuli, but in depression, the pattern is reversed such that depressed individuals will avoid positive stimuli, a pattern that has been dubbed "double bias" (Duque & Vázquez, 2015; Peckham et al., 2010). These biases towards negative and away from positive stimuli are also thought to be distinct from each other (Shane & Peterson, 2007).

Under this conceptualization, depression is partly maintained by the individual absorbing greater amounts of negative information by preferentially attending to it, and filtering out positive information by attending away from it. Importantly, disengaging from attention to negative stimuli is also thought to be impaired and responsible for longer response times and fixation times on negative stimuli (Gotlib & Joormann, 2010; Koster et al., 2005). This difficulty disengaging from negative stimuli is also thought to be a component of rumination (De Raedt & Koster, 2010; Koster et al., 2005), which is known to play a role in the maintenance of depression (S. Nolen-Hoeksema, 2000) and is associated with worse outcomes (Susan Nolen-Hoeksema et al., 2008).

The 'gold standard' for measuring attention bias to date has been the dot-probe task (MacLeod et al., 1986), though it is not without fault (Schmukle, 2005). The dot-probe task presents participants with both emotional and neutral stimuli simultaneously, one on either side of the screen. Upon removal of the stimuli, a probe appears in the previous location of either the emotional stimuli (a congruent trial) or neutral stimuli (an incongruent trial). Longer response times for incongruent trials compared to congruent trials indicate attentional bias for emotional stimuli. Presumably, if the participant takes longer to respond to the probe when it is in the location of the neutral stimulus, it is because they were attending to the emotional stimulus. Conversely, faster reaction times when the probe is in the location of the emotional stimulus suggests the participant had already been attending to the stimuli in that location.

The literature has mostly supported evidence of biased attention in depression, though there have been some equivocal findings. Stronger evidence for attention bias is obtained when considering stimuli presented for durations of at least 1000 versus 500 ms (Bradley et al., 1997; Mogg et al., 1995), the use of the dot-probe task over the emotional Stroop task, and the use of

faces as stimuli over emotional words in the dot-probe (LeMoult & Gotlib, 2019). Conceptually, the process of attending to stimuli is one where the participant does not initially attend to the dysphoric stimuli (accounting for null findings under 500 ms), but once their attention is captured, they have difficulty disengaging and may continue to process the stimuli even after it has been removed (responsible for the increased response latencies seen at 1000 ms) (Gotlib & Joormann, 2010; MacLeod et al., 1986; Mathews & MacLeod, 2005).

Biased attentional processes are not believed to be merely concomitant with or consequences of depression, but to confer future vulnerability to new episodes. Formerly depressed patients exhibit bias towards negatively valenced faces (Joormann & Gotlib, 2007), as do never-depressed daughters of mothers with a history of depression (Joormann et al., 2007). Further, investigators have found attentional bias predicts both the onset and the course of depression. Fixation time on negative stimuli prospectively predicted the onset of future depressive symptoms in soldiers (Beevers et al., 2011). Individuals with stronger bias towards sad stimuli and greater reactivity following a mood induction exhibited more difficulty recovering after that event (Clasen et al., 2013) suggesting attention bias might help maintain negative mood states. Additionally, attention bias appears to predict future change in symptom severity several weeks ahead (Beevers & Carver, 2003; Disner et al., 2017). Taken together, these findings indicate attention bias may be implicated in the development, worsening, and persistence of depression, and that attention bias correlates with consequential metrics of depression severity and course.

Importantly, attentional bias is thought to not only confer risk, but to also play a causal role in the maintenance of depression. Prior research has found that manipulating attention bias through attention bias modification (ABM) can influence depression outcomes. Changes in

attentional bias are correlated with changes in depression symptoms in adults diagnosed with MDD (Beevers et al., 2015), and modification of attention bias through attention training reduces depression symptoms, suggesting that attention for negative stimuli is implicated in the maintenance of depression symptoms (Wells & Beevers, 2010). Further, positive attention bias training produces reductions in recurrence risk for depression, suggesting that these biases may also play a role in depression recurrence (Browning et al., 2012). Evidence has been mixed, however, and some results suggest ABM might only work for certain samples (Baert et al., 2010). Nevertheless, attention bias shows promise as a therapeutic target.

Conventional conceptualizations of attention bias as a stable, trait-like entity may account for many of the inconsistencies in the current literature. Traditionally, bias scores have been computed by subtracting reaction times of congruent trials from reaction times for incongruent trials; a positive score reflects bias toward emotional faces, and a negative score reflects bias away from emotional faces (Mogg et al., 1995). This method distills attention bias into difference scores of aggregate means across trials. However, there is mounting evidence that attention bias is a far more dynamic process than previously thought, and this aggregate means method might obscure the intricacies of attention bias. Additionally, reaction-time based metrics have been criticized for being a potentially poor proxy for attention (Armstrong and Olatunji, 2011). Eye-tracking metrics on the trial-level derived from free-viewing tasks may offer a better path towards advancing our understanding of attentional bias as a more proximal measurement of attention. Longer, free-viewing tasks may help shed light on more elaborative processing of stimuli, rather than capturing only one "snapshot" as reaction-time metrics do (Armstrong & Olatunji, 2012).

The present study examined measures of attentional bias derived from eye-tracking data collected via a free-viewing task. The task was modeled after the one described in Lazarov, Abend, and Bar-Haim (2016), except instead of neutral and disgust stimuli, we created two tasks: one utilizing neutral and happy stimuli, and one utilizing neutral and sad stimuli. Lazarov and colleagues also developed a similar free-viewing task for depression; however, the task combined both happy and sad faces within the matrix (Lazarov et al., 2018). The authors highlighted that while this made the task more efficient, it restricted their ability to tease apart the independent effects of happy and sad biases. Thus, in the present study, we had two separate tasks consisting of happy and neutral faces, and sad and neutral faces, in order to examine the influence of these biases more clearly. Additionally, we felt it was important to keep the entire task as single valence (e.g. sad/neutral or happy/neutral) as opposed to alternating valence in each trial so that we could look at trial-by-trial fluctuations in attention. In addition to testing the psychometrics of the task with new stimuli, we also examined several trial-level outcomes within mixed-effects models: dwell time on emotional areas of interest (AOIs) per trial; latency to first fixation; and length of first fixation. Dwell time was calculated by summing up the fixations on either emotional or neutral AOIs in each trial. We also examined two summary-level outcomes (e.g. collapsing across trials): the proportion of trials where the first fixation was on emotional stimuli; and the proportion of trials where total fixation time for emotional stimuli exceeded neutral stimuli.

Methods

Participants

Participants were n = 130 undergraduate college students who received course credit for their participation. Originally, n = 138 participants completed the study but 8 were excluded for missing data for one of the two tasks, or missing the majority of the trials in the task (due to a technical malfunction). Participants were eligible for the study so long as they were (a) between the ages of 18-45 years old; (b) able to speak, read, and understand English fluently; and (c) willing and able to provide informed consent. The study was approved by the university Institutional Review Board and all participants gave written consent to participate.

Average age was 19.4 (SD = 1.4) and the sample was majority female (56.2%). The majority of the sample was white (48.5%) and non-Hispanic (67.7%). While we did not recruit for a clinical sample, all participants were administered a depression scale (Beck Depression Inventory-II). The average depression score was 9.1 (SD = 7.9). Full participant demographics can be found in Table 1.

Ethical approval for the study was given by the University of Texas at Austin Institutional Review Board gave approval for the study and prior written consent was obtained from all participants.

Materials

Depression severity was measured using the Beck Depression Inventory (BDI-II; (Beck et al., 1996). The BDI-II is a widely-used 21-item questionnaire that measures the "core" symptoms of depression as defined by the Diagnostic and Statistical Manual (DSM-5; (American

Psychiatric Association, 2013)), as well as other cognitive, motivational, and physical symptoms. Past research has documented decent test-retest reliability and validity for the BDI-II. In the present study, we administered a 20-item version that excluded the suicidal ideation item. Internal consistency for the 20-item BDI was strong (alpha = .91, 95% CI[.87, .93]).

APPARATUS

Eye position was measured using a video-based eye-tracker (EyeLink 1000 Plus Desktop Mount; SR Research, Osgoode, ON, Canada). Sampling was done at a rate of 250 Hz using the participant's dominant eye. Stimulus presentation was controlled by OpenSesame, a graphical experiment builder, with the back-end set to utilize PsychoPy (Mathôt et al., 2012). Data acquisition utilized Eyelink software. Stimuli were presented on a 23.6-inch CRT monitor (ViewPixx; VPixx Technologies, Quebec, Canada), at a screen resolution of 1920 x 1080 pixels (120 Hz refresh rate). Data was processed using Eyelink Data Viewer.

EYE-TRACKING TASK AND STIMULI

Stimuli were chosen from the FACES dataset, which was developed to create a naturalistic dataset of facial expressions from people of varying ages (Ebner et al., 2010). The total dataset consists of n = 2,052 photos taken of young, middle-aged, and older men and women. All models used for the image database were Caucasian and did not have any distinctive features (e.g. beards, piercings, etc). In our task, we did not use the older actor photos and drew from the young and middle-aged pools evenly.

In order to ensure stimuli were unambiguous (e.g. neutral faces could not be mistaken for sad faces), images were chosen based on previously documented accuracy ratings of the emotional faces (i.e. the percentage of raters who accurately identified the intended emotion;

(Ebner et al., 2010). Image file names were sorted by their accuracy rankings for the image, and the highest-ranked stimuli were chosen. We chose the top stimuli from the list, with a few exceptions: since we needed an equal balance of genders and ages (described below), once the quota for a particular demographic characteristic was filled, we skipped to the next available image of the desired group. For instance, if we already reached the needed number of female happy faces, we skipped over female faces to get to the next highest-ranked male face. Additionally, when we later cropped the images to be 200 x 200 pixels, if an actor's face was partially cropped, the image was replaced with the next best stimuli to ensure eye gaze was not drawn to the face because of the crop. (Note: Each matrix contained one emotional face and one neutral face by that same actor. We prioritized the ranking of whichever emotion was poorer. For instance, if accuracy for sad images had been lower than neutral, we would sort by the sad accuracy rankings and choose the corresponding neutral images to the "best" sad stimuli. However, if the accuracy for neutral images had been lower, we would have prioritized the accuracy of those stimuli first).

In designing the task, we followed the parameters used by Lazarov, Abend, and Bar-Haim (2016). For each task, we chose 64 photos of 16 male and 16 female actors, each contributing a neutral and emotional expression. These photos were randomly separated into four pools containing 16 images each. Fifteen trials were generated from each pool for a total of 60 trials. The pools were generated with the following constraints: (a) each actor could appear only once on the matrix, (b) there was an even split of genders in each matrix (8 male and 8 female), (c) there was an even split of valences in each matrix (e.g. 8 neutral and 8 sad), and (d) the four inner faces always contained two emotional and two neutral faces. We did not exclude faces that exposed teeth as we excluded faces that became partially cropped and wanted to keep the images

with the highest emotion ratings. The 60 unique matrices were randomized so that each participant saw them in a different order, but all received the same stimulus presentations at some point in the task. An example trial is presented in Figure 1.

EYE-TRACKING MEASURES

Within each matrix, sixteen areas of interest (AOIs) were generated, but for the purpose of these analyses, they were collapsed into two categories: neutral and emotional AOIs. Consistent with Lazarov, Abend, and Bar-Haim (Lazarov et al., 2016), we generated several trial-level outcome variables: dwell time on emotional AOIS, latency to first fixation, and length of first fixation. Given the right-skewed distributions of the latency to first fixation and length of first fixation, we restructured these two as binarized variables using a median split. Additionally, we computed two additional summary-level variables (e.g. collapsed across trials for each participant): the proportion of trials where the first fixation was an emotional fixation, and the proportion of trials where dwell time was greater for emotional AOIs than neutral AOIs.

PROCEDURE

Participants were told they were taking part in a study attempting to better understand how people interact with facial stimuli. The experiment consisted of two separate tasks which utilized sad and neutral faces in the matrices, or happy and neutral faces. Each participant completed both tasks in a counterbalanced order. Participants sat in an illuminated room (12.0 cd/m2) at a distance of 60 cm from the screen. Each subject's dominant eye was determined using a modified version of the near-far alignment task (Miles, 1930). Prior to beginning the task, a thirteen-point calibration routine was used to map the subject's gaze onto the screen coordinates.

Both versions of the task consisted of 60 trials separated into 2 blocks. A fixation dot was presented for 1000 milliseconds, followed by the matrix stimulus presentation for 10,000 milliseconds. Each free-viewing task took approximately 11 minutes to complete. Both versions of the task began with a practice trial. Participants were first presented with a fixation dot and told to fixate on it when it appeared. Subjects were then given instructions to look at the images in the matrix freely and naturally. Between each 30-trial block, participants were encouraged to take a break to rest their eyes, as well as between tasks.

DATA ANALYSIS

Data analysis was conducted in R (version 4.0.0) and made extensive use of the tidyverse packages, as well as an in-house package itrak developed for processing eye-tracking data (https://github.com/jashu). Mixed effects models were run using the lmerTest package (Kuznetsova et al., 2017). All analysis code can be found in a supplementary document titled, "Matrix Analyses.Rmd" located on the Texas Data Repository at https://doi.org/10.18738/T8/IYR8MP.

We tested for evidence of biased attentional processing by fitting five models. First, we examined dwell time on emotional AOIs using a mixed-effects model. The interaction between depression severity and stimuli valence was treated as a fixed effect, and the two random effects were random slope of trial and random intercept with respect to participant, and random intercept with respect to stimulus presentation.

The second model was a generalized linear mixed-effects model for the binarized latency to first fixation outcome, calculated using a median split. We first attempted to fit a linear mixed-effects model to the latency outcome, modeled as a continuous variable. However, upon running residual plots to test model assumptions, both the normality and homoscedasticity assumptions

were found to be violated. We then converted the outcome into a binary variable, using a median split because of the right-skewed distribution of the variable. We then tested an interaction between depression severity and stimuli valence as a fixed effect, and the two random effects of random slope of trial and random intercept with respect to participant, and random intercept with respect to stimulus presentation.

The third model also underwent the same process of testing for assumption violations and transformation of the outcome variable as model 2. The final model was a generalized linear mixed-effects model for binarized length of first fixation, again created using a median split. We first tested the model also including the same fixed and random effects as the first two models, but the model failed to converge. Therefore, we iterated through the appropriate random effects in accordance with the guidelines set forth by (Barr et al., 2013) until the model converged. In this model, the interaction of depression severity and stimuli valence was again a fixed effect in the model, but the random effects were limited to random slope of trial and random intercept for participant.

Finally, in the fourth and fifth models, a generalized linear model with a quasibinomial distribution was used to model the effect of depression severity on each of the summary-level outcomes. The fourth model examined the proportion of trials where the first fixation was on emotional stimuli. The fifth and final model examined the effect of depression severity on the proportion of trials where dwell time for emotional AOIs exceeded dwell time for neutral AOIs. Because these models utilized summary-level statistics, the models had to be done separately for each stimulus valence.

Results

PSYCHOMETRICS

To calculate split-half reliability we calculated Spearman's correlations with a 95% confidence interval using 10,000 bootstrapped iterations. For the sad task version, mean dwell time for emotional AOIs had strong reliability (r = .91, 95% CI [.88, .95]). Mean latency to first fixation was also strong (r = .66, 95% CI [.56, .78]), as was mean length of first fixation (r= .63, 95% CI [.51, .75]). The metric indicating the proportion of trials where the first fixation was on a sad AOI also had weak reliability (r = 0.05, 95% CI [-0.12, .22]), and the proportion of trials where dwell time for emotional AOIs exceeded dwell time for neutral AOIs was fair (r =.40, 95% CI [.24, .56]).

The happy version had strong reliability as well for mean dwell time for happy AOIs (r = .85, 95% CI [.79, .91]), and good reliability for mean latency to first fixation (binarized) (r = .56, 95% CI[.43, .69]). Mean length of first fixation was also good (r =0.59, 95 % CI [.46, .73]. The metric indicating the proportion of trials where the first fixation was on a happy AOI was poor (r = -0.05, 95% CI [-0.23, .13]), and the proportion of trials where dwell time for emotional (happy) AOIs exceeded dwell time for neutral AOIs was fair (r =.33, 95% CI[.16, .51]).

Internal consistency was calculated for each task using the omega function in the psych library. The omega value for emotional dwell time in the sad task was 0.95, indicating strong internal consistency. Nearly all of the stimulus presentations mapped onto one general factor (plots of the factor structure can be found in the supplementary materials). The happy version of the task was similarly strong, with an omega value of 0.94 and nearly all stimulus presentations mapping onto a general factor.

MODEL ONE

For the mixed-effects model predicting dwell time on emotional AOIs, the interaction between BDI score and valence was significant (B = -0.0598, SE = 0.0187, p = .0014). Full results can be found in Table 2, and an effects plot can be found in Figure 2. This corresponds to a 60 ms decrease in dwell time for every 1 standard deviation increase (7.87 points) in the BDI-II when stimuli valence was sad, relative to a BDI of 0 when the participants are viewing the happy stimuli. In other words, with a 7.87-point increase in BDI score, dwell time on emotional stimuli decreases by 60 ms when viewing sad faces, and 25 ms when viewing happy faces. This indicates that participants who had higher depression severity spent less time engaging with the sad stimuli over the course of the trial.

MODEL TWO

In the binarized latency to first fixation generalized linear model, the interaction term predicted higher odds of slower latency to first fixation odds ratio (*OR)* = 1.10, 95% CI [1.02, 1.18], p = .008. These results indicate that a participant with greater depression severity and viewing the sad stimuli would have 1.10 increased odds of taking longer (e.g. slower) to fixate on the first image than a participant with a BDI score of 0 viewing the happy stimuli. In other words, a 7.87-point increase in BDI score is associated with a 1.10 increase in odds of being slower to fixate on the first image when the stimuli are sad and neutral, compared to a 1.03 increase in odds when the stimuli are happy and neutral. Full results for this model can be found in Table 3, and an effects plot can be found in Figure 3.

MODEL THREE

Model three was a generalized mixed-effects model predicting the binarized length of first fixation. Neither the interaction term nor main effects were significant for this model, *OR* = 1.00, 95% CI [0.93, 1.07], p = .950. Full results can be found in Table 4, and an effects plot in Figure 4.

MODEL FOUR

In the fourth model, a generalized linear model with a quasibinomial distribution was fit to predict the proportion of trials where the first fixation was on emotionally-valenced stimuli. Two separate models were run for sad stimuli and happy stimuli. There was not a significant effect of depression severity in predicting increased odds of emotional first fixations in either the sad task, *OR* = 1.01, 95% CI [0.97, 1.05], p = .758, or the happy version of the task, *OR* = 1.01, 95% CI [0.96, 1.06], p = .630. Full results for both the sad and happy models can be found in Table 5, and plots of the results in Figure 5.

MODEL FIVE

The final model was also a generalized linear model with a quasibinomial distribution, this time fit to predict the proportion of trials where dwell time for emotional AOIs exceeded dwell time for neutral AOIs. Again, there was not a significant effect of depression severity in predicting the odds of having more trials with greater emotional dwell time in either the sad task, *OR* = 1.03, 95% CI [0.96, 1.10], p = .435, or the happy version of the task *OR* = 0.99, 95% CI [0.92, 1.06], p = .693. Full results can be found in Table 6 and plots in Figure 6.

Discussion

In the present study, we developed and tested two free-viewing eye-tracking tasks utilizing either happy or sad facial stimuli. Each task consisted of 60 trials separated into 2 blocks, with each trial lasting for 10-seconds (total task time was approximately 11 minutes each). Stimuli for this task were carefully chosen based on accuracy scores of viewers aiming to name the emotional expression, with the hope that the emotional and neutral stimuli would be distinct and unambiguous. Additionally, sad and happy stimuli were separated into different tasks effects of negative and positive biases. Finally, our data was analyzed on a trial level, allowing for insight into the potentially dynamic nature of attention bias.

We examined the psychometric properties of several metrics derived from the eye-tracking data, and found both tasks to have strong overall internal consistency, with nearly all stimulus presentations mapping onto a general factor. We then examined whether attention was influenced by depression severity, and if that effect differed across stimuli valence, as well as the potential influence of stimulus presentation and trial number. We found evidence that depression severity and task valence interact to influence dwell time on emotional stimuli. Specifically, for every 1 SD increase in BDI-II score (7.87 points), participants spent 60 ms less looking at emotional stimuli when those stimuli were sad, compared to participants with a BDI-II score of 0 looking at happy stimuli. In other words, contrary to our hypothesis, more depressed participants showed evidence of biased attention by spending less time engaging with sad stimuli.

We also found a significant effect of the interaction of depression severity and stimuli valence on latency to first fixation, such that participants with greater depression severity had higher odds of taking longer to fixate on the first AOI when they were looking at sad stimuli (*OR)* = 1.10, 95% CI [1.02, 1.18], p = .008. This was also contrary to our hypothesis, as

participants were more likely to be slow to fixate when they were presented with sad stimuli and were more depressed. None of the other models found evidence for biased attentional processing in the outcomes of interest.

None of the models for length of first fixation, proportion of trials where the first fixation was emotional, or proportion of trials where dwell time for emotional AOIs exceeded neutral AOIs, were significant. It is worth noting that the outcome metrics that could not be reliably predicted were also the metrics with the worst split-half reliability.

These results differ from previous findings suggesting that depressed individuals maintain their gaze on negative stimuli for longer than on positive stimuli during a free-viewing task, and orient less to positive stimuli (Armstrong & Olatunji, 2012). One explanation is that our sample was not a clinically depressed sample, and overall depression severity was low (M = 9.1). Armstrong and Olantunji had found the aforementioned effect to be strongest in individuals meeting full diagnostic criteria for Major Depressive Disorder; according to the clinical cutoffs of the BDI-II, only 13% of our sample would have fallen in the moderate-to-severe depression range. It is possible that there are moderating effects by depression severity levels, and our mildly depressed group may exhibit a different pattern than a more clinically depressed group would have.

Lazarov et al. 's 2018 study blended happy and sad stimuli within the same free-viewing task, and found evidence that individuals who were clinically-depressed and had higher depressive symptomology fixed longer on sad faces than did individuals with low depressive symptomology (e.g. PHQ-9 < 4). Additionally, they also found that students with low depression scores had a longer dwell time on happy faces (Lazarov et al., 2018). At first glance, this finding could be interpreted as evidence of greater dwell time on positive stimuli in individuals with

lower levels of depression. However, as the authors pointed out, it is difficult to interpret the directionality of bias with happy and sad stimuli in the same task. Lazarov et al.'s results therefore could also be construed as avoidance of negative stimuli by individuals with minimal depression symptoms. Future studies should investigate for evidence of differential patterns of attention by depression severity.

Our finding of slower latency to first fixation also differs from the literature in two ways. First, others have found latency to first fixation to be an unreliable metric (Lazarov et al., 2016), while our binarized variable for latency to first fixation had good reliability for both the sad and happy tasks (*rs* = .31 and .57, respectively). Additionally, while others have not found differences by depression status in latency to first fixation, in our sample higher depression severity was associated with higher odds of slow fixation on the first AOI in the sad task.

Taken together, these results suggest that individuals with greater depression symptoms may interact with emotional facial stimuli differently from their less-depressed peers. Contrary to previous research that suggests individuals with depression have a preference for negative stimuli, individuals with higher levels of depression spent less time looking at emotional stimuli when those stimuli were sad. It will be important for future research to examine more closely how changes in attentional bias may unfold over time. For example, much of our current theory that attention bias in depression is characterized by increased engagement with negative stimuli comes from research done with the traditional dot-probe task. It is important to remember that the dot probe only measures where participants were looking at one point in the trial: the moment before the reaction-time response was elicited. Eye-tracking data of free-viewing tasks, on the other hand, give information about how participants interact with stimuli over the course of the whole trial. Using tasks with prolonged view time (Gotlib & Joormann, 2010) and complex

stimulus presentations (Lazarov et al., 2018) may highlight within-trial fluctuations in attentional bias and individual-level differences in how attentional processing unfolds.

However, these results should be interpreted with some caution. We did not recruit for a depressed sample, and the overall mean depression severity for the sample was low. Further evaluation with a more clinically-oriented sample is needed to assess whether these metrics are truly affected by depression severity. Additionally, this sample is young (M = 19.4 years old) and rather homogenous, and may not represent a generalizable sample. Additionally, it should be noted there are a wealth of other metrics that can be derived from the eye-tracking data output. The metrics chosen for this study were chosen based on precedence in the literature and an attempt at approximating indices of bias similar to those generated in previous research. However, it is certainly possible that better metrics of attention bias with better psychometric properties exist. In addition to utilizing better computer tasks, future research should explore the optimal parameters of gaze data.

These findings serve as preliminary support for a novel eye-tracking task paradigm adapted for depression. Future research could examine optimal metrics derived from the task, and further evaluate the influence of depression severity and stimuli valence on attentional processing.

Figures

Figure 1. Sample Trial: Matrix Stimulus Presentation

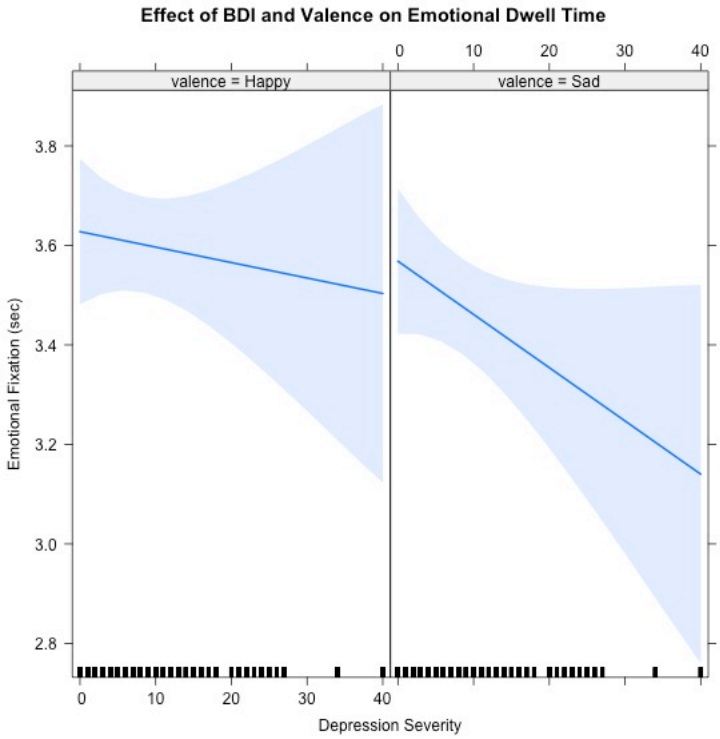

Figure 2. Model One Effect Plot

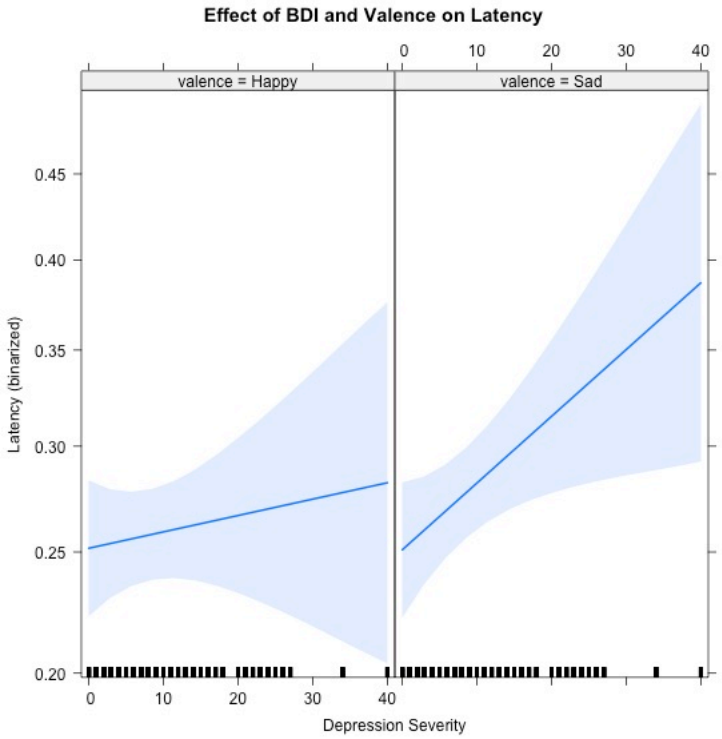

Figure 3. Model Two Effect Plot

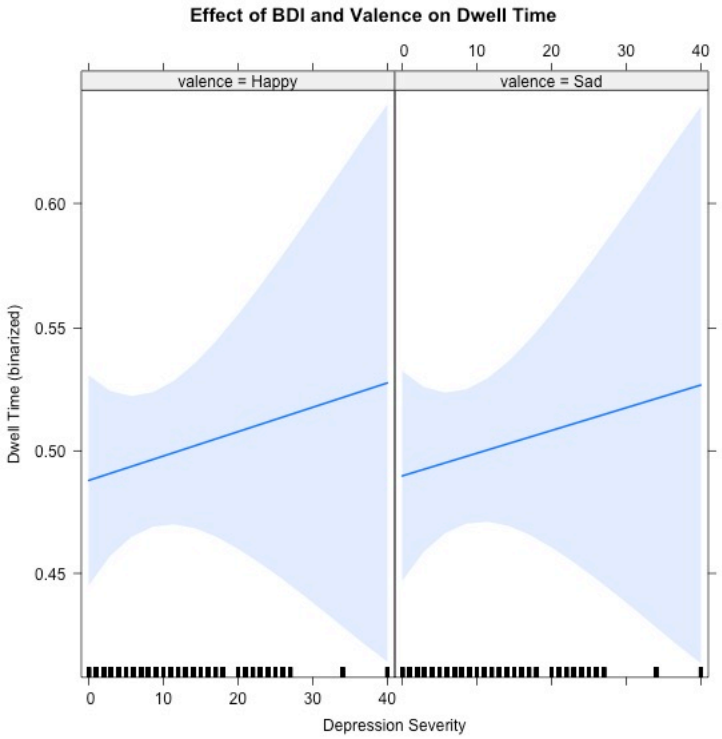

Figure 4. Model Three Effect Plot

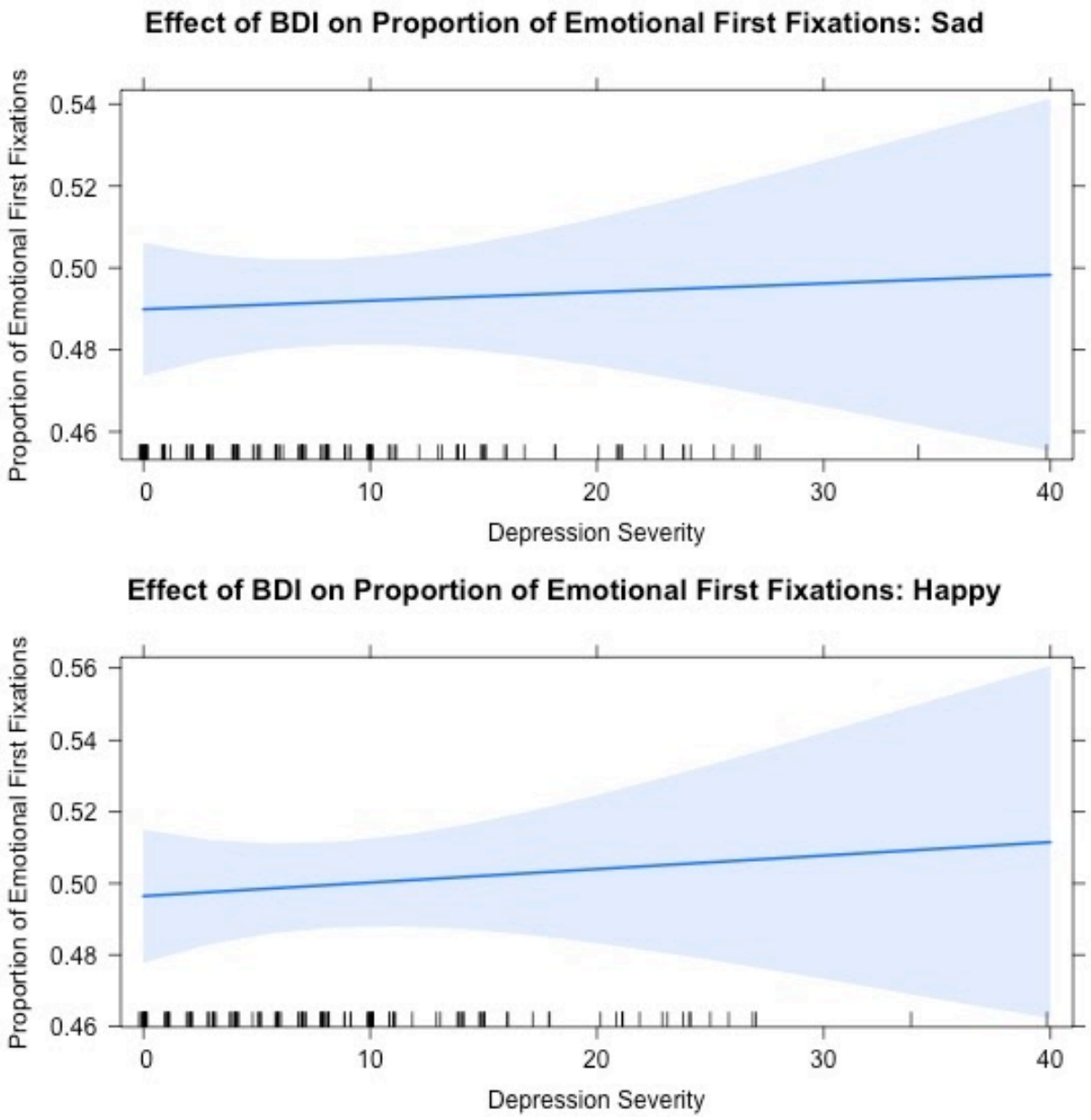

Figure 5. Model Four Plots

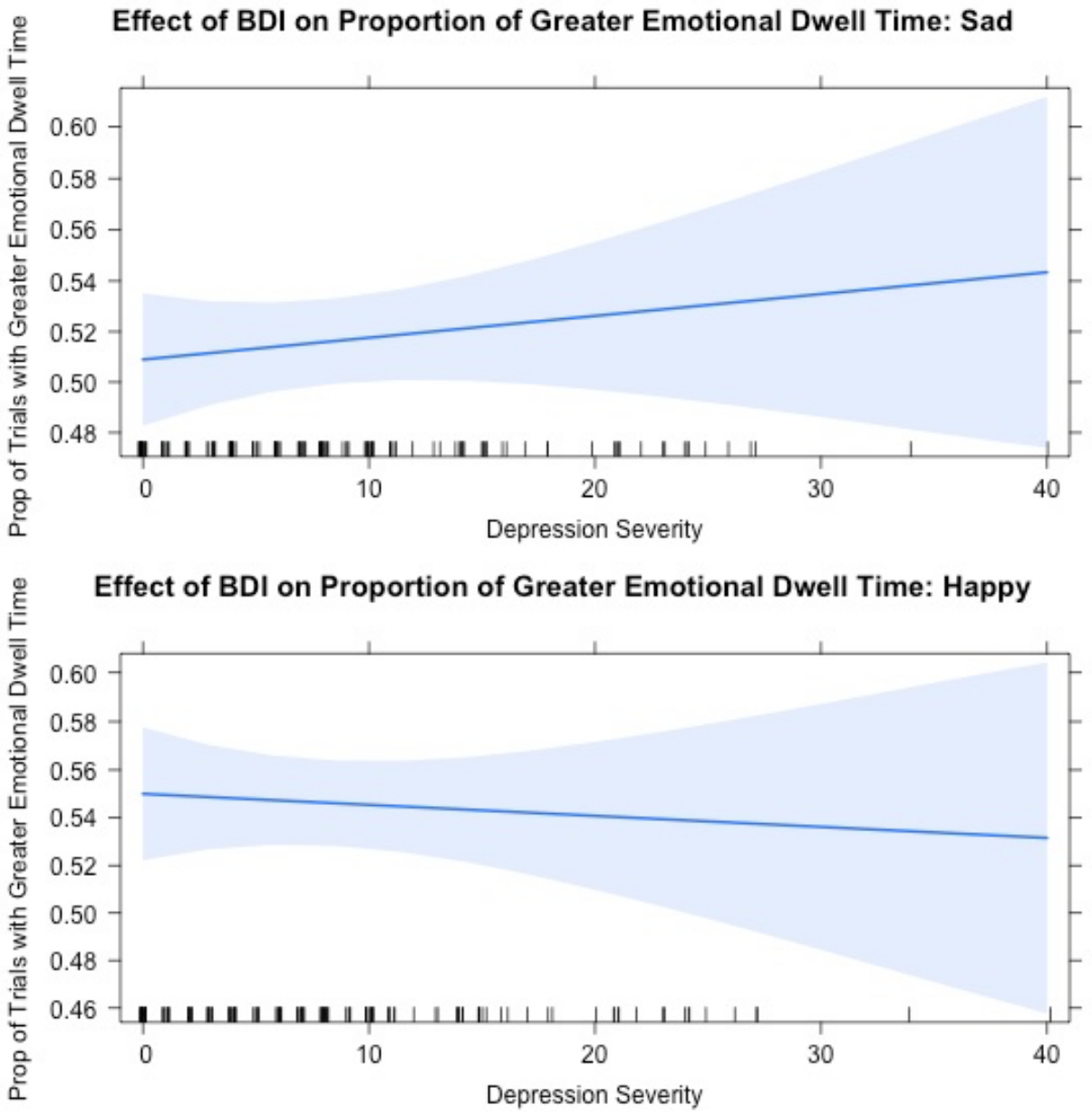

Figure 6. Model Five Plots

Tables

Table 1. Participant Demographics

Characteristic	N = 130
Age in years, mean (SD)	19.4 (1.4)
Female gender (%)	73 (56.2%)
Hispanic ethnicity (%)	42 (32.3%)
Race (%)	213 (99.1%)
American Indian/Alaska Native	4 (3.1%)
Asian	38 (29.2%)
Black or African American	8 (6.2%)
White	63 (48.5%)
Multiracial	7 (5.4%)
Unknown or not reported	10 (7.7%)
Single (%)	129 (99.2%)
Years in school (SD)	13.9 (1.1)
Household Income (%)	
$0 – $24,999	16 (12.3%)
$25,000 – $49,999	16 (12.3%)
$50,000 – $74,999	12 (9.2%)
$75,000 - $99,999	27 (20.8%)
$100,000 +	59 (45.4%)
BDI-II (SD)	9.1 (7.9)

Table 2. Mixed-Effects Model Predicting Dwell Time on Emotional AOIs

Effect	Variance	Estimate (SE)	t	Pr(>|t|)
Emotional Dwell Time				
Random Effects				
Participant				
Intercept	0.3113			
Trial	0.5148			
Stimuli				
Intercept	0.0106			
Fixed Effects				
Intercept		3.6280 (0.0744)	48.728	<.0001***
BDI		-0.0245 (0.0479)	-0.5160	0.6104
Valence (reference = Sad)		-0.0594 (0.0342)	-1.734	0.0834
BDI:Valence		-0.0598 (0.0187)	-3.204	0.0014**

For BDI, 1 unit = 1 SD (7.87 points)
*** indicates significance at the .01 level*
****indicates significance at the .001 level*

Table 3. Generalized Mixed-Effects Model Predicting Latency to First Fixation (Binarized)

Effect	Variance	B (SE)	OR	95% CI (OR)	z-value	Pr(>|z|)
Random Effects						
Participant						
Intercept	0.2270					
Trial	0.3717					
Stimuli						
Intercept	0.0021					
Fixed Effects						
Intercept		-1.0897 (0.0823)	0.3363	0.2857, 0.3952	-13.247	< .0001 **
BDI			1.0311	0.9279, 1.1461	0.572	0.5675
		0.0306 (0.0536)				
Valence			0.9963	0.8910, 1.1139	-0.066	0.9476
(reference = Sad)		-0.0037 (0.0569)				
BDI:Valence			1.0988	1.0248, 1.1783	2.647	0.0081 **
		0.0942 (0.0356)				

For BDI, 1 unit = 1 SD (7.87 points)
*** indicates significance at the .01 level*

Table 4. Generalized Mixed-Effects Model Predicting Length of First Fixation (Binarized)

Effect	Variance	B (SE)	OR	95% CI (OR)	z-value	Pr(>|z|)
Random Effects						
Participant						
Intercept	0.3695					
Trial	0.0698					
Fixed Effects						
Intercept		-0.0485 (0.0877)	0.9528	0.8013, 1.1328	-0.551	0.582
BDI		0.0314 (0.0576)	1.0319	0.9211, 1.1561	0.545	0.585
Valence (reference = Sad)		-0.0021 (0.0512)	1.0073	0.9111, 1.1137	0.143	0.886
BDI:Valence		-0.0003 (0.0334)	0.9979	0.9347, 1.0653	-0.063	0.950

Table 5. Generalized Linear Model Predicting Proportion of Trials where First Fixation was on Emotional Stimuli

Sad	B (SE)	OR	95% CI (OR)	t-value	Pr(>|t|)
Coefficients					
Intercept	-0.0405 (0.0329)	0.9603	0.9003, 1.0243	-1.232	0.220
BDI	0.0066 (0.0215)	1.0067	0.9651, 1.0501	0.308	0.758
Happy	B (SE)	OR	95% CI (OR)	t-value	Pr(>|t|)
Coefficients					
Intercept	-0.0142 (0.0377)	0.9859	0.9157, 1.0615	-0.377	0.707
BDI	0.0119 (0.0246)	1.0120	0.9643, 1.0621	0.483	0.630

Table 6. Generalized Linear Model Predicting Proportion of Trials Where Dwell Time for Emotional AOIs Exceed Dwell Time for Neutral AOIs

Sad	B (SE)	OR	95% CI (OR)	t-value	Pr(>|t|)
Coefficients					
Intercept	0.0358(0.0531)	1.0364	0.9340, 1.1502	0.674	0.502
BDI	0.0273 (0.0348)	1.0276	0.9600, 1.1002	0.784	0.435
Happy	B (SE)	OR	95% CI (OR)	t-value	Pr(>|t|)
Coefficients					
Intercept	0.2010 (0.0566)	1.2226	1.0942, 1.3663	3.548	<.0001***
BDI	-0.0146 (0.0370)	0.9855	0.9165, 1.0597	-0.396	0.6931

*** *indicates significance at the .001 level*

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