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A Computational Account of the Mechanisms Underlying Face Perception Biases in Depression

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Here, we take a computational approach to understand the mechanisms underlying face perception biases in depression. Thirty participants diagnosed with major depressive disorder and 30 healthy control participants took part in three studies involving recognition of identity and emotion in faces. We used signal detection theory to determine whether any perceptual biases exist in depression aside from decisional biases. We found lower sensitivity to happiness in general, and lower sensitivity to both happiness and sadness with ambiguous stimuli. Our use of highly-controlled face stimuli ensures that such asymmetry is truly perceptual in nature, rather than the result of studying expressions with inherently different discriminability. We found no systematic effect of depression on the perceptual interactions between face expression and identity. We also found that decisional strategies used in our task were different for people with depression and controls, but in a way that was highly specific to the stimulus set presented. We show through simulation that the observed perceptual effects, as well as other biases found in the literature, can be explained by a computational model in which channels encoding positive expressions are selectively suppressed.

General Scientific Summary
This study found that participants with depression are impaired in their ability to detect happiness in faces, and in their ability to detect both happiness and sadness in ambiguous faces. Our model-based signal detection analysis suggests that these effects are perceptual rather than decisional in nature.

Keywords: information processing biases, perception, depression, emotion

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Cognitive models of depression suggest that the development and maintenance of this disorder stem from individuals' characteristic ways of attending to, interpreting, and remembering stimuli in their environment, such as selective attention toward negative aspects of experience or interpreting objectively ambiguous information as negative (Beck, 2008; Disner et al., 2011). Biased attention and cognition have been associated with sustained negative affect (e.g., Bar-Haim et al., 2007; Peckham et al., 2010); affective psychopathology (e.g., Bar-Haim et al., 2010; Wilkinson & Goodyer, 2006); and prediction of future development of depression (e.g., Abela & Hankin, 2011; Beevers et al., 2011). Thus, there is considerable support for cognitive models of depression (for reviews, see Disner et al., 2011; Gotlib & Joormann, 2010).

One of the ways in which biases are expressed in depression is in the processing of face emotion. In-depth reviews and meta-analyses (e.g., Bistricky et al., 2011; Bourke et al., 2010) have concluded that people with depression show a bias toward interpreting ambiguous faces (e.g., neutral or morphed) as expressing negative emotion, and a general impairment in processing of emotional faces. Interpersonal theories of depression posit that depressed individuals are particularly alert for signs of interpersonal rejection or negative feedback in an effort to reduce social rejection (Joiner & Metalsky, 1995; Surguladze et al., 2004). Indeed, depression is commonly accompanied by impairments in social functioning (Bistricky et al., 2011; Surguladze et al., 2004). Biased processing of expression information might be a key mechanism producing or exacerbating such impairments, as decoding facial expression

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correctly is critical for adequate social interaction (Leppänen & Hietanen, 2001; Marsh et al., 2007).

Currently, there is little understanding of the mechanisms underlying face processing biases in depression. A first important question is whether or not there are any perceptual mechanisms underlying such biases (i.e., people with depression perceiving emotional expression differently), aside from any decisional or cognitive mechanisms (i.e., people with depression interpreting emotional expression differently). Because there is evidence of higher-level biases in depression, the simplest explanation is that face processing biases are decisional in nature. Whether biases are perceptual or decisional has an impact on how they should be addressed in treatment. Reducing perceptual biases is likely to require extensive feedback-based training like that provided by attentional bias modification (ABM; Bar-Haim, 2010; Macleod, 2012), aimed at inducing perceptual and attentional effects. Decisional biases can be manipulated through short training interventions and verbal instructions (Ashby et al., 2001), and might not require special treatment beyond traditional therapy.

Similarly, whether or not depression affects face perception could have an impact on how generalizable the results of ABM and other forms of feedback learning are. Generalization of learning increases when task-relevant stimulus features are "separable" from irrelevant stimulus features (Garner, 1974; Goldstone, 1994); separable features are those that can be selectively attended and processed independently from one another.

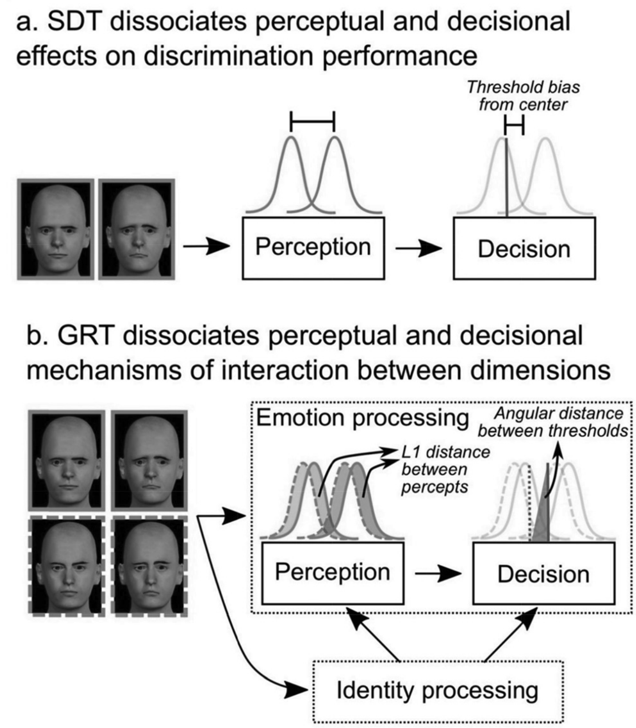
In ABM, the relevant task features are those related to face emotion, whereas the most common irrelevant features are those related to face identity. In healthy participants, learning involving such face dimensions generalizes well, similarly to traditional separable dimensions (Soto & Ashby, 2019). A deficit in the separability of emotion from identity would impair generalization of ABM-induced learning to new faces. The sum of our current knowledge about this issue comes from a single study (Gilboa-Schechtman et al., 2004), which found that depressed participants had more trouble than controls ignoring emotional expression while processing face identity. Again, it is not clear whether such results were due to perceptual versus decisional factors.

Dissociating Perceptual Versus Decisional Mechanisms of Bias

The most influential framework used to dissociate the contribution of perceptual and decisional processes in perceptual tasks is signal detection theory (SDT; Green & Swets, 1966). Imagine that the task of an individual is simply to indicate whether the faces shown in Figure 1a show a sad expression. According to SDT, this process involves two steps. First, the perceptual system extracts sensory evidence that the face is showing a sad expression, as represented by the "Perception" box in Figure 1a. This process is influenced by perceptual noise, so the presentation of the same face in different occasions should lead to different levels of sensory evidence. Such noisy representations are represented in Figure 1a by two normal distributions, one for the neutral face (red or left side) and one for the sad face (blue or right side). In this example, both distributions have a standard deviation equal to one, so the distance between their means represents d', a commonly-used measure of perceptual discriminability. Second, the observer sets up a decision bound, represented by the "Decision" box in Figure 1a. This is a threshold indicating how much sensory evidence is required to decide that the face is showing

Figure 1

Schematic Explanation of the Assumptions Behind SDT (a) and GRT (b)



Note. SDT = signal detection theory; GRT = general recognition theory.

a sad expression. The lower this bound, the more bias exists to indicate that the face is sad. SDT provides ways to separately quantify these perceptual and decisional factors.

In the traditional analysis of a discrimination task, an overall proportion of correct responses is computed from the trials in which the participant correctly identifies face emotion. SDT can dissociate between perceptual and decisional factors because it uses more detailed information about patterns of errors. For example, moving the threshold in Figure 1a to the right would result in more correct identifications of neutral faces (the participant would change a bias to respond "sad" for a bias to respond "neutral"), but at the cost of more errors in the identification of sad faces. The full pattern of correct responses and errors, together with the constraints imposed by the model (e.g., the assumption of normally distributed noise), allows to independently infer d' and bias from data.

The extension of SDT to multiple perceptual dimensions, known as general recognition theory (GRT; for a review, see Ashby & Soto, 2015), allows researchers to study how different stimulus components interact during processing. According to GRT, processing of one face property can affect processing of a second face property both at the perceptual and decisional levels. Figure 1b shows an example. As before, imagine that the task is to detect sadness in a face. However, now the face will also vary in identity. In Figure 1b, the top faces correspond to one identity, and the bottom faces correspond to another (although they might look very similar to some readers). As in SDT, emotion processing of each face involves a perceptual stage, in which the stimulus produces a noisy representation of evidence for sadness, and a decision stage, in which a threshold is used to determine whether the evidence is high enough to report sadness in the face.

As shown in Figure 1b, the processing of identity in the faces can interact with emotion processing in two ways. The first way is perceptual: Changes in identity could affect how face emotion is perceived. For example, focus on the two blue distributions, representing stimuli showing sadness. The top identity is represented by a distribution drawn with a solid line, and the bottom identity by a distribution drawn with a dotted line. The area between the two distributions, shaded in blue, is a measure of their distance commonly known as *L1* distance. It measures to what extent changes in identity produce changes in perceptual representations of sad faces. Similarly, it is possible to measure the *L1* distance between the two faces showing a neutral expression (area shaded in red on the left side). Note how in this example the actual discriminability of emotion, measured through d' (i.e., the distance between the solid red and blue (right) distributions, and between the dotted red (left) and blue (right) distributions), is the same across identities. However, identity clearly influences perception of sadness. In GRT, this is known as a violation of perceptual separability, and it is different from discriminability.

The second way in which processing of identity and emotion can interact is at the level of decision making, as shown in the right part of Figure 1b. The threshold used to make decisions about sadness might change depending on face identity. This is represented by two different thresholds in Figure 1b, one to determine sadness in the top identity (solid green or right) and the other to determine sadness in the bottom identity (dotted green or left). In GRT, this interaction is known as a violation of decisional separability, and it can be measured by the distance between bounds (angular distance is preferred due to the way in which the model is implemented).

To the best of our knowledge, only one study in children has used SDT to dissociate perceptual and decisional contributions to face biases in depression (Schepman et al., 2012), although other researchers have attempted the dissociation through other means (Gilboa-Schechtman et al., 2008; Surguladze et al., 2004). Clearly, there is a lack of research determining whether depression produces biases in the perception of facial expression, beyond the cognitive and decisional biases that it produces.

The Current Study

Here, we use SDT to dissociate perceptual and decisional mechanisms underlying face processing biases in depression, by performing a model-based analysis of data from a face identification task. The task involves four stimuli, which result from the combination of two face properties (identity and emotion) with two levels each (e.g., Joe vs. Bob, Neutral vs. Sad). In each trial of this simple task, a stimulus is presented and it must be identified through a specific response. The stimuli were made confusable through morphing. The pattern of confusion errors was fitted to a version of GRT (Soto et al., 2015), and measures of sensitivity, bias, and perceptual and decisional separability were computed directly from the estimated model parameters and compared between groups.

Participants were presented with three different identification tasks, involving different combinations of emotions: neutral versus sad, neutral versus happy, and sad versus happy. To determine whether any results obtained with one set of stimuli would generalize to a different stimulus set, we performed a second session on a different day, using stimuli obtained from a second pair of face identities. The stimuli were carefully controlled so that the discriminability of identity and expression was comparable across stimulus sets.

Previous research shows that when ambiguity is experimentally increased, biases observed in depression become stronger (Schepman et al., 2012). Thus, the study included a final session on a third day, which was identical to the first session but included stimuli that were made ambiguous by increasing similarity in both the identity and emotion dimensions.

Because the intensity of the expression itself can reveal or obscure any deficits shown by depression in emotion recognition, it was important to equate the intensity of the sadness and happiness expressions. This is not a common step in previous research (for review, see Bourke et al., 2010), but we deemed it necessary to obtain data that could constrain potential mechanisms underlying the observed biases (e.g., the specificity of the bias to a particular expression). We obtained data from a pilot study on the discriminability of different levels of expression against neutral, and chose levels of sadness and happiness with similar discriminability.

Method

Participants

Sixty adult participants from the Austin, Texas area were recruited for this study, half of them (n = 30) in the MDD (Major Depressive Disorder) group and the other half (n = 30) in the Control group. No participants were included in either group that had current use of psychoactive drugs, steroidal or psychotropic medications, serious medical complications (e.g., cancer, diabetes, epilepsy or head trauma), heavy tobacco use defined as smoking 20 cigarettes per day or $>$ 20 pack per year, recent heavy alcohol use defined as 5 or more drinks on the same occasion on each of 5 or more days in the past 30 days, or were at imminent risk of self-harm or harm to others or having a recent history of suicidal behavior (either a Columbia-Suicide Severity Rating Scale score of type 4 or 5 or suicidal behavior in the past 2 months). We did not administer a drug test to confirm the participants' self-report.

Participants in the MDD group had mean age of 23.33 (range 18–32), and 70% (n = 21) were female. Self-reported ancestry was as follows: 53% (n = 16) were European, 23% (n = 7) were Asian, 13% (n = 4) were African American or Black, 3% (n = 1) were American Indian or Alaska Native, 13% (n = 4) were more than one race or reported that none of the categories were applicable, and 47% (n = 14) were Hispanic. They were screened to have a score of 11 or greater on the Quick Inventory of Depressive Symptoms (QIDS-SR; Rush et al., 2003) and to meet *DSM–5* criteria for Major Depressive Disorder according to the Mini International Neuropsychiatric Interview (MINI; Sheehan et al., 1997). Participants were excluded if they had current or past bipolar disorder, psychotic disorder, and/or schizophrenia.

Participants in the Control group had mean age of 23 (range 19–35), and 73% (n = 22) were female. Self-reported ancestry was as follows: 40% (n = 12) were European, 30% (n = 9) were Asian, 17% (n = 5) were African American or Black, 3% (n = 1) were American Indian or Alaska Native, 13% (n = 4) were more than one race or reported that none of the categories were applicable, and 28% (n = 11) were Hispanic. Participants were excluded if they had any current or past psychiatric disorder. They were screened to have a score of 6 or less on the QIDS and to never had experienced an episode of MDD. Participants were excluded if they had any current or past psychiatric disorder. All participants were compensated at a rate of $20/hr.

Materials

QIDS-SR (Rush et al., 2003)

A 16-item self-report questionnaire that assesses the nine diagnostic symptom domains used to characterize a major depressive episode. The psychometric properties of the QIDS-SR are very good and are detailed in the online supplemental materials.

MINI (Sheehan et al., 1997)

Research assistants trained on diagnostic interviewing completed in-person interviews for eligible participants, using Version 7.2 of the Mini International Neuropsychiatric Interview for the *DSM–5*. The MINI is a standardized instrument used for brief screenings to diagnose a variety of psychiatric disorders. More details about interviewer training and evaluation can be found in the online supplemental materials.

Stimuli

A set of highly-controlled face stimuli was created. We developed four three-dimensional face models using the software MakeHuman v1.1.0 (http://www.makehumancommunity.org/). Identical models for eyeballs, eyebrows, skin, and teeth were used across identities. MakeHuman allows users to develop expression pose models independently from the identity shape models. Thus, the exact same expression pose model was applied to all identities. We used pose models for happiness and sadness developed and validated in previous research (Hays et al., 2020). We applied these pose models to the four face identity models, producing a total of 12 combinations of expression (neutral, sad, and happy) and identity (four male identities) models. Each model was rendered to a high-resolution image, from a frontal viewpoint (see examples in Figure 1b and all models in Figure S1 of the supplemental materials).

We used JPsychoMorph 1.0 to morph the original images and obtain intermediate levels of identity difference and emotional expression, in 10% increment steps. We then performed a pilot study to obtain psychometric curves that allowed us to choose levels of identity and emotional expression yielding a given discrimination performance (for details, see online supplemental materials).

Three stimulus sets were created based on the results of the pilot study. Identities were grouped into two stimulus sets: "Bob versus Joe" and "Sam versus Tom." There were two versions of the first stimulus set: nonambiguous, with stimuli yielding approximately $d' = 2.0$ in the pilot study, and ambiguous, with stimuli yielding approximately $d' = 1.25$ in the pilot study. The second stimulus set had only a nonambiguous version (i.e., $d' = 2.0$).

Procedure

The study consisted of three separate sessions of about 90 minutes each, all identical except for the stimulus set presented to the participants. The first and second sessions involved the nonambiguous "Bob versus Joe" and "Sam versus Tom" stimulus sets, respectively. The third session involved the ambiguous "Bob versus Joe" stimulus set.

We included a brief familiarization procedure at the beginning of each session. Participants were instructed that their first task would be to learn the faces of two unfamiliar people. They were asked to memorize the faces and their names, and warned that later their recognition of the faces would be tested. These instructions were followed by the presentation of two 60-s videos, each showing a different face through changes in camera viewpoint and emotional expression (neutral, happy, angry, fearful, disgusted, sad, and surprised). Each video was repeated twice, accompanied by the name of the face presented (Bob, Joe, Sam, or Tom) and instructions to memorize the face.

After familiarization, participants were presented with three different identification tasks, separated by resting periods of 2 minutes in duration. The order of presentation of each task was shuffled for each participant and session. The three tasks differed only on the emotional expressions involved: neutral versus sad, neutral versus happy, and sad versus happy. Each combination of identity and emotional expression was reported by the participants through a different key. One identity was assigned to the "left" keys: "Q" for happy, "A" for neutral, and "Z" for sad. The other identity was assigned to the "right" keys: "Y" for happy, "G" for neutral, and "V" for sad. Note that "top" keys were always assigned to happy, "middle" keys to neutral, and "bottom" keys to sad. Only four of the keys were functional (i.e., recorded a response and advanced the trial) in each task.

At the beginning of each task, instructions were displayed indicating that the participant's task would be to identify four faces, each assigned to a single response key. The four faces were shown, labeled with each face's name, emotional expression, and response key. The instructions also highlighted that the left keys were assigned to one identity and the right keys to the other, and that the top keys were assigned to one expression and the bottom keys to the other. Participants were warned that faces would be shown very briefly and were instructed to respond as accurately and as fast as possible.

Each task consisted of 20 blocks of 20 trials each, 400 trials total. Each block involved five presentations of each of the four stimuli, and trials were randomized within blocks. A trial started with the presentation of a white fixation crosshair in the middle of the screen for 500 ms, followed by the presentation of the face stimulus for 200 ms. The trial ended either with the participant's response or when 2 s passed since the presentation of the face stimulus, whichever happened first. Participants were given feedback about the correctness of their responses, consisting of the word "Correct!" in blue, or the word "Incorrect!" in red. When participants failed to respond before the deadline, they saw the words "Too Slow!" in red. There was a 1-s intertrial interval before the start of the next trial.

Table 1
Results of the Model-Based Analysis of Data Using Signal Detection Theory

Analysis	Statistics [95% confidence interval within brackets]						Conclusion
	Neutral vs. Sad		Neutral vs. Happy		Happy vs. Sad		
	Control	MDD	Control	MDD	Control	MDD	
(a) Perceptual Discriminability of Emotion Statistic used: Mean d'							
Does MDD influence it?	2.83[2.79, 2.99]	2.76[2.72, 2.91]	**3.40[3.35, 3.59]**	**3.17[3.13, 3.33]**	3.95[3.94, 4.23]	3.86[3.85, 4.13]	*Only for happiness.* Discriminability of happiness was impaired in MDD
Does the result depend on specific face identities?	2.56[2.51, 2.69]	2.54[2.51, 2.67]	**3.74[3.72, 3.96]**	**3.32[3.30, 3.52]**	3.99[3.97, 4.29]	3.84[3.85, 4.11]	*No.* Results remained the same when identities were changed.
Does the result depend on face information ambiguity?	**2.70[2.65, 2.84]**	**2.46[2.42, 2.60]**	**3.39[3.37, 3.61]**	**2.99[2.97, 3.15]**	**3.76[3.76, 4.02]**	**3.51[3.43, 3.73]**	*Yes.* Ambiguity produced poorer discriminability for MDD across all emotion pairs.
(b) Perceptual Separability of Emotion Statistic used: *L1* distance							
Does MDD influence it?	.067[.057, .081]	.067[.053, .084]	.067[.051, .085]	.040[.024, .057]	.014[.003, .030]	.018[.008, .038]	*No.* Deviations from perceptual separability were similar between groups for all emotions
Does the result depend on specific face identities?	**.028[.013, .047]**	**.064[.052, .082]**	.004[.002, .026]	.019[.006, .036]	.013[.003, .032]	.013[.006, .035]	*Only for sadness.* With deviations from perceptual separability being stronger for MDD.
Does the result depend on face information ambiguity?	.036[.026, .050]	.040[.031, .059]	.065[.049, .084]	.049[.034, .063]	.015[.006, .032]	.019[.010, .036]	*No.* Results did not change when ambiguity was increased.
(c) Perceptual Separability of Identity Statistic used: *L1* distance							
Does MDD influence it?	.034[.025, .053]	.040[.030, .054]	.098[.085, .111]	.096[.084, .108]	.045[.031, .059]	.066[.050, .083]	*No.* Deviations from perceptual separability were similar between groups for all emotions.
Does the result depend on specific face identities?	.070[.055, .088]	.039[.028, .058]	.099[.087, .114]	.098[.084, .118]	.101[.082, .117]	.109[.097, .127]	*No.* Results did not change when the two identities presented were changed.
Does the result depend on face information ambiguity?	.051[.035, .068]	.041[.028, .060]	.007[.002, .025]	.015[.004, .030]	.034[.027, .053]	.020[.009, .036]	*No.* Results did not change when ambiguity was increased.
(d) Threshold Bias of Emotion Statistic used: Median distance from center							
Does MDD influence it?	.02[−.08, .09]	−.01[−.07, .05]	−.04[−.12, .02]	−.10[−.17, −.03]	−.05[−.11, .02]	.03[−.07, −.14]	*No.* No differences in threshold bias were found between groups.
Does the result depend on specific face identities?	−.04[−.13, .00]	.02[−.08, .05]	−.10[−.19, −.04]	−.09[−.16, −.03]	−.09[−.19, −.03]	−.12[−.22, −.07]	*No.* Results did not change when the two identities presented were changed.
Does the result depend on face information ambiguity?	−.11[−.18, −.058]	−.02[−.061, .09]	−.07[−14, .00]	−.02[−.08, .06]	−.09[−.18, −.03]	−.08[−.16, −.03]	*No.* Results did not change when ambiguity was increased.

(*table continues*)

Table 1 (*continued*)

Analysis	Statistics [95% confidence interval within brackets]						Conclusion
	Neutral vs. Sad		Neutral vs. Happy		Happy vs. Sad		
	Control	MDD	Control	MDD	Control	MDD	
(e) Decisional Separability of Emotion							
Statistic used: Mean degree of rotation							
Does MDD influence it?	5.8[3.4. 8.8]	1.5[−0.8, 4.2]	**11.3[9.7, 13.7]**	**6.3[4.6, 8.6]**	**5.9[4.6, 7.9]**	**9.9[8.0, 12.9]**	*Yes.* Deviations from decisional separability differed between groups for some emotions.
Does the result depend on specific face identities?	**3.2[0.9, 5.4]**	**−3.8[−6.1, −1.5]**	4.5[2.4, 6.7]	6.6[3.6, 9.5]	4.6[2.5, 6.9]	3.6[1.6, 6.2]	*Yes.* Differences were found again, but the pattern changed with change in identity.
Does the result depend on face information ambiguity?	7.4[5.4, 10.0]	9.0[6.3, 11.6]	9.1[6.1, 12.2]	6.1[3.5, 8.5]	6.4[4.2. 9.4]	9.5[7.6, 11.8]	*Yes.* No differences between groups were found when ambiguity was increased.
(f) Decisional Separability of Identity							
Statistic used: Mean degree of rotation							
Does MDD influence it?	**0.0[−2.7, 1.8]**	**−10.4[−12.2, −8.2]**	−3.7[−5.3, −2.5]	−2.5[−3.7, −1.3]	**1.2[0.1, 2.0]**	**-−2.6[−4.7, −1.2]**	*Yes.* Deviations from decisional separability differed between groups for some emotions.
Does the result depend on specific face identities?	0.8[−1.3, 2.6]	−3.1[−5.4, −0.1]	0.3[−1.2, 1.6]	−1.6[−3.9, 0.4]	−4.8[−6.6, −2.8]	−6.9[−8.8, −5.4]	*Yes.* Differences between groups were not found when the identities were changed.
Does the result depend on face information ambiguity?	**−6.9[−8.5, −5.4]**	**−1.3[−3.8, 0.7]**	8.7[6.0, 10.6]	5.4[3.7, 7.2]	3.5[1.7, 4.9]	3.9[2.3, 5.5]	*Yes.* The pattern of differences changed when ambiguity was increased.

Note. MDD = major depressive disorder. For each case, estimates of the statistic used and their 95% confidence intervals are provided for each group. Highlighted in bold are all the cases in which the confidence intervals for the control and MDD groups did not overlap, suggesting a reliable difference between groups. The italic terms emphasize the conclusion.

Model-Based Data Analysis

The data from each task within a session were analyzed separately.

SDT analyses assume that performance is the result of a well-learned task. Thus, we discarded data from the early period during which participants were still learning the task. Learning curves were obtained by averaging performance within a moving window of 100 trials, starting with trials 1–100, then trials 2–101, and so on. An exponential function was fitted to such learning curves, and the trial in which the slope of the fitted curve was smaller than .001 for the first time was chosen as a cutoff: Only subsequent trials were included in the final analysis. In addition, SDT analyses require that performance be well-above chance and below perfect, so data from participants who had a performance below 40% correct or above 95% were excluded. Detailed information about the number of participants included in each analysis and their accuracy in the identification task is reported in Table S1 of the online supplemental materials.

Data from each group and each identification task were separately fitted to GRT with individual differences (GRT-wIND; Soto et al., 2015), using procedures detailed in the online supplemental materials and implemented in the R package *grtools* (Soto et al., 2017). Once the best-fitting parameters were obtained, they were used to compute measures of discriminability and separability for each face dimension. Discriminability was measured by computing d' directly from the model for each participant (see Figure 1a). The mean discriminability is reported. Threshold bias was measured by computing distance of the bound from the center point across perceptual distributions. Deviations of perceptual separability were measured by computing the $L1$ distance between distributions (shaded area in Figure 1b), and deviations of decisional separability by computing the degree of rotation of bounds (shaded angular distance in Figure 1b).

We used a parametric bootstrap procedure (Good, 2006) to obtain 95% confidence intervals on these measures. Each step in the procedure consists of generating a new data sample from the fitted model, and then fitting the GRT-wIND model to such simulated data. The obtained parameter values can then be used to compute the measures described in the previous paragraph. This process was repeated 1,000 times for each model, resulting in an empirical distribution of the d' and $L1$ measures, which was used to directly obtain 95% confidence intervals using the simple percentile method (i.e., 25th and 975th 1,000-quantiles). We used a parametric rather than a nonparametric bootstrap procedure because (1) our analysis assumes a model for the data distribution, so in this case the parametric bootstrap is appropriate, and (2) using the nonparametric bootstrap with small sample sizes (< 100) such as ours leads to imprecise confidence intervals (Good, 2006). We considered cases in which the confidence intervals for the Control and MDD groups did not overlap as suggesting a reliable difference between the groups for that specific comparison. This is considered a rather conservative method to detect differences between groups (Schenker & Gentleman, 2001), corresponding to a test with $\alpha \leq .01$ (Cumming & Finch, 2005).

Results

The mean QIDS depression score was significantly higher for MDD ($m = 14.0$, $sd = 3.86$) than for control ($m = 2.13$, $sd = 1.72$) participants, $t(40.04) = 15.39$, $p < .001$. On the other hand, groups did not differ in mean percentage of participants excluded in total (MDD: $m = 9.6$, $sd = 5.4$; Control: $m = 14.1$, $sd = 6.4$; $t(15.54) = 1.59$, $p > .1$), excluded due low performance (MDD: $m = 4.8$, $sd = 3.8$; Control: $m = 8.5$, $sd = 6.3$; $t(13.12) = 1.52$, $p > .1$), excluded due to high performance (MDD: $m = 4.4$, $sd = 3.3$; Control: $m = 5.2$, $sd = 2.9$; $t(15.75) = .5$, $p > .1$), or in percentage of trials excluded from the data of included participants (MDD: $m = 3.4$, $sd = 10.2$; Control: $m = 3.5$, $sd = 9.1$; $t(471.86) = .12$, $p > .1$).

The online supplemental materials include plots of average confusion matrices (Figures S3–S4; we do not discuss such matrices here because the patterns of results captured by the model parameters are not easily discernible from the raw data) and detailed information about the fit of the model to data (Table S2). The model showed excellent fit to the data, with all R^2 values in the .98–.99 range.

The supplemental materials also include simulations showing that parameters of the model show very good recoverability and identifiability with the amount of data gathered here, and that the model can effectively dissociate between perceptual and decisional factors contributing to the confusion data.

The main results are shown in Table 1, which is subdivided into six analyses described below. In each case, the table includes estimates of the statistic used and its 95% confidence interval for each group. Highlighted in bold are all the cases in which the confidence intervals for the Control and MDD groups did not overlap. The same results are shown in a graphical form in Figures S1–S6 of the online supplemental materials.

Perceptual Effects

Perceptual Discriminability of Emotion

Table 1a shows the results of our analysis of emotion discriminability in terms of d' (the distance between perceptual distributions shown in Figure 1a) For the nonambiguous stimuli used in the first two sessions, an impairment in discriminability was observed for the MDD group only in the Neutral versus Happy task. The same pattern of results was observed with the two stimulus sets, and thus this seems like a reliable effect that generalizes across identities. Thus, people with MDD appear to have more difficulty discriminating neutral versus happy emotion with unambiguous stimuli.

With increased ambiguity during the third session, an impairment in discriminability of face emotion was observed across all emotion pairs (bottom panel) for the MDD group compared to the control group. This general deficit with ambiguous stimuli is in line with previous reports (Schepman et al., 2012).

Perceptual Separability of Emotion

Table 1b shows the results of our analysis of perceptual separability of emotion—that is, whether the perception of emotion is influenced by face identity. The wealth of the evidence suggests that MDD does not influence the perceptual separability of emotion. The *L1* distances between recovered perceptual distributions (bolded areas in Figure 1b) were very similar between groups for most tasks and stimulus sets, and the 95% confidence intervals overlapped in most cases. Increasing face ambiguity did not change the results, contrary to what was found in the analysis of emotion discriminability reported above.

The only exception was a decrease in perceptual separability (i.e., increase in *L1* distance) for the MDD group in the Neutral versus Sad discrimination, but only for the second pair of identities. This suggests that some specific identities might influence the detection of sadness, perhaps because shape features that are specific to some identities are confused with features of sadness. However, we see very little value in drawing conclusions from such context-dependent results. In sum, the overall pattern of results suggests that depression does not influence the perceptual separability of emotion.

Perceptual Separability of Identity

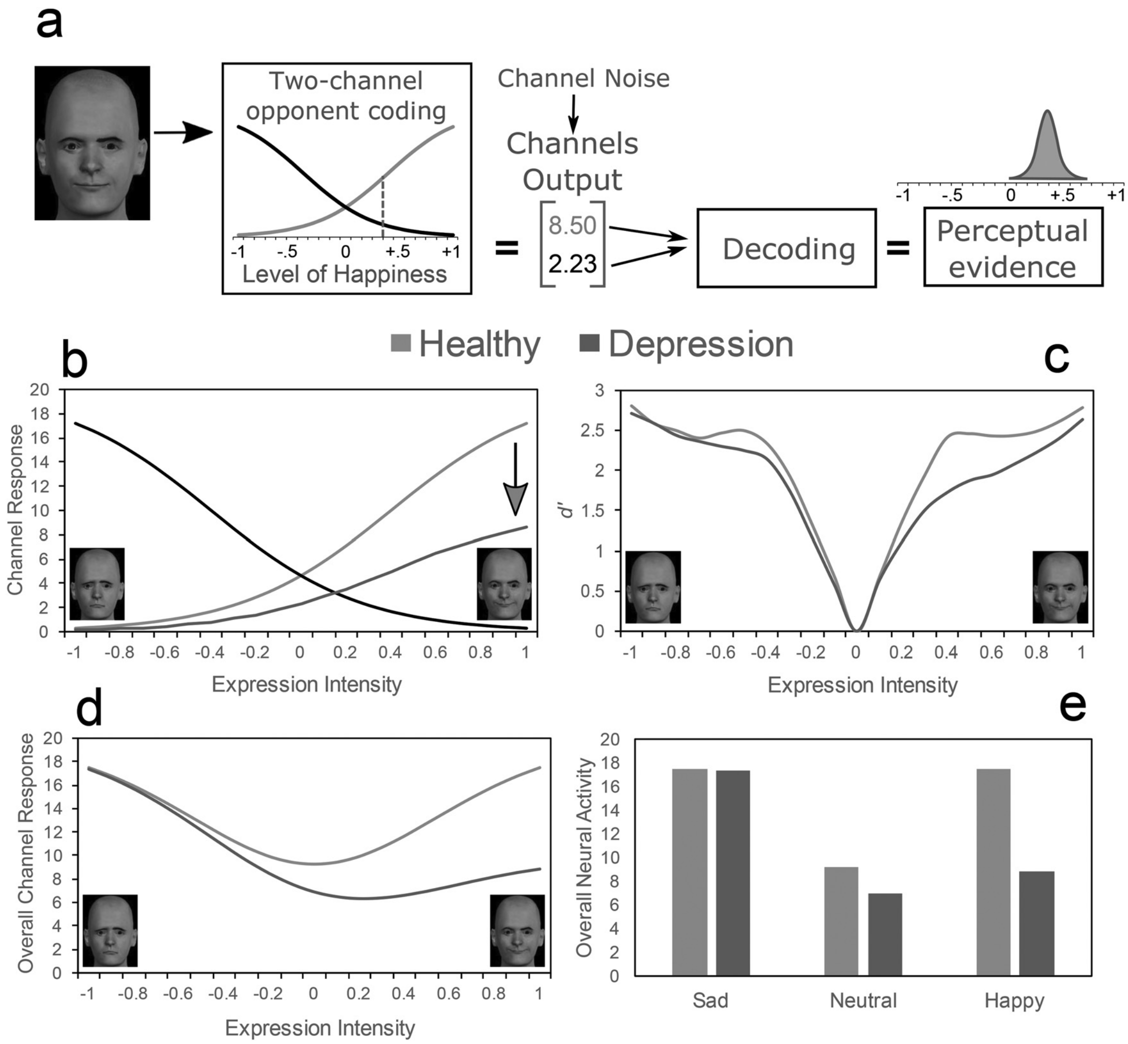
Table 1c shows the results of our analysis of perceptual separability of identity—that is, whether the perception of identity is influenced by face emotion. Here, all of the evidence suggests that MDD does not influence the perceptual separability of identity. The recovered perceptual distributions and their *L1* distances are very similar between groups for all tasks and stimulus sets, and the 95% confidence intervals on the *L1* distances overlapped in all cases. The result generalizes across identities and is not influenced by face ambiguity.

This result is at odds with previously-reported impairments in filtering of information about emotional expression when identity is being classified (Gilboa-Schechtman et al., 2004). Because the selective attention task used by Gilboa-Schechtman and colleagues cannot distinguish between perceptual and decision-making mechanisms of interaction between dimensions, the most likely explanation for their results is that the observed impairment was not perceptual in nature, but stems from decision-making mechanisms.

Summary of Perceptual Effects

We only found consistent perceptual effects of depression on the perceptual discriminability of emotion. In particular, happiness was in general more difficult to detect by MDD patients, and there was a general deficit on emotion discrimination with ambiguous stimuli. The results suggest that there are no effects of depression on perceptual separability of emotion or identity. In sum, the

Figure 2
A Model of Face Expression Encoding in Depression



Note. The main model in (a) is composed of a two-pool opponent coding system for face expression that has empirical support in the previous literature, which together with optimal decoding produces the distributions of perceptual evidence for a given expression assumed by signal detection theory. The main assumption of the model in (b) is that in depression the channels encoding positive expressions show suppressed responses. This assumption is enough to explain (c) the drop in sensitivity (d′) found for happy expressions regardless of intensity and for low-intensity (i.e., highly ambiguous) sad expressions found in our study, and (d–e) the drop in the ability of relatively positive expressions to compete for attention when presented with relatively negative expressions.

results suggest that depression does not influence the perceptual separability of identity.

Decisional Effects

Threshold Bias of Emotion

Table 1d shows the results of our analysis of threshold bias (the distance of the bound from the center of the model shown in Figure 1a) in the discrimination of emotion. Here, all of the evidence suggests that MDD does not influence decision bias, as the 95% confidence intervals on threshold bias overlapped in all cases. The result generalizes across identities and is not influenced by face ambiguity.

Decisional Separability of Emotion

Table 1e shows the results of our analysis of decisional separability of emotion—that is, whether decisions about emotion were influenced by face identity. Here, deviations from decisional separability are measured through mean degree of rotation (the "angular distance" shown in Figure 1b). The results suggest that it is possible to find group differences in decisional separability, but they are highly inconsistent. For example, in the first session we find that the MDD group shows more separability (i.e., lower degree of rotation) than the Control group for Neutral versus Happy, but less separability for Happy versus Sad. When identities were changed, both effects disappeared and instead we found a significant difference for Neutral versus Sad. Similarly, all effects disappeared when participants were presented with ambiguous faces. The results suggest that MDD patients use different decisional strategies from controls, but that they depend strongly on the presented stimulus set.

Decisional Separability of Identity

Table 1f shows the results of our analysis of decisional separability of identity—that is, whether decisions about identity were influenced by face emotion. As before, it is possible to find group differences, but results are inconsistent across analyses. Significant differences were found for Neutral versus Sad, both with the original stimulus set and its ambiguous version, but these effects are in opposite directions. A significant difference was also found for Happy versus Sad with the original stimulus set. As before, we interpret these results as suggesting that MDD patients use different decisional strategies from controls, but that they depend strongly on the presented stimulus set.

Summary of Decisional Effects

Our results suggest that depression does not influence overall threshold biases in the discrimination of emotion in our task. However, we found that MDD patients do use different decisional strategies than those shown by control participants, but that those differences show absolutely no consistency across stimulus sets.

Discussion

In this study, we used a highly controlled stimulus set and an SDT model-based analysis to determine whether any perceptual biases exist in the recognition of face emotion in depression, aside from higher-level decisional and cognitive biases. We found that MDD patients were in general impaired in their ability to detect happiness (i.e., discriminate it from neutral faces), regardless of face identity and ambiguity. This is in line with the prediction of cognitive theories of major depression (Beck, 2008; Disner et al., 2011) and with several previous reports in the literature (reviewed in Bistricky et al., 2011). Inaccurate recognition of happy expressions in MDD has not been consistently established in the prior literature (Bourke et al., 2010), but this might partly be due to a lack of control of stimulus factors (e.g., intensity of expressions) and decisional biases.

We also found that face ambiguity has an important role on whether or not perceptual effects can be found, in accordance to previous studies (Schepman et al., 2012). Impairments in discriminability of all pairs of emotional expressions were found when ambiguous stimuli were used. The modulation of perceptual deficits by expression intensity might be one of the reasons why some prior studies have found global deficits of facial emotion processing or no deficits at all (for a review, see Bourke et al., 2010), with the other likely culprits being lack of control for expression intensity and decisional biases.

There was little evidence suggesting that MDD influences perceptual interactions between face expression and identity. Thus, there are no reasons to expect that people with depression would have trouble "filtering out" information about emotional expression when they perceptually process face identity, as previously suggested (Gilboa-Schechtman et al., 2004). A likely possibility is that prior results stem from decisional rather than perceptual mechanisms. We found that MDD patients show different patterns of violation of decisional separability than control participants, but that those differences are not consistent across stimulus sets. Determining exactly what factors can explain differences in decisional strategies will require further research.

Our results also suggest that people with depression" filter out" information about identity when they perceptually process face expression. This is important, because generalization of face expression learning to unseen identities might depend on such ability to "filter out" identity information (Soto & Ashby, 2019). Such feedback-based expression learning may include ABM, but not be limited to it.

In sum, the most important and consistent results we found were perceptual in nature and focused on the discriminability of face emotion, with MDD patients showing lower sensitivity to detect happiness, and to discriminate emotion in ambiguous faces.

Directions for Future Work

Interpersonal theories suggest that people with depression are alert for signs of negative social feedback (Joiner & Metalsky, 1995; Surguladze et al., 2004). On the contrary, in our results depression was associated mainly with a reduction in responsivity to happy faces. If our results generalize from our highly controlled tasks to the real world, we would expect depression to be accompanied by a dulled sensitivity to positive social feedback, either alone or in addition to the heightened sensitivity to negative social feedback proposed by interpersonal theories.

The results of prior studies on face perception biases in depression have been highly heterogeneous (for reviews, see Bistricky et al., 2011; Bourke et al., 2010). Such heterogeneity could result from a lack of control for emotion intensity in the stimuli and from decisional factors, both of which showed to be important in our study. In addition, anxiety often co-occurs with depression (Kessler & Walters, 1998), and it might produce an independent effect on expression perception. An important next step for computational work in this area would be to use computational modeling to understand idiosyncratic ways in which expression processing is affected in specific individuals and its relation to symptomatology.

Our stimuli and design also have some limitations compared to other studies. For example, our methods require many trials with the same faces, which restricts the number of identities and emotions that can be tested. We focused on male, Caucasian faces, and a single pose model for each expression. This allowed tight stimulus control, but more research is necessary to test the generalizability of our results.

A final important point is that while current feedback-based treatments attempt to reduce biases toward negative face expressions, the results reported here suggest that more attention should be paid to increasing perceptual sensitivity to evidence of positive face expressions (e.g., happiness) as a target for treatments.

Mechanisms of Face Perception Bias in Depression: A Working Hypothesis

An advantage of SDT is that it can be linked to channel models from the psychophysics literature (e.g., Seriès et al., 2009; Soto et al., 2018), which allow one to propose mechanistic explanations for differences in perceptual discriminability. We finish this work by taking advantage of this link, and propose a computational model of face perception biases in depression. A large body of work supports a two-channel opponent coding system for face emotion (e.g., Burton et al., 2015; Cook et al., 2011), illustrated in the left part of Figure 2a. In this model, level of happiness is encoded by two channels, represented in the figure by curves of different color. The red channel responds most strongly to happy expressions, and its response decreases with less evidence of happiness in a face. The black channel responds most strongly to an anti-happy expression, an expression with the opposite features as happiness, in relation to a neutral expression. When a face is presented to this model, it outputs two channel responses, which include channel noise added during processing. Note that the happiness level is not explicitly represented in the channel responses; perceptual evidence for happiness must be computed from the channels' output. Because of channel noise, the computed perceptual evidence is also noisy (i.e., the purple distribution in Figure 2a), just as assumed by SDT's representation of happiness (see a full formal description in the online supplemental materials).

We assume that in depression the channels encoding happiness and other rewarding emotions show suppressed activity, as shown by the orange arrow in Figure 2b. Such channels are correlated with the representation of anti-sadness (Hsu & Young, 2004; Rutherford et al., 2008), so we simplify the model by having a single continuum going from sadness to happiness.

Figure 2c shows a simulation of the discriminability of happy and sad expressions against neutral, as a function of expression intensity. More ambiguous expressions are closer to zero at the middle of the scale. The simulation reproduces the asymmetrical results found in the present study: In depression (blue curve or bottom) there is a large drop in sensitivity to happy expressions throughout most values of intensity, whereas the same drop is found for sad faces only at lower levels of intensity (i.e., high ambiguity). That is, the model explains deficits in the detection of sadness in ambiguous stimuli as an indirect result of suppressed representation of positive expressions, in an opponent-channel system.

The model also predicts prior results that it was not explicitly designed to explain, like evidence of unimpaired and unbiased identification of unambiguous expressions (see Bistricky et al., 2011). In Figure 2c, as expression intensity increases, the gap between blue (bottom) and red (top) curves becomes smaller and eventually closes for happy expressions, as shown for sad expressions.

A number of studies have used paradigms in which multiple faces are displayed simultaneously to determine whether people with depression show biased attention toward negative or away from positive expressions. Figure 2d shows the overall channel activity (i.e., the sum of activity in the two channels) produced by a variety of expressions in a negative-positive continuum, and Figure 2e shows the specific values expected for unambiguously sad, neutral, and happy faces. Assuming that attention is biased toward a face proportionally to this overall activity, differences in height between bars represent the relative ability of the stimuli to compete for attention if they were presented in a display together. The model predicts that depression would be accompanied by a drop in the ability of happy faces to compete for attention, either against neutral or sad faces, as well as a smaller increase in the ability of sad faces to compete for attention against neutral faces. Several studies have confirmed such predictions (for a review, see Bistricky et al., 2011), although inconsistently.

We must stress that the simulations in Figure 2 are presented as a proof of concept rather than as a full-fledged model of face perception biases in depression. Such a theory would require additional details and is outside the scope of this study. However, our simulations show that it is possible to formalize mechanistic explanations of perceptual biases in depression that make clear and quantitative predictions.

One result that is not explained by this model is that people with depression consistently show a tendency to interpret ambiguous/neutral stimuli as negative (for a review, see Bourke et al., 2010). Here, we found no evidence that such an effect stems from a decisional bias. Assuming that the effect is truly perceptual, a more complete version of the model might explain such results by suboptimal computation of evidence for emotion (Seriès et al., 2009).

Conclusion

The present work is a step forward toward a better understanding of the mechanisms underlying face perception biases in depression, and toward formalizing the assumptions behind cognitive theories of depression in the form of concrete, testable computational models. Face perception is a particularly advantageous area for such developments, as faces are complex stimuli with social significance, but they are also easy to manipulate and intensely studied in basic research. We hope that the approach taken here can be expanded to incorporate other biases found in depression.

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