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Anger Bias in the Evaluation of Crowds

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People are good at categorizing the emotions of individuals and crowds of faces. People also make mistakes when classifying emotion. When they do so with judgments of individuals, these errors tend to be negatively biased, potentially serving a protective function. For example, a face with a subtle expression is more likely to be categorized as angry than happy. Yet surprisingly little is known about the errors people make when evaluating multiple faces. We found that perceivers were biased to classify faces as angry, especially when evaluating crowds. This amplified bias depended on uncertainty, occurring when categorization was difficult, and it reached peak intensity for crowds with four members. Drift diffusion modeling revealed the mechanisms behind this bias, including an early response component and more efficient processing of anger from crowds with subtle expressions. Our findings introduce bias as an important new dimension for understanding how perceivers make judgments about crowds.

Keywords: anger, crowd, emotion bias, emotion perception, threat

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The ability to discriminate facial expressions allows perceivers to gather information about others' internal affective states and intentions, influencing how people interact with and react to each other (Frijda & Mesquita, 1994). Indeed, people are quite skillful at categorizing prototypical displays of emotion on individual faces (Calvo & Nummenmaa, 2016). Yet perceivers often have to evaluate subtle (Fridlund, 1994), difficult to see, or obscured expressions and, in some instances, these judgments must be made quickly. When expressions are ambiguous, perceptual sensitivity is diminished and errors in emotion classification become inevitable. These errors, however, are not random; they reflect the engagement of systematic biases or heuristics which most likely evolved to deal with uncertainty (Johnson & Fowler, 2011) and serve to optimize the utility of affective judgments (Lynn & Feldman Barrett, 2014). For example, people tend to misinterpret single faces as being negative or hostile (Neta et al., 2009, 2013; Neta & Tong, 2016; Neta & Whalen, 2010). Furthermore, observers are especially likely to employ this negativity bias when evaluating members of groups stereotypically considered as threatening (e.g., men, Black people; Becker et al., 2007; Halberstadt et al., 2020; Hess et al., 2009; Holbrook et al., 2014; Hugenberg, 2005; Johnson et al., 2012; Shasteen et al., 2015). Thus, emotional classification is informed by both perceptual sensitivity *and* systematic bias; each impacts the way people see and understand individuals' affective states.

However, people often encounter others in small groups and crowds, not just on an individual basis. To evaluate the emotion of collectives of faces, humans rely on a process known as ensemble coding (e.g., Alvarez, 2011; Whitney & Yamanashi Leib, 2018). This visual mechanism enables rapid extraction of summary or gist information about multiple facial expressions at once (Elias et al., 2017; Haberman & Whitney, 2007) as well as many other visual features (Alvarez & Oliva, 2008; Ariely, 2001; Chong & Treisman, 2003; Parkes et al., 2001; Sweeny et al., 2013; Sweeny & Whitney, 2014; Yamanashi Leib et al., 2012). Ensemble coding also supports more complex social judgments about crowds and group membership (Goldenberg et al., 2020; Lamer et al., 2018; Phillips et al., 2018). For example, perceivers are able to evaluate the ratio of women to men in a crowd with high accuracy and evaluate their fit with that group accordingly (Alt et al., 2019; Goodale et al., 2018). Crucially, the crowd percepts that emerge from ensemble coding can be exceptionally accurate (Alvarez, 2011), in some cases allowing perceivers to estimate the collective attributes of a crowd with more precision than the attributes of an individual, including evaluating facial expression (Elias et al., 2017). In effect, a rapidly growing literature on ensemble coding has bolstered the idea that perception of multiple people is, by nature, efficient and maybe even superior to perception of individuals. However, crowd perception is not exempt from systematic bias, and surprisingly little research has been conducted on the errors that occur when perceivers make rapid judgments about multiple faces. This is problematic because, for reasons which we

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describe below, biases may not only be present but may even be exaggerated for judgments of a crowd's emotion. Current attempts at disentangling sensitivity and bias when people evaluate emotion from multiple faces are limited, and thus the scientific knowledge about crowd perception is out of balance and underspecified. Here, we begin to address this gap by evaluating *anger bias*—a tendency to judge facial expressions as angry—in the context of single faces and multiple faces. We measure bias while also measuring perceptual sensitivity, paying special attention to how the two components relate to each other.

How might emotional bias, specifically a bias to report anger, manifest in the context of evaluating multiple faces at once? To inform our predictions and provide theoretical context, we look first to perspectives on negativity bias as it occurs for judgments of individuals. We then turn to theory about how people tend to behave in crowds and groups, and the intuitions perceivers may have about crowds.

Biased evaluations, in general, are often portrayed as being adaptive (Johnson et al., 2013; Johnson & Fowler, 2011). For example, error management theory is predicated on the idea that overestimating the presence of threat is less costly than underestimating its presence, and it proposes that people avoid high-risk mistakes to minimize potentially negative outcomes (Haselton et al., 2009; Johnson et al., 2013; Nesse, 2005). For example, people are more likely to judge a body as belonging to a man than a woman when primed with fear (Johnson et al., 2012). Negative events also have a stronger psychological effect on people than positive events, and people underestimate the frequency of positive emotion, but not negative emotion (Baumeister et al., 2001). With regard to expression categorization, people may more liberally endorse the presence of anger, especially when their judgments are made with little confidence or low perceptual sensitivity (Holbrook et al., 2014). For example, when judging the emotion of individuals holding various household objects, observers more readily ascribed anger to individuals who were holding objects that could be used as weapons (e.g., garden shears) than those holding objects that did not easily afford such outcomes (e.g., a watering can; Holbrook et al., 2014). This adaptive mechanism is not limited to facial expressions—systematic bias similarly cultivates protective auditory judgments about the proximity of an approaching target (Neuhoff, 1998), and it encourages loss-aversion during decision making (Kahneman & Tversky, 1984). Of course there are special circumstances which can lead perceivers to adopt positive biases, like when they are asked to evaluate in-group members (Lazerus et al., 2016) or are given additional time to make a decision (Neta & Tong, 2016), but *initial* judgments about affect on individual faces tend to be negative. Perceivers may be inclined to judge individuals as expressing threat (or anger) presumably to avoid danger (Becker et al., 2007; Gibson, 1979; Holbrook et al., 2014). Additionally, perceived threat may depend on an agent's capacity to inflict harm on the viewer. If a single individual is assumed to pose potential harm, then it stands to reason that many people, or a crowd, could carry an increased affordance to inflict harm based on their numerosity alone. Indeed, the more men present in a crowd, the more threatening that crowd is reported to be (Alt et al., 2019). Yet it is still unclear how numerosity, and the potential for threat that comes with it, may impact systematic bias to categorize a crowd' s emotion. Threat and motivation to approach are both implicitly associated with the facial expression of anger (Adams et al., 2006). It may be the case that negative biases, specifically a bias to report seeing anger, are exaggerated when people make rapid judgments of multiple faces compared to when people judge individual faces.

Research on how people behave in crowds also supports the prediction that negative biases may be especially strong when evaluating the emotional expressions of multiple faces at once. Crowds appear to facilitate a process of deindividuation, which allows the individuals within them to act more aggressively than they would were they alone (Festinger et al., 1952; Le Bon, 1897; Vilanova et al., 2017). For example, when individual identities are protected within a crowd, people are more likely to behave violently and anticipate impunity for antisocial behavior (Vilanova et al., 2017). Indeed, people have been shown to be more aggressive when they are anonymous members of small crowds (Mann et al., 1982). Of course, not all crowds are antagonistic or violent, and crowds can also increase positive prosocial outcomes and behaviors, like social facilitation, performance enhancement, and division of labor (Baumeister et al., 2016). However, crowds *can* have more aggressive potential than individuals, and this depends on the extent to which differentiation between individuals in a crowd is discouraged, and individuals in the crowd escape identification and accountability (Baumeister et al., 2016). Perceivers may possess lay theories about this, or at least have some intuition about it. For example, perceivers attribute individuals less of a mind when they are part of a large, cohesive, and entitative group (Morewedge et al., 2013), and people associate groups with higher social status and dominance than individuals (Cao & Banaji, 2017; Pun et al., 2016). It may therefore be the case that perceivers employ systematic biases to protect them from greater anticipated threat when evaluating the emotion of crowds relative to evaluating the emotion of individuals.

Thus, there are many reasons to predict that perceivers should be systematically biased when they make judgments about the emotions of crowds, and that these biases should be stronger than those engaged for judgments of individuals. Yet, these biases are underspecified in the current scientific approach to crowd perception. From a signal-detection perspective, biases are most robustly and cleanly measured when perceptual sensitivity is low, and in fact, loss of sensitivity may even engage bias (Lynn & Feldman Barrett, 2014). We thus designed our experiments to assess bias when expressions were more and less ambiguous (following the recommendation of previous research on face crowds; Yang et al., 2013). We assessed how bias differed based on the number of faces in a setting (e.g., an individual vs. a crowd) and based on the ambiguity of those faces' expressions (using different intensities of expression and by obstructing the faces). The experiments in this investigation thus focus on what are known as *context* effects of bias, or the situations in which biases occur (Haselton et al., 2009). That is, perceptual uncertainty and the presence of other faces are different contexts (the latter being perhaps the most common context in which judgments of faces are known to occur; Wieser & Brosch, 2012), and we were interested in how each impacted the strength of anger bias, and how uncertainty and numerosity interacted. In order to measure how anger bias depended on a pure effect of seeing multiple faces, we limited our initial experiments to include sets of identical faces. We considered this stripped-back approach as a necessary first step for testing whether our predictions held up under restricted conditions (Mook, 1983) and maintaining internal validity (Risko et al., 2012), especially given the potential complexity of our results (Banaji & Crowder, 1989). Our long-term goal was to set the stage for future research to examine what are known as *content* effects of bias, or the different classes of information upon which biases engage (Haselton et al., 2009), including gender, race, and age.

We made the following predictions. First, when perceivers make judgments about the emotion of faces, they should be biased to categorize those faces as angry. Second, this anger bias should be strongest when ambiguity about emotional expression is high and perceivers' ability to discriminate facial expressions is compromised, reflecting the inverse relationship between sensitivity and bias and the engagement of a heuristic. Third, anger bias should be stronger for judgments of crowds than for judgments of individuals, particularly when perceptual uncertainty is high, reflecting a pure effect of numerosity driving bias when diagnostic perceptual information is lacking. These predictions reflect our conception of both uncertainty and crowd context as sources of bias, with the latter crowd bias manifesting as a function of the former uncertainty bias. We tested and found support for these predictions in the six experiments described below.

Experiment 1: Are Crowds Particularly Susceptible to Being Misperceived as Angry?

Method

Observers

Eighty-three undergraduate students (57 women, 26 men) from the University of Denver participated in Experiment 1. This experiment was run as part of a larger study on emotion perception and affective reactions. The number of observers in this sample reflected an attempt to capture potentially weak physiological effects associated with this larger study that are not described in detail here. Our post hoc observed-power for examining the main effect of crowd size in this experiment was 0.71 (with alpha set at .05, captured by a matched-pairs t test between bias in the crowd and single conditions, accounting for the correlation between these conditions). All participants provided informed consent and received course credit for their participation. Each observer had normal or corrected-to-normal visual acuity and completed the experiment in a dimly lit room. This study was approved by the Institutional Review Board at the University of Denver, and the research was carried out in accordance with the provisions of the World Medical Association Declaration of Helsinki.

Stimuli

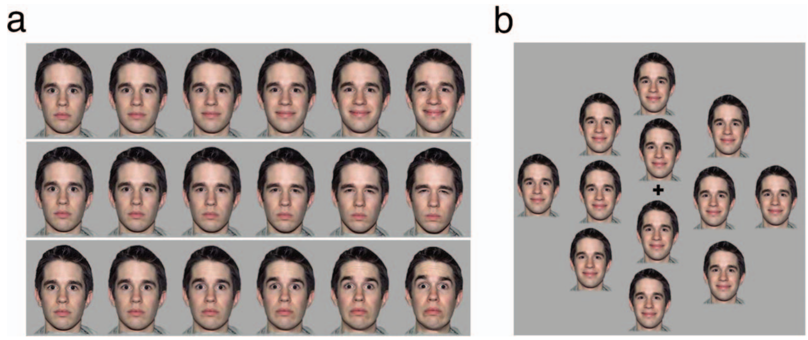
Our face set consisted of four White men from the NimStim face set (Tottenham et al., 2009). We were interested in examining anger bias across a range of facial expression intensities. Consistent with our theorizing in the Introduction, we predicted that anger bias would emerge most strongly for judgments of weaker intensity facial expressions, because they are more difficult to discriminate and therefore introduce more uncertainty than high-intensity facial expressions. To create a range of facial expression intensities, we morphed full-intensity exemplar expressions from each of the four actors with their own neutral faces. Specifically, we used Fantamorph software (Version 5) to create linear interpolations (i.e., morphs) between a neutral expression and two emotional expressions—angry or happy—for each of the actors. A norming experiment run prior to this investigation confirmed that these interpolations did indeed produce linear changes in perceived intensity for all the stimuli in our set (see the online supplemental materials). Note that the appropriateness of our stimulus set (and our ability to measure changes in the magnitude of anger bias) did not depend on the lowest-intensity expressions being perceived as *perfectly* neutral in valence—a bias can be measured even with stimuli that contain diagnostic visual information (e.g., a moderate level of expressiveness).

In our first experiment, we presented faces with five levels of emotional intensity (20%, 40%, 60%, 80%, and 100%) from these two expression ranges. We used a Gaussian edge-blurring tool (Adobe Photoshop CS6, Version 13.0) to smooth the external face contours and hair and to diminish the appearance of rough edges. The background of each image was then replaced with a uniform gray color (RGB = 170, 170, 170). The stimuli were presented in MATLAB (R2014b) on a uniform background (RGB = 170, 170, 170; luminance = 27.5 cd/m^2) on a CRT monitor with a screen size of 27.3 cm × 36.5 cm, a resolution of 1024 × 768. Observers were seated 57 cm in front of the monitor. Each face subtended a visual angle of 3.75° × 4.53°. The distance between each face was approximately 5.84° (distance varied because the horizontal and vertical position of each face was randomly jittered, in both the horizontal and vertical directions, by a number between 1 and 15 pixels randomly selected from a uniform distribution). The entire face set subtended a visual angle of 23.48° by 23.48°.

Procedure

We used a within-subjects design in which each observer viewed and evaluated emotional expressions from single faces (the single condition) and from collections of 12 faces (the crowd condition). The task was to categorize a single person's or a crowd's facial expression(s) as "happy" or "angry" by pressing the right or left arrow keys (counterbalanced across observers). Observers were limited to a binary decision to ensure that they could not opt out of making an emotional classification. This was particularly important because we predicted enhanced bias on trials in which emotion classification was difficult and uncertainty was high. There was no time limit to provide a response. On each trial, faces were randomly distributed around a centrally presented fixation point. In the single condition, one face appeared at one of the four central positions (randomly selected on each trial) to ensure that any potential differences in emotion discrimination (i.e., sensitivity) between single and crowd conditions would not be due to differences in visual acuity (that is, both conditions included diagnostic information in parafoveal vision). In the crowd condition, the faces appeared in 12 positions scattered across the screen. Faces within each crowd were identical, always with the same actor and intensity of facial expression. For example, a crowd trial could feature 12 images of the same person depicting a 40% happy expression (see Figure 1). We introduced this redundancy intentionally, accepting that it degraded our crowds in terms of real-word sources of variability, such as facial structure, gender, expressiveness, and identity, because it pro-

Figure 1
Face Stimuli and an Example of a Crowd of Faces



Note. (a) Morphs between a neutral expression and happy (top row), angry (middle row), and fearful (bottom row) expressions from one actor in our stimulus set, which we produced by morphing faces from the NimStim set of facial expressions (Tottenham et al., 2009). Intensities depicted here include 0%, 20%, 40%, 60%, 80%, and 100%. (b) A set of 12 faces from Experiment 1. Face identities were identical within each crowd on a given trial for many of the experiments in this investigation. This ensured that our predicted result of increased bias for evaluations of crowds (relative to individuals), were it to occur, could be accounted for by numerosity alone. See the online article for the color version of this figure.

vided a more important upside for our initial investigation. That is, because the crowds did not contain any additional information for categorizing the expression, any difference in bias in the crowd condition relative to the single condition could only be attributable to the increase in number of faces. The identity and intensity of the face, however, varied across trials.

To prevent observers from focusing on specific locations, we randomly and independently jittered the location of each face by one to 15 pixels both horizontally and vertically on each trial. Single faces and crowds were presented for 100 ms, a presentation time brief enough to prevent observers from making deliberate saccades to individual faces (Findlay & Walker, 1999). Each face was followed by a pattern mask (70 rectangular pieces derived from the preceding image, randomly reshuffled into a new image on every trial) shown for 250 ms. This approach ensured that the emotional faces and scrambled masks matched in terms of low-level image characteristics, thus decreasing the visibility of the masked image (Enns & Oriet, 2007) and preventing residual visual processing (Rolls et al., 1999). Upon viewing each single face or crowd, observers indicated whether that person's or crowd's emotional expression was happy or angry. Identity, emotion category, and emotion intensity were randomly determined on each trial. Trials were randomized for each block and observer. Each observer completed six blocks for a total of 480 trials. Each condition (e.g., a crowd of happy faces at 20% intensity) was repeated for 24 trials across all six blocks.

Analyses

We used signal detection theory (SDT) for our primary analyses, which allowed us to separately measure both sensitivity and bias in perceptual decision making (e.g., whether a signal—in this case anger—was present) in the context of uncertainty. In this experiment, there were two possible responses (angry or happy), resulting in four possible SDT outcomes (see Table 1 in the online supplemental materials): "hit" (angry face[s] identified as angry), "miss" (angry face[s] identified as happy), "false alarm" (happy face[s] identified as angry), and "correct rejection" (happy face[s] identified as happy).

Based on these four response outcomes, we derived d', an index of sensitivity which captures an observer's ability to correctly discriminate between two alternatives, in this case happy and angry expressions (Macmillan & Creelman, 2005). We also calculated criterion, or c, which measures an observer's bias to respond a certain way (i.e., "angry") relatively independent of whether the signal (in this case, anger) was present or not (Lynn & Feldman Barrett, 2014; Macmillan & Creelman, 1990). Illustrations of how hit rates and false alarms rates combine to produce d' and c values are included in Figure 2.

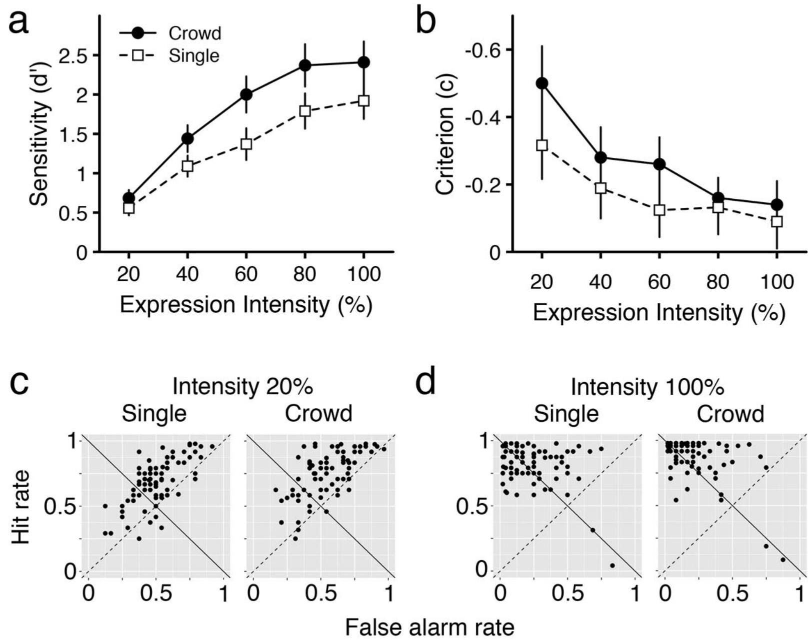
See the online supplemental materials for more information about how we calculated d' and criterion. We provide the raw data as well as the calculated Hits, False Alarms, Misses, Correct Rejections, Hit Rates, and False Alarm Rates for each experiment at https://osf.io/8npx6/ (Mihalache & Sweeny, 2020). Additionally, we include plots visualizing Hit Rates and False Alarm Rates for Experiments 1–5. We also conducted additional exploratory analyses with reaction time (RT) as our dependent variable for Experiments 1–5. However, because RT was not our primary interest, we share these analyses and results in online supplemental materials folder with our data and analyses online.

Results

We began with a repeated-measures ANOVA using d' as our dependent variable with factors of Numerosity (single, crowd) and Intensity (20%, 40%, 60%, 80%, and 100%). This analysis yielded main effects of Numerosity $F(1, 82) = 119.2$, $p < .001$, $\eta_p^2 = 0.40$, and Intensity $F(4, 328) = 178.4$, $p < .001$, $\eta_p^2 = 0.82$, and an interaction between Numerosity and Intensity $F(4,$

Figure 2

Sensitivity and Bias for Classifications of Single Faces and Crowds in Experiment 1



Note. Sensitivity (a) and bias (b) for classification of angry and happy expressions in Experiment 1. Each panel depicts performance across changes in expression intensity, separately for crowds and single faces. Increasingly negative criterion values are plotted up the *y*-axis in panel b, reflecting a liberal bias for classifying anger. Error bars in each panel represent 95% confidence intervals. (c) Scatterplots illustrating combinations of hit rates and false-alarm rates for the single and crowd conditions when intensity of expression was 20%. Each data point in each scatterplot represents one observer. Points to the left of the dashed diagonal line reflect a d' value greater than zero. d' values approach their maximum value toward the upper left corner of each plot. Points to the right of the solid diagonal line reflect negative criterion values, indicating anger bias. Note that when sensitivity (d') is low, there is more room for bias to vary toward the upper right corner (toward strong anger bias) or to the bottom left corner (toward strong happy bias). This is precisely why we were especially interested in differences in bias when sensitivity was low, and closely matched between the single and crowd conditions, in the low-intensity conditions. (d) Scatterplots illustrating combinations of hit rates and false-alarm rates for the single and crowd conditions when intensity of expression was 100%. Here, clustering of the data in the upper left corner of the figures reflects (a) high sensitivity, reflected also in high d' values, especially in the crowd condition, and (b) an accompanying (and necessary) return of criterion values toward zero.

328) = 9.51, $p < .001$, $\eta_p^2 = 0.10$ (Figure 2a). These results are not surprising—emotion categorization should be (and was) better when faces portrayed intense expressions, especially when many faces were present to carry this information. This d' analysis is nevertheless an important first step. We predicted an increase in anger bias when uncertainty was high, and this initial analysis confirmed that sensitivity was indeed poor (and the expressions on the faces were relatively ambiguous) at lower intensities of facial expression.

We then turned to our main analysis, evaluating criterion first relative to a null-value of zero and then as a function of numerosity and emotional intensity. Note that a criterion (c) value of zero indicates no bias, a negative value reflects a liberal bias to report the presence of anger, and a positive value reflects conservative use of the anger response label. We found an overall bias to overreport facial expressions as angry in response to both single faces as well as crowds of faces. When collapsed across all intensities of facial expression, average criterion was consistently negative: −0.17 (95% CI [−0.25, −0.91]) in the single face condition (one-sample t test: $t[82] = -4.28$, $p < .001$, $d = 0.47$) and −0.27 (95% CI [−0.35, −0.20]) in the crowd condition (one-sample t test: $t[82] = -7.70$, $p < .001$, $d = 0.85$). Across observers, the strength of anger bias for evaluations of single faces and crowds was positively related ($R^2 = 0.60$), suggesting a shared mechanism.

A repeated-measures ANOVA with criterion as our dependent variable revealed main effects of Numerosity, $F(1, 82) = 16.57$, $p < .001$, $\eta_p^2 = 0.13$, and Intensity, $F(4, 328) = 25.84$, $p < .001$,

$\eta_p^2 = 0.37$, as well as an interaction between Numerosity and Intensity $F(4, 328) = 3.82$, $p < .01$, $\eta_p^2 = 0.05$. Observers were more likely to misclassify crowds as being angry compared with single faces, and this amplification of anger bias in response to crowds was particularly evident at lower intensities of facial expression.[1] Anger bias, in general, was present at lower intensities for both crowds and single faces, dissipating at higher intensities of facial expression (Figure 2b). These data suggest that high perceptual uncertainty (and accompanying low perceptual sensitivity) and seeing multiple faces (e.g., crowds) independently and interactively engage anger bias.

Experiment 2: Is Amplified Evaluative Bias for Crowds Especially Strong for Categorizations of Anger?

Angry and fearful expressions can signal potential threat, but unlike anger, which is typically associated with approach behavior from another person, fear is associated with avoidant behavior (Adams et al., 2006). If the bias we measured in Experiment 1 is in place to prevent perceivers from making high-risk mistakes and to minimize potentially negative outcomes (Haselton et al., 2009; Johnson et al., 2013; Nesse, 2005), it should be specific for judgments of anger and/or stronger for evaluations of anger compared with fearful expressions.

Experimentally speaking, such an anger bias would persist even in a design context in which perceivers only discriminated angry from fearful faces. If, on the other hand, the bias reflects a more generic heuristic to report negative emotion relative to positive emotion, then an anger-specific bias should not be present when perceivers discriminate angry and fearful expressions. Experiment 2 disambiguated these hypotheses. We favored the former hypothesis, predicting a liberal bias specific to the classification of anger.

Method

Observers

To obtain the same power as in Experiment 1 (with alpha set at .05, based on a simple two-tailed matched-pairs t test between bias in the crowd and single conditions), we would have, of course, needed to once again collect data from 83 observers. But unlike Experiment 1, we did not run Experiment 2 while simultaneously collecting physiological data. In Experiment 1, observers were required to wait four seconds between image presentations, so as not to interfere with the physiological recording. This was not a concern in Experiment 2, which allowed us to nearly double the trial count for each observer. We thus decided to run 30 observers. Thirty new observers (24 women, six men) provided consent and participated in Experiment 2. Each observer had normal or corrected-to-normal visual acuity.

Stimuli and Procedure

The stimuli and procedures were identical to those in Experiment 1 with the exception that observers were required to discriminate between two negatively valenced facial expressions—angry and fearful. We used the same morphing procedure as in Experiment 1 to create faces with six intensities of fearful and angry expressions (2%, 20%, 40%, 60%, 80%, and 100%). Because we predicted that anger bias would be amplified under conditions of uncertainty, we included an extremely low intensity (2%) of facial expression in this experiment and several of our subsequent experiments. We selected this intensity because it was the lowest value at which a target emotion was present (it would have been impossible to calculate hit and false alarm rates with a truly neutral expression). Observers discriminated between fearful faces and the angry faces from the previous experiment. Observers completed 10 blocks for a total of 960 trials, with the exception of three observers who completed nine blocks for a total of 864 trials. Each condition (e.g., a crowd of fearful faces at 20% intensity) was repeated for 40 trials across all 10 blocks.

Results

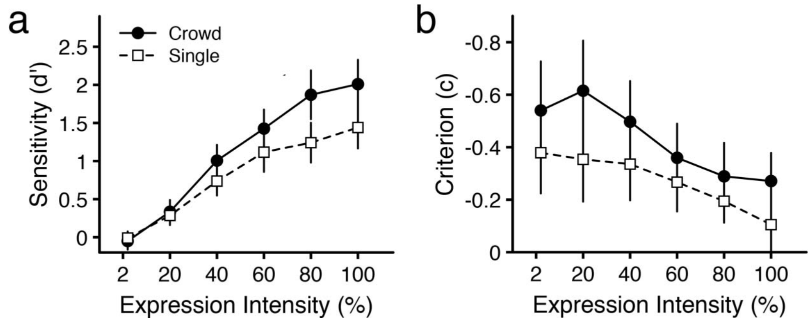
In this experiment, each observer's d' (sensitivity) and criterion (bias) were calculated for responding "angry" or "afraid." A repeated-measures ANOVA with d' as the dependent variable yielded main effects of Numerosity, $F(1, 29) = 54.61$, $p < .001$, $\eta_p^2 = 0.34$, and Intensity, $F(5, 145) = 97.69$, $p < .001$, $\eta_p^2 = 0.91$, as well as an interaction between Numerosity and Intensity $F(5, 145) = 10.12$, $p < .001$, $\eta_p^2 = 0.26$ (Figure 3a). Consistent with Experiment 1, sensitivity, or the ability to discriminate between facial expressions, improved with increases in the intensity of expression, especially for judgments of crowds.

Criterion analyses revealed that anger bias persisted in this experiment with observers misclassifying single faces and crowds as "angry" relative to "afraid." Note again that a negative value of criterion (c) reflects a liberal bias to report the presence of anger. When collapsed across all intensities of facial expression, average criterion was -0.27 (95% CI $[-0.38, -0.16]$) in the single-face condition (one-sample t test against a null-value of zero: $t(29) = -4.96$, $p < .001$, $d = 0.90$) and -0.43 (95% CI $[-0.57, -0.29]$) in the crowd condition (one-sample t test: $t(29) = -6.36$, $p < .001$, $d = 1.16$). Across observers, the strength of anger bias with single faces and crowds was positively related ($R^2 = 0.77$). A repeated-measures ANOVA with criterion as the dependent variable yielded main effects of Numerosity $F(1, 29) = 23.46$, $p < .001$, $\eta_p^2 = 0.38$, and Intensity $F(5, 145) = 11.25$, $p < .001$, $\eta_p^2 = 0.56$, and an interaction between Numerosity and Intensity $F(5, 145) = 2.33$, $p < .05$, $\eta_p^2 = 0.07$. These results are consistent with Experiment 1, showing that observers are more likely to evaluate faces as angry when facial expressions are weak and that this bias is amplified for judgments of crowds compared to single individuals, especially when uncertainty was high and sensitivity was low (Figure 3b). Importantly, this experiment provided evidence that observers did not merely adopt a generic negative bias when required to decide between two oppositely valenced emotions, such as happy and angry. Instead, high uncertainty attributable to low intensity of expression (and accompany-

[1] We did not follow up on this interaction with additional statistical tests because (a) we were not especially interested in comparing the strength of bias between the single-face and crowd conditions at any one level of expressive intensity, (b) we were more interested in the overall pattern, and (c) we preferred to limit the number of tests in our investigation. We do include follow-up tests in Experiment 4 and 5 because, in these cases, we were interested in effects at specific levels of crowd size, or between particular conditions.

Figure 3

Sensitivity and Bias for Classifications of Single Faces and Crowds in Experiment 2



Note. Sensitivity (a) and bias (b) for classification of angry and fearful expressions in Experiment 2. Each panel depicts performance across changes in expression intensity, separately for crowds and single faces. Error bars in each panel represent 95% confidence intervals.

ing loss of sensitivity) interacted with numerosity to elicit a potent evaluative bias specific to anger.

Experiment 3: Is Anger Bias for Crowds Amplified by Other Kinds of Perceptual Uncertainty, or Is It Specific to Emotional Ambiguity?

If anger bias is engaged most strongly when diagnostic information relevant to discriminating expressions is limited, then ambiguity from very basic perceptual dimensions, like visibility, may trigger bias similarly to the weak expressive intensity in Experiments 1 and 2. For example, observers have been shown to sometimes misclassify masked faces as angry (Nikitin & Freund, 2015), and abused children have been shown to be biased to report the presence of anger in pixelated faces, with their bias diminishing as the images became clearer (Pollak, 2008). We predicted that occluding the faces, and thereby limiting visibility and increasing uncertainty, should result in the same patterns of sensitivity and bias for evaluations of anger in single faces and crowds that we observed in Experiment 1. Such a result would suggest that anger bias is a heuristic that operates when perceptual decisions are compromised via uncertainty from a variety of sources.

Method

Observers

Thirty new observers (27 women, three men) provided consent and participated in Experiment 3. We selected this sample size based on the large effect of set size in Experiment 2, which produced observed power of .99 with an N of 30. Each observer had normal or corrected-to-normal visual acuity.

Stimuli and Procedure

The stimuli and procedures were identical to those in Experiment 1 with some adjustments that allowed us to test whether perceptual uncertainty, independent of expressive intensity, enhanced biased evaluations of anger. We kept the intensity of facial expressions constant at 40% across all trials because this midrange value elicited a consistently stronger bias for the crowd condition compared with the single condition in our previous two experiments. We instead varied the visibility of the faces by introducing visual noise. On a given trial, 0%, 15%, 30%, 45%, 60%, 75%, or 90% of the image pixels in each face were occluded by gray pixels (see Figure 4). Each face on crowd trials was occluded by the same amount of visual noise. Each observer completed 10 blocks for a

Figure 4

Range of Occlusion Levels for Experiment 3

Note. The range of occlusion levels (90%, 75%, 60%, 45%, 30%, 15%, and 0%) for one actor and expression in our stimulus set, which we produced by morphing faces from the NimStim set of facial expressions (Tottenham et al., 2009). See the online article for the color version of this figure.

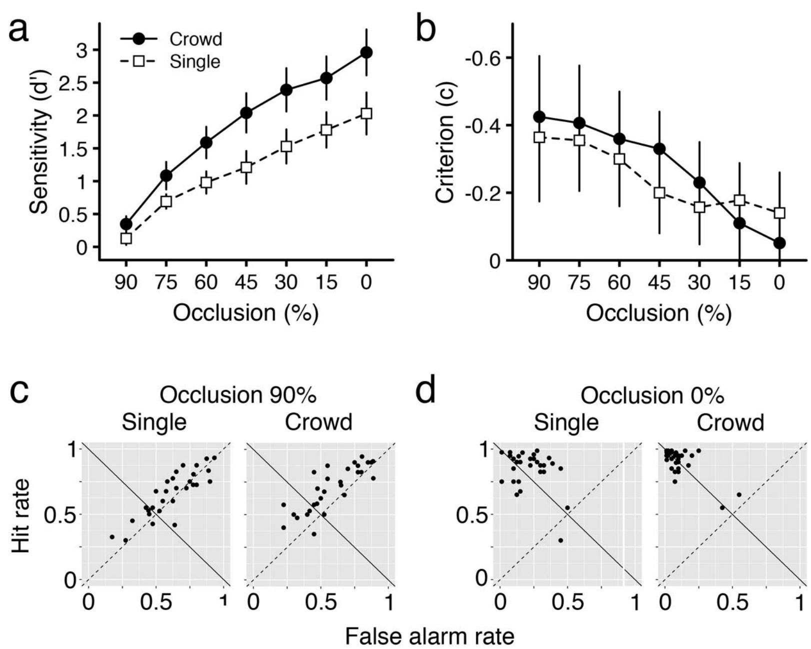
total of 1,120 trials, with the exception of two observers who completed nine blocks (1,008 trials total) and two observers who completed 12 blocks (1,344 trials total). Each condition (e.g., a crowd of happy faces with 30% occlusion) was repeated for 40 trials across all 10 blocks.

Results

We conducted a repeated-measures ANOVA with d' as the dependent variable and factors of Numerosity (single, crowd), and Occlusion (0%, 15%, 30%, 45%, 60%, 75%, or 90%). This analysis yielded main effects of Numerosity, $F(1, 29) = 92.63$, $p < .001$, $\eta_p^2 = 0.71$, and Occlusion, $F(6, 174) = 130$, $p < .001$, $\eta_p^2 = 0.92$, as well as an interaction between Numerosity and Occlusion, $F(6, 174) = 9.88$, $p < .001$, $\eta_p^2 = 0.25$ (Figure 5a). Sensitivity increased as occlusion decreased, with crowds being easier to discriminate relative to single faces, especially when the faces were easier to see.

Consistent with Experiments 1 and 2, observers demonstrated a tendency to classify facial expressions as angry. When collapsed across all magnitudes of occlusion, average criterion was −0.24 (95% CI [−0.37, −0.12]) in the single-face condition (one-sample t test against a null-value of zero: $t(29) = -3.89$, $p < .001$, $d = 0.71$) and −0.28 (95% CI [−0.40, −0.15]) in the crowd condition (one-sample t test: $t(29) = -4.55$, $p < .001$, $d = 0.83$). Across observers, the strength of angry bias for evaluations of single faces and crowds was positively related ($R^2 = 0.67$). A repeated-measures ANOVA with criterion as the dependent variable yielded a main effect of Occlusion, $F(6, 174) = 11.73$, $p < .001$, $\eta_p^2 = 0.48$, no main effect of Numerosity, $F(1, 29) = 0.75$, $p = .4$ (Figure 5b), and an interaction between Numerosity and Occlusion, $F(6, 174) = 3.10$, $p < .01$, $\eta_p^2 = 0.10$. When considered with the results of Experiments 1 and 2, these results suggest that people produce biased evaluations of anger when perceptual uncer-

Figure 5
Sensitivity and Bias for Classifications of Single Faces and Crowds in Experiment 3



Note. Sensitivity (a) and bias (b) for classification of angry and happy expressions in Experiment 3. Each panel depicts performance across changes in the amount of face occlusion, separately for crowds and single faces. Error bars in each panel represent 95% confidence intervals. (c) Scatterplots illustrating combinations of hit rates and false-alarm rates for the single and crowd conditions when occlusion was 90%. Points to the left of the dashed diagonal line reflect a d' value greater than zero. d' values approach infinity toward the upper left corner of each plot. Points to the right of the solid diagonal line reflect negative criterion values, indicating anger bias. Note that when sensitivity (d') is low, there is more room for bias to vary toward the upper right corner (toward strong anger bias) or to the bottom left corner (toward strong happy bias). (d) Scatterplots illustrating combinations of hit rates and false-alarm rates for the single and crowd conditions when occlusion was 0%. Note that sensitivity in the crowd condition was quite high, reflected by the clustering of the data in the upper left of the graph, which also restricts the extent to which bias can materialize. Bias was freer to manifest in the single condition at low levels of occlusion, where sensitivity was lower, which may account for the reversal to stronger anger bias in the single condition in this case.

tainty, and not just emotional uncertainty, is high. Of note, at the lowest levels of occlusion (e.g., 0% and 15%), anger bias was numerically higher in the single condition relative to the crowd condition. This is a function of the inverse relationship between sensitivity and bias. Only a paltry amount of bias was even possible in the crowd condition at these levels of occlusion because sensitivity was quite high, which was not the case with single faces (see Figure 5d). This illustrates that anger bias for single faces *can* exceed anger bias for crowds so long as perceptual uncertainty for single faces is greater than for crowds.

Experiment 4: How Does the Strength of Anger Bias Relate to the Size of a Crowd?

Crowds are powerful visual signals. For example, people are more likely to orient their attention toward a crowd's point of gaze than that of an individual (Gallup et al., 2012; Milgram et al., 1969). Importantly, this amplified influence of crowds on perceiver behavior is nonlinear, increasing from one to five members but plateauing with increases in size up to 15 members (Milgram et al., 1969). We predicted the strength of anger bias would have a similar relationship with crowd size.

Method

Observers

Thirty new observers (24 women, six men) provided consent and participated in Experiment 4. We selected this sample size based on the results of Experiments 2 and 3. Each observer had normal or corrected-to-normal visual acuity.

Stimuli and Procedure

The stimuli and procedures were identical to those in Experiment 1 with the exception that the number of faces displayed on each trial was variable, and featured 1, 2, 4, 6, 12, or 24 faces. As in Experiment 2, we also included the additional intensity of facial expression (2%). We included more incremental increases in size for the smaller crowds (e.g., 2, 4, 6) because we expected that each additional member may have a more substantial perceived impact in smaller sets, whereas the magnitude of anger bias may already peak by the time a crowd reaches 12 or 24 members. On each trial, observers indicated whether the face or faces depicted a happy or an angry expression. Each observer completed three blocks for a total of 864 trials. Each condition (e.g., a crowd of four happy faces with intensities collapsed) was repeated for 72 trials across all three blocks. Additional information about the locations of the faces in this Experiment can be found in the online supplemental materials.

Results

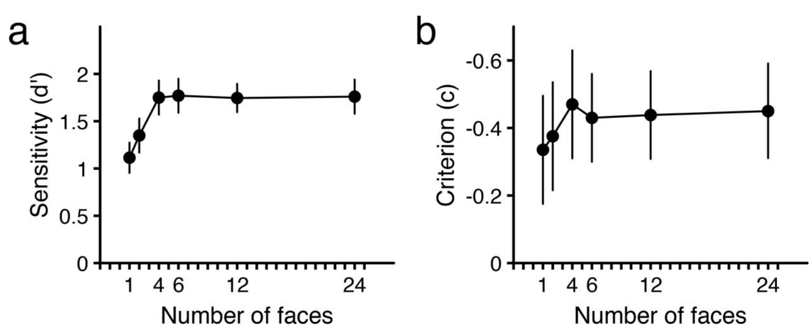
This experiment included several combinations of Numerosity (six levels) and Intensity (six levels). Because evaluating each level of intensity for each crowd size would yield 36 values of d' (and criterion) and the goal of this experiment was to examine the impact of crowd size, we simplified our analyses and increased power by conducting our signal detection analyses only across the six levels of numerosity (collapsing across intensities). A repeated-measures ANOVA with d' as the dependent variable yielded a main effect of Numerosity, $F(5, 145) = 27.54$, $p < .001$, $\eta_p^2 = 0.49$. This indicates that sensitivity for discriminating happy and angry expressions increased with the number of faces in the crowd until it plateaued around four to six members (Figure 6a).

A repeated-measures ANOVA with criterion as the dependent variable yielded a main effect of Numerosity, $F(5, 145) = 3.95$, $p < .01$, $\eta_p^2 = 0.12$. Post hoc comparisons between adjacent numerosity values indicated that anger bias increased nonlinearly with the number of faces in the crowd, reaching peak potency at four faces (Figure 6b). Observers endorsed more anger bias in response to four faces relative to two faces, $t(29) = 2.98$, $p < .01$, $d = 0.22$, but there were no significant differences between two faces and one face, $t(29) = 1.15$, $p = .26$, $d = 0.09$, four faces and six faces, $t(29) = 1.04$, $p = .30$, $d = 0.10$, six faces and 12 faces, $t(29) = -0.16$, $p = .87$, $d = 0.02$, or 12 faces and 24 faces, $t(29) = -0.59$, $p = .56$, $d = 0.04$.

We note that the inverse relationship between sensitivity and bias seen in our other experiments does not appear to be present in Figure 6. This is because all levels of emotional intensity were

Figure 6

Sensitivity and Bias for Classifications of Single Faces and Crowds in Experiment 4



Note. Each panel depicts performance across changes in the number of faces visible to observers. Error bars in each panel represent 95% confidence intervals.

included for each value of set size in Experiment 4. Put another way, these patterns reflect the main effects of set size for both dependent variables present in our other experiments; bias was overall stronger for crowds, as was sensitivity, but their interaction across emotional intensity is not shown in this case.

Experiment 5: Does Anger Bias Occur for Crowds With Additional Variability in Identity?

Real-world crowds contain variability in terms of facial-expression intensity, gender, age, race, and of course, identity. We restricted these potential sources of content bias in Experiments 1 through 4 to isolate the effect of numerosity and focus our investigation instead on contextual sources of bias. In Experiment 5, we began to evaluate anger bias while reintroducing one natural source of variability, in this case identity. We predicted that observers would continue to adopt an amplified anger bias in response to crowds whose members consisted of different identities, especially under conditions of higher uncertainty. Because our overall focus was on contextual bias, this experiment was an effort to demonstrate that our results do not require that all the faces in a crowd are identical and to lay groundwork for future examinations of how anger bias interacts with other sources of content variability in crowds.

Method

Observers

Thirty new observers (19 women, 11 men) provided consent and participated in Experiment 5. We selected this sample size based on the results of Experiments 2, 3, and 4. Each observer had normal or corrected-to-normal visual acuity.

Stimuli and Procedure

The stimuli and procedures were identical to those in Experiment 1 with a few notable exceptions. Unlike the previous experiments in which each crowd consisted of members with the same identity, Experiment 5 included two types of crowds—one in which each identity within the crowd was identical (homogeneous) and another in which each identity was different[2] (heterogeneous). The crowd condition also limited displays to four faces rather than 12, because Experiment 4 showed that sensitivity and bias plateau around this crowd size. The faces in the single and crowd conditions were restricted to the four central positions around the fixation point. Observers discriminated between the happy and angry faces from the previous experiments. Each observer completed eight blocks for a total of 1,152 trials. Each condition (e.g., a crowd of homogeneous happy faces at 20% intensity) was repeated for 40 trials across all eight blocks.

Results

We conducted a repeated-measures ANOVA with d' as the dependent variable and factors of Crowd Type (single, homogeneous crowd, heterogeneous crowd) and Intensity (2%, 20%. 40%, 60%, 80%, 100%). This analysis yielded main effects of Crowd Type, $F(2, 58) = 59.81$, $p < .001$, $\eta_p^2 = 0.56$, Intensity, $F(5, 145) = 157.1$, $p < .001$, $\eta_p^2 = 0.92$, as well as an interaction between Crowd Type and Intensity, $F(10, 290) = 13.96$, $p < .001$, $\eta_p^2 = 0.33$ (Figure 7a). Sensitivity for discriminating expressions improved as emotional intensity increased across all conditions. The interaction shows that sensitivity in the single-face condition was lower than sensitivity in the homogeneous and heterogeneous crowd conditions at higher intensities of emotional expression. Of note, there was no difference in sensitivity between crowds composed of identical versus different identities for five out of the six comparisons; we conducted six paired samples t tests comparing the two types of crowds at each level of Intensity: 2% $p = .73$, 20% $p = .34$, 40% $p < .01$, 60% $p = .49$, 80% $p = .45$, 100% $p = .4$ ($\alpha = .008$ with a Bonferroni correction for multiple comparisons).

Consistent with the previous experiments, observers demonstrated an overall tendency to classify facial expressions as angry. When collapsed across all intensities of facial expression, the average criterion was -0.44 (95% CI $[-0.60, -0.29]$) in the single-face condition (one-sample t test against a null-value of zero: $t(29) = -5.78$, $p < .001$, $d = 1.05$), -0.44 (95% CI $[-0.57, -0.30]$) in the homogeneous crowd condition (one-sample t test: $t(29) = -6.73$, $p < .001$, $d = 1.23$), and -0.44 (95% CI $[-0.57, -0.30]$) in the heterogeneous crowd condition (one-sample t test: $t(29) = -6.61$, $p < .001$, $d = 1.21$). A repeated measures ANOVA with criterion as the dependent variable yielded a main effect of Intensity, $F(5, 145) = 50.47$, $p < .001$, $\eta_p^2 = 0.81$, no main effect of Crowd Type, $F(2, 58) = 0.04$, $p = .96$, and an interaction between Intensity and Crowd Type, $F(10, 290) = 10.79$, $p < .001$, $\eta_p^2 = 0.27$ (Figure 7b). Of note, there was no difference in criterion (i.e., bias) between crowds composed of identical versus different faces as revealed by six paired-samples t tests comparing the two types of crowds at each level of intensity: 2% $p = .97$, 20% $p = .38$, 40% $p = .91$, 60% $p = .86$, 80% $p = .82$, 100% $p = .31$ ($\alpha = .008$ with a Bonferroni correction for multiple comparisons).

This experiment suggests that our main findings—stronger anger bias for judgments of crowds when expressions are ambiguous and perceptual sensitivity is low—do not require seeing a collective of identical faces. They can occur with no drop-off in strength for judgments of crowds with variable identities. It is possible that heterogeneity may impact bias for crowds with more than four faces, but our results at least suggest that it has no effect for set sizes of four. As in Experiment 3, when expressive intensity was high, anger bias flipped to being stronger for judgments of single faces than crowds. We explain this flip at length in the Discussion as the result of a predictable inverse relationship between sensitivity and bias.

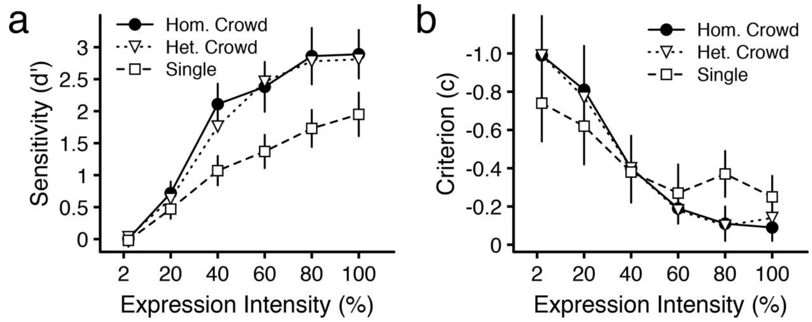
Experiment 6: Examining Anger Bias With Drift-Diffusion Modeling

We have demonstrated thus far that perceivers are systematically biased to classify subtle facial expressions as angry, especially when viewing crowds. What processes cause this bias to occur? Biases can be rooted in distinct cognitive or perceptual mechanisms that appear superficially similar when measured using a signal-detection approach (Morgan et al., 2012; Witt et al.,

[2] We are unable to show an example of the mixed identity condition because of copyright restrictions.

Figure 7

Sensitivity and Bias for Classifications of Single Faces, Homogeneous Crowds, and Heterogeneous Crowds in Experiment 5



Note. Each panel depicts performance across changes in expression intensity, separately for homogeneous crowds (same identity), heterogeneous crowds (unique identities), and single faces. Error bars in each panel represent 95% confidence intervals.

2015), as we did in the previous experiments. For example, an early stage, cognitive response bias may predispose an observer toward a certain categorization even before a trial begins. Alternatively, a bias in sensory processing may manifest as visual information becomes available to a perceiver, for example, in the rate at which their visual system gathers information about a particular type of face or crowd. It may be the case that perceivers' perceptual systems accumulate information about angry faces more quickly than happy faces. Finally, bias may be present in the decision stage, for example, in the sense that perceivers may require different amounts of information to endorse one category (e.g., angry) or the other. The previous experiments captured bias at the tail end of a chain of perceptual and cognitive processes, and thus our measurement of bias could have reflected any one of these mechanisms, or even a combination of them. Indeed, arbitrating between cognitive and perceptual effects is notoriously challenging and sometimes requires the use of convergent or creative methods (Firestone & Scholl, 2016).

The goal of Experiment 6 was to use drift-diffusion modeling (e.g., Ratcliff & McKoon, 2008) to isolate the cognitive or perceptual mechanisms that drive anger bias during perception of low-intensity single faces and crowds. We tailored our examination around three parameters from the model—starting value (z), drift rate (v), and threshold separation (a)—to separately examine each of the potential sources of bias described above. In keeping with the previous experiments, we also measured performance using the signal-detection approach, capturing both sensitivity in terms of d' and bias in terms of criterion. Predictions are described below, but first we wish to briefly describe the drift-diffusion approach and methodological adjustments we implemented to accommodate it.

Method

Observers

We did not have a strong a priori sense for likely effect sizes in terms of the modeling parameters in our experimental design. We thus looked to recent work using drift-diffusion modeling in the context of emotion perception (Lerche et al., 2019) to determine our sample size of 90 observers. Diffusion models have been reliable with as few as 25–48 trials per condition (Correll et al., 2015; Lerche & Voss, 2018). However, the number of trials required depends on the specific parameters being estimated and the proportion of errors. Because we were interested in drift rate, starting value, and decision thresholds rather than intertrial variability in these parameters, we followed recent recommendations for a medium number of trials (i.e., ~100 trials per condition) to allow the model to converge (Voss et al., 2015). We anticipated being able to collect up to 800 trials per observer. We thus designed our experiment to include two levels of numerosity (crowd and single), two expressive intensities (low and high), and two emotions (angry and happy), limiting our data to eight cells per observer. Crossing our design in this way, we were able to collect 96 trials per condition, which we pretested and confirmed to be sufficient for the model to converge using three pilot observers. We then proceeded with 90 new observers (60 women, 28 men, and two observers who declined to respond) who provided consent and participated in Experiment 6. Each observer had normal or corrected-to-normal visual acuity.

Stimuli and Procedure

The stimuli and procedures were similar to those in Experiment 1 with a few notable differences. First, the faces remained on the screen indefinitely, until each observer responded on each trial. Using a brief duration (e.g., 100 ms) as we did in the previous experiments would not have been ideal because estimates of information accumulation would have been based, in part, on lingering visual short-term memory (STM; VSTM) traces (Ratcliff & McKoon, 2008). Although diffusion analyses can still be reliable with these types of designs, we elected to leave the faces on the screen until response, ensuring that estimates of drift rate were based on pure sensory accumulation. Thus, in addition to measuring anger bias in a new way, this experiment provided an unexpected (but welcome) test with longer presentation times. Second, we used visual noise to obscure the visibility of each face (70%, in this case) on every trial, as in Experiment 3. We reintroduced this manipulation to make the task more difficult, potentially offsetting potential improvements in performance that might come with the unlimited viewing time, and to draw out potential differences between the modeling parameters. Third, based on the results of Experiments 4 and 5, we elected to display crowds of four faces with unique identities. That is, the same four men's faces were used throughout the task, but no faces were duplicated on a given trial. Fourth, we limited the emotional intensities of the crowds and single faces to 20% and 60% to accommodate the increased number of trials in each condition necessary for running the drift-diffusion analysis. We selected these intensities to examine effects of bias when sensitivity was both low and relatively high, but without making the task too easy. All the faces in each crowd had the same intensity of expression on a given trial.

The task was straightforward; observers viewed a single face or a set of four faces scattered around a central fixation point and indicated with a button press whether the emotion on the screen was anger or happiness. Observers were instructed to spread their attention across the entire screen, were asked never to look directly at the faces, and were encouraged to respond relatively quickly while at the same time prioritizing accuracy, striking a balance between the two. The experiment began with a practice block of 16 trials. Observers then completed two blocks for a total of 768 trials. Each condition (e.g., a crowd of angry faces at 20% intensity) was repeated for 96 trials across the entire experiment.

Results

Signal Detection Results

Regarding our signal-detection measures, we expected to replicate our previous results, including greater sensitivity for high-intensity crowds and a strong anger bias for low-intensity crowds. A repeated-measures ANOVA with d' as the dependent variable yielded main effects of Numerosity, $F(1, 89) = 73$, $p < .001$, $\eta_p^2 = 0.45$, and Intensity, $F(1, 89) = 189.6$, $p < .001$, $\eta_p^2 = 0.68$, as well as an interaction between Numerosity and Intensity $F(1, 89) = 33.45$, $p < .001$, $\eta_p^2 = 0.27$ (Figure 8a). Consistent with Experiment 1, sensitivity, or the ability to discriminate between facial expressions, improved with increases in the intensity of expression, especially for judgments of crowds.

Criterion analyses revealed that anger bias persisted in this experiment with observers misclassifying single faces and crowds as "angry," with an especially strong bias for low-intensity crowds. A repeated measures ANOVA with criterion as the dependent variable yielded main effects of Numerosity, $F(1, 89) = 4.32$, $p < .05$, $\eta_p^2 = 0.05$, and Intensity, $F(1, 89) = 63.1$, $p < .001$, $\eta_p^2 = 0.41$, and an interaction between Numerosity and Intensity, $F(1, 89) = 7.41$, $p < .01$, ($\eta_p^2 = 0.08$; Figure 8b).

Drift-Diffusion Modeling

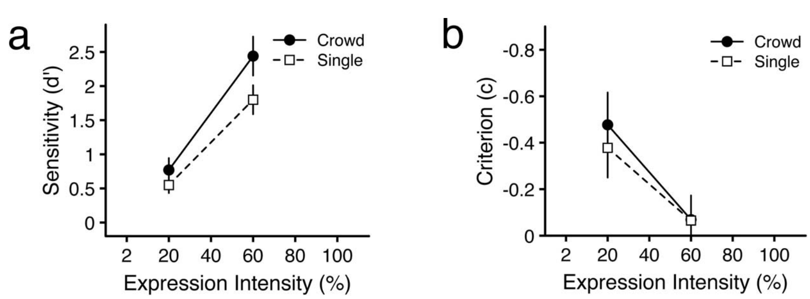
We next conducted analyses using the Ratcliff diffusion model (Correll et al., 2015; Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff & Tuerlinckx, 2002; Voss et al., 2004; Wagenmakers, 2009). This model is based on the assumption that people accumulate information about a stimulus over time and render a binary decision about that stimulus once accumulated information has passed a decision threshold. There are four primary parameters that the model is capable of estimating: (a) *starting value* (z): the degree to which an observer has an a priori bias to respond one way or another; (b) information accumulation or *drift rate* (v): sensitivity to information provided by the stimulus and task difficulty; (c) *threshold separation* (a): how conservative an observer is, or how much information an observer requires before making a decision; and (d) *nondecision time* ($t0$): orienting to stimuli and response execution. More information about how estimates of these parameters were calculated and how they relate to the variables in this experiment can be found in the online supplemental materials.

Drift-Diffusion Analyses

We ran the diffusion model using Voss and Voss's (2007) *fast-dm* software. We allowed parameter estimates of starting value (z) to vary only by set size and emotional intensity. We held nondecision time ($t0$) constant across cells of the design. We adopted this parameterization as it mapped most closely onto our hypotheses about perceptual and cognitive processes that could contribute to anger bias. However, results do not differ appreciably with other parameterizations (i.e., if we allow nondecision time to vary by cell or starting value to vary by emotion; see the online supplemental materials). Consistent with recommendations, we excluded trials with response times of less than 200 ms and greater than 5 s (1.5% of trials; Voss et al., 2013). The average KS index was nonsignificant ($Fit_M = .42$), indicating that the observed and estimated data likely represent the same population and that the

Figure 8

Sensitivity and Bias for Classifications of Single Faces and Crowds in Experiment 6



Note. Each panel depicts performance across changes in expression intensity, separately for crowds and single faces. Error bars in each panel represent 95% confidence intervals.

diffusion model is appropriate for evaluating our data. Examining data on an observer-by-observer basis, four observers had poor fits ($p < .05$). However, excluding them from analyses did not meaningfully change the interpretations made below (see footnote 4).

Predictions

We had hypothesized that the bias to report anger as indexed by criterion, especially at low-intensities, could reflect (a) the resting biases observers bring to each trial, (b) the rate at which they accumulate information about certain expressions in crowds, (c) the thresholds they use to report seeing anger, or a combination of these three mechanisms. We assessed each of these possibilities using the starting value, drift rate, and separation threshold parameters, respectively. Observed parameter estimates and standard deviations are reported in Table 1.

Starting Value. First, if anger bias was attributable to resting bias closer to the angry than the happy decision threshold, then observers would have a starting value of less than .5, and this would be especially true for low-intensity crowds. In this case, it would be easier for respondents to reach the anger decision threshold than the happy decision threshold. One-sample *t* tests indicated that starting value was significantly less than .5 regardless of trial type and intensity ($ps < .025$), indicating a resting bias to say that faces were angry. Furthermore, a 2 (Numerosity: Single vs. Crowd) × 2 (Intensity: Low vs. High) repeated-measures ANOVA on starting value indicated that this early cognitive resting bias was strongest when the stimuli were most ambiguous (i.e., for low-intensity faces), $F(1, 89) = 4.79$, $p = .031$, $\eta_p^2 = 0.051$.[3] There was no effect of numerosity on starting value, $F(1, 89) = 1.03$, $p = .312$, $\eta_p^2 = 0.01$, but there was a marginal interaction between numerosity and intensity, $F(1, 89) = 2.83$, $p = .096$, $\eta_p^2 = 0.031$. Starting value was closer to the angry threshold when faces had low than high-intensity emotion, and this was marginally stronger for single face than crowd trials. Overall, these parameter estimates for starting value suggest that observers had a resting bias to respond "angry," and this was amplified when facial expressions are ambiguous.

Drift Rate. Second, if anger bias was attributable to drift rate (i.e., rate of information accumulation), then observers should accumulate information about anger more quickly than information about happiness. However, drift rate reflects both perceptual sensitivity and the amount of information available in the stimulus. Thus, drift rate should be lower when less perceptually diagnostic information is visible, meaning it should be lowest on trials where faces have weak expressivity and where there is a single face present. A 2 (Numerosity: Single vs. Crowd) × 2 (Intensity: Low vs. High) × 2 (Emotion: Angry vs. Happy) repeated-measures ANOVA on drift rate[4] (v) revealed the expected main effect of intensity, $F(1, 89) = 167.32$, $p < .001$, $\eta_p^2 = 0.65$, such that observers accumulated information at a higher rate when the stimuli contained more expressive intensity. There was also a main effect of numerosity, $F(1, 89) = 6.38$, $p = .013$, $\eta_p^2 = 0.067$, such that observers accumulated information at a higher rate for crowds compared with single faces. The results with intensity and numerosity are consistent with previous characterizations of the drift parameter being related to the difficulty of information accumulation (Voss et al., 2004). Critically, however, there was also a main effect of emotion, $F(1, 89) = 26.55$, $p < .001$, $\eta_p^2 = 0.23$, and an interactive effect of emotion and intensity, $F(1, 89) = 61.76$, $p < .001$, $\eta_p^2 = 0.41$, such that drift rate was larger for anger than happiness, but *only* at low intensities. No other significant effects emerged ($ps > .125$). Indeed, focused comparisons to assess information accumulation of anger versus happiness while holding ambiguity in the stimuli constant revealed that observers accumulated information about anger more quickly than happiness from low-intensity single faces, $t(89) = 6.14$, $p < .001$, $d = .65$, and low-intensity crowds, $t(89) = 7.01$, $p < .001$, $d = .74$, but not from high-intensity single faces, $t(89) = .32$, $p = .747$, $d = .03$, or high-intensity crowds, $t(89) = .24$, $p = .810$, $d = .03$.[5] Thus, sensory accumulation can in part explain the observed anger bias in our previous studies such that observers accumulated information about anger at a higher rate than happiness, but only when emotional expressions were unclear.

Threshold Separation. Third, if anger bias was attributable only to differences in threshold separation (i.e., the amount of information required before a decision is made), then thresholds should be lowest for angry, low-intensity crowds. A 2 (Numerosity: Single vs. Crowd) × 2 (Intensity: Low vs. High) × 2 (Emotion: Angry vs. Happy) repeated-measures ANOVA on threshold separation revealed main effects of intensity, $F(1, 89) = 17.15$, $p < .001$, $\eta_p^2 = 0.162$, numerosity, $F(1, 89) = 210.64$, $p < .001$, $\eta_p^2 = 0.703$, and emotion, $F(1, 89) = 46.71$, $p < .001$, $\eta_p^2 = 0.344$. However, these main effects were qualified by two-way interactive effects. Specifically, numerosity interacted with emotion such that observers were more *conservative* in terms of deciding that faces were angry than happy, and this was especially true for crowds, $F(1, 89) = 8.76$, $p = .004$, $\eta_p^2 = 0.090$. This cannot explain the anger bias and would have instead worked against it. Emotion also interacted with intensity, $F(1, 89) = 13.99$, $p < .002$, $\eta_p^2 = 0.136$, such that observers were more conservative in terms of deciding that faces were angry than happy, and this was especially true when faces expressed emotion with high intensity. Thus, even though observers started closer to the angry threshold, they required more information to pass the angry threshold. Neither the two-way interaction of intensity and numerosity, $F(1, 89) = .55$, $p = .460$, $\eta_p^2 = 0.006$, nor the three-way interaction reached significance, $F(1, 89) = 2.06$, $p = .155$, $\eta_p^2 = 0.02$. In summary, response threshold does not explain the anger bias we have consistently observed in the preceding experiments. In fact, observers were more conservative to indicate that faces were expressing anger and instead required more information to make their response.

[3] The only change that resulted from excluding the four participants with poor fits was that the main effect of intensity on starting value changed from significant to marginal, $F(1, 85) = 3.60$, $p = .061$.

[4] Drift rate output from *fast-dm* reflects which threshold is typically reached, meaning that drift rate values are typically negative for Anger responses and positive for Happy responses. For example, a drift rate of 1 for Happy high-intensity crowd trials and a drift rate of −1 for Angry high-intensity crowd trials would mean that information about happiness and anger were accumulated at equal rates on these trials. Yet, because of their signs, they would appear statistically different. Thus, following past work (Voss et al., 2004, 2015), we reverse-scored drift rates for Angry trials to make those parameters directly comparable to drift rates on Happy trials.

[5] We used the Cohen's *d* formula for dependent-samples *t* tests also used by G*Power (Faul et al., 2007).

Table 1
Drift Diffusion Model Parameters by Trial Type

Parameter	Single				Crowd			
	Low intensity		High intensity		Low intensity		High intensity	
	Angry	Happy	Angry	Happy	Angry	Happy	Angry	Happy
Error rate	.29 (.20)	.54 (.21)	.21 (.19)	.26 (.18)	.23 (.21)	.54 (.25)	.16 (.21)	.20 (.19)
RT (in ms)	940 (210)	950 (200)	910 (180)	860 (150)	1,180 (330)	1,220 (360)	1,060 (250)	1,010 (240)
Starting value (*z*)	.45 (.10)		.48 (.09)		.45 (.09)		.48 (.09)	
Drift rate (*v*)	.81 (.82)	−.05 (.75)	1.36 (0.95)	1.33 (0.99)	.95 (.83)	−.06 (.86)	1.43 (1.01)	1.41 (0.96)
Decision threshold (*a*)	1.55 (0.38)	1.49 (0.33)	1.53 (0.38)	1.37 (0.29)	2.04 (0.53)	1.95 (0.58)	2.04 (0.54)	1.77 (0.45)

Note. Numbers in parentheses are standard deviations.

Discussion

Our hypotheses for the diffusion model parameters regarded how starting value, drift rate, and response threshold could each explain anger bias. If the systematic bias to judge crowds as angry, especially under perceptual ambiguity, was attributable to participants' resting bias to begin closer to the anger threshold, observers would have had a starting value of less than .5 especially for low-intensity crowds. This hypothesis was partially supported such that observers had an especially strong resting bias toward anger on low-intensity trials, but this was not amplified for judgments of crowds. If the systematic bias to judge low-intensity crowds as angry owed to the efficiency of information accumulation, then drift rate (*v*) should have been larger for angry than happy trials. Indeed, observers had superior accumulation of anger than happiness when expressions were ambiguous and superior accumulation of information from crowds than single faces (given that there was more information available). Finally, we hypothesized that anger bias could also be explained by the amount of information required before a decision was made such that the threshold (*a*) should be smallest for angry, low-intensity crowds. This hypothesis was not supported; observers were more conservative to indicate anger than happiness and required more information to evaluate crowds than single faces. So observers were good at seeing the emotion of crowds (i.e., high drift rate), but at low-intensities, they were *only* good at seeing the emotion of angry crowds. Even though observers required more information to make their decision that a crowd was angry than happy, they also started closer to the angry threshold. Thus the criterion bias to report anger, especially at low-intensities, reflects the resting biases observers bring to each trial and the rate at which they accumulate information about anger in low-intensity crowds, but not the thresholds they use to report seeing anger.

General Discussion

Summary and Mechanisms

This series of studies demonstrated that people are biased to classify facial expressions as angry, and that this can be especially so when viewing crowds of faces. We isolated a few contextual factors that elicit and escalate these erroneous evaluations, including numerosity and especially uncertainty (in terms of subtlety or visibility of facial expressions). When uncertainty was high, observers showed a tendency to overendorse anger for single faces and especially for crowds. This additional bias was nonlinearly related to crowd size, peaking when sets had approximately four constituents. Anger bias also persisted independently of the content of crowds, or at least the content we examined here. Specifically, bias to report anger occurred regardless of whether angry faces were discriminated against positive (happy) or negative (fearful) expressions, indicating that it did not simply reflect a generic negativity bias, although one may very well exist. Anger bias also occurred with equal strength for crowds made up of identical or unique identities.

Seeing multiple faces does not invariably trigger endorsements of anger. Our results indicate, instead, that potent anger bias for crowds emerges precisely when any heuristic should, which is when diagnostic information is scarce and perceptual sensitivity is diminished (Johnson & Fowler, 2011; Lynn & Feldman Barrett, 2014). Bias and sensitivity are lawfully related in two ways. First, reduction in bias *must* occur as a perceiver acquires high sensitivity. And second, loss of sensitivity may *cause* latent biases to emerge, allowing perceivers to maximize the utility of their judgments (Lynn & Feldman Barrett, 2014). The first of these two laws explains why reductions in bias (criterion) accompanied increases in sensitivity (d') in our experiments. Put another way, bias is the manifestation of particular types of errors, and reduction in the frequency of these errors (and thus, bias) is inseparable from improvements in perception. It also explains why in some cases, the magnitude of anger bias "flipped" when the faces were most clearly visible or expressive, respectively, with numerically weaker bias sometimes occurring for judgments of crowds compared to single faces (in Experiments 3 and 5). This result may seem to contradict our predictions at first glance, but it reflects the fact that bias must diminish when sensitivity is exceptionally high (Lynn & Feldman Barrett, 2014). In these two instances, sensitivity was much greater for judgments of crowds than for single faces at high intensities of expression. As a result only a paltry amount of bias was even possible for the crowd judgments, whereas bias was freer to manifest for judgments of single faces (the scatterplots in Figure 5 illustrate this process of bias compression for judgments of crowds). This pattern did not occur in every experiment, but these instances illustrate that anger bias for single faces *can* exceed anger bias for crowds, so long as perceptual uncertainty for the former is much greater than for the latter.

Anger bias was always greater for judgments of crowds compared with single faces when uncertainty was high and perceptual sensitivity was relatively low. This difference is our main finding, and, crucially, it cannot be accounted for by the fact that, overall, bias tends to reduce as sensitivity increases. Our main findings thus do not reflect a generic ceiling or floor effect, which would have affected both conditions equally. We propose that our results reflect a sort of antagonistic, push–pull relationship between bias and sensitivity. First, anger bias emerges in the context of uncertainty, which can be introduced via reduced expressivity or the addition of noise on the faces. These sources of uncertainty reduce perceptual sensitivity overall, resulting in large reductions in d' values. When that uncertainty is paired with the perception of a crowd, bias emerges with especially high potency. In parallel, crowds provide perceivers with more diagnostic information than single faces, and this introduces a separate, counteractive boost in sensitivity, especially when faces have high intensities of expression. This boost sometimes materializes for judgments of low-intensity expressions (although it was numerically small, and inconsistent across the experiments), but in these cases it was not enough to wash out the strong bias induced by the numerosity of the crowds. By examining the strength of bias as it related to changes in perceptual sensitivity, we found that anger bias for crowds can be quite potent, but it can nevertheless be diminished or reversed, and like all biases, its utility depends on whether a perceiver has more reliable information on which to base their decision.

The signal-detection approach we used in Experiments 1–5 did not articulate whether anger bias is rooted in perceptual or cognitive mechanisms (Morgan et al., 2012; Witt et al., 2015). We thus conducted a drift-diffusion analysis (Ratcliff & Childers, 2015) in Experiment 6 to more clearly arbitrate between the mechanisms and sources of anger bias, distilling it into discrete estimates of decision criteria and sensory processes. First, perceivers had higher boundary separation for making decisions about crowds of faces than single faces. They were conservative about evaluating crowds of four faces, requiring the accumulation of additional visual information to categorize their expressions relative to when they evaluated single faces, prioritizing accuracy over speedy judgments. This is notable because perceivers were instructed to find a balance between these two outcomes. Second, perceivers had larger drift rates for judgments of crowds compared to single faces. Naturally, drift rates were also larger for trials with highly expressive faces. Perceivers' visual systems thus processed crowds of highly expressive angry and happy faces efficiently, allowing them to arrive at rapid and accurate categorizations *despite* their large boundary separations. These findings are consistent with the amplified d' values we observed for judgments of high-intensity crowds relative to single faces in all of our signal detection analyses. Notably, greater drift rates make incorrect classifications less likely (Ratcliff & McKoon, 2008), consistent with the inverse relationship between sensitivity and bias in signal-detection theory (Lynn & Feldman Barrett, 2014), and across our experiments. Conversely, drift rates were much smaller for faces with low expressive intensity, especially happy faces. This inefficient visual processing of happy faces left more time and opportunity for random noise to occasionally push the accumulation of evidence toward an incorrect decision (i.e., an angry "false alarm"). Finally, and crucially, perceivers had strong resting biases to categorize faces as being "angry," especially when faces had low expressive intensity. When struggling to categorize a low-intensity crowd, this response bias would have made observers even more likely to erroneously report the presence of anger. Indeed, the error rate for judgments of low-intensity happy crowds was approximately 50% compared with just 20% for angry crowds. Thus, the amplified criterion bias to classify weakly expressive crowds as "angry" we found in each of our experiments appears to reflect an interaction between cognitive and perceptual processes, particularly the resting biases observers bring to each trial and the rate at which they accumulate information about angry and happy faces. It is important to keep in mind that the additional explanatory power of Experiment 6 came by virtue of its unique design, and thus comparisons with Experiments 1 through 5 must be made with some caution. For example, it is plausible that perceivers' decisions would have been more deliberative than those made in the first five experiments, given the long presentation times and the probability that perceivers may have fixated the faces, in some instances.

Limitations and Future Directions

Many investigations have examined processing biases for individual faces with full-intensity expressions that unambiguously signal threat (Vuilleumier & Huang, 2009), particularly when those faces are seen in the context of other faces (Shasteen et al., 2015). Conversely, ours is one of just a few investigations to have examined judgment biases for entire crowds of faces (Douilliez et al., 2012; Lange et al., 2008; Yang et al., 2013), and as far as we know of, the only one to do so with relatively subtle, ambiguous expressions. Not surprisingly, then, our work has limitations that we could not address in this initial investigation, and there are several questions yet to be answered. We address these topics in the paragraphs below.

First, we based our predictions on what we believed to be logical and intuitive extrapolations from social psychological theory on affordances (Becker et al., 2007; Gibson, 1979; Holbrook et al., 2014) and group behavior (Baumeister et al., 2016; Festinger et al., 1952; Le Bon, 1897; Vilanova et al., 2017); namely, that crowds should have greater ability to inflict harm on a perceiver compared to individuals, and that perceivers may have some intuition that crowds have more aggressive potential than individuals. However, because we did not test these assumptions directly, we cannot draw conclusions about how they may have contributed to our results. Our results are nevertheless consistent with these theoretical frameworks, and our work provides a methodological blueprint for future research that could take this step. In fact, recent work demonstrates that affordances about groups can be inferred from ensemble coding (Goodale et al., 2018), and as these authors say, "A perceiver need not be immersed in an environment, real or imagined, to feel the weight of being outnumbered" (p. 1672).

Second, it is unclear how the bias we have demonstrated here extends beyond some of the design parameters we selected for testing in the lab. Real-world events are often fraught with fleeting, chaotic, and unpredictable information, requiring quick action. Anger bias may be a heuristic for guiding decision making in the face of these sorts of pressures that can be rewarded and strengthened over time (Johnson & Fowler, 2011). Indeed, negatively biased evaluations of single faces are amplified in the context of unpredictable exposure (Davis et al., 2016) and rapid evaluation, and are diminished when observers are required to delay their judgments (Neta & Tong, 2016). The fact that our results replicated in Experiment 6 with much longer (in fact, unlimited) durations suggests some invariance to timing, but future work should more thoroughly examine whether anger bias with crowds is similarly malleable. Additionally, anger bias may be a heuristic that emerges specifically when perceivers are forced into categorical decisions. This is important to consider given evidence that, when given the chance, people tend to provide multidimensional evaluations of facial expressions, attributing a mixture of emotions (Hall & Matsumoto, 2004; Riediger et al., 2011). Thus, it is unclear whether a similarly strong anger bias would have emerged, especially for judgments of crowds, if the observers in our investigation had not been forced into a binary decision. There is, nevertheless, value in investigating binary choices, as many actions or decisions are ultimately based on coarse categorical evaluations.

Third, our decision to focus on *contextual* effects of bias—particularly the interaction of crowd size and expression intensity—necessitated the use of a highly controlled, albeit limited, stimulus set and an approach of displaying homogeneous crowds of identical faces, at least for our initial experiments. This approach added value not for its generalizability but because it allowed us to test whether the biases we predicted held up under restricted conditions (Mook, 1983) and to maintain internal validity (Risko et al., 2012) and thus better isolate and understand mechanisms (Banaji & Crowder, 1989). We did demonstrate our effect with more heterogeneous sets of faces in Experiments 5 and 6, but even these crowds were unnatural in the sense that the same four identities were seen across hundreds of trials, and the frequency of happiness and anger remained fixed within each experiment. Although these experiments employed multiple identities and emotion expressions, it will nonetheless be important to assess how these mechanisms unfold when there is greater variability in the identity of expressers (Judd et al., 2012). Future investigations should examine (a) crowds with more diverse identities, or even crowds of real faces seen in-person (Veljaca & Rapee, 1998) and (b) how perceivers recalibrate their hit and false alarm rates as they learn that the probability of encountering one facial expression is greater than that of the other (Lynn & Feldman Barrett, 2014). Future work should also employ analytical approaches that allow for analysis of the random variance introduced by stimuli and participants (e.g., multilevel models; see Alt et al., 2019; Goodale et al., 2018 for examples) given that averaging across participants or stimuli can introduce error and exaggerate the size of effects (Judd et al., 2012). How our results translate to contexts with more fluid affective displays rates, or even display rules, is an open question.

Fourth, our investigation left open several questions regarding the possibility of *content* effects, or the classes of information that influence bias (Haselton et al., 2009). We mostly avoided examining how the content of faces, aside from the emotion itself, influenced bias, largely because the types of content that could do so are vast, and in our opinion, it was important to examine context first. One important potential source of content bias in the perception of emotional crowds is gender. People are biased to judge others to be men, presumably because gender categorizations take into account others' affordances (Johnson et al., 2012), as is the case with categorizations of emotion. In fact, the perceived threat of a crowd is known to depend on the number of men within it (Alt et al., 2019). Men also tend to be more physically aggressive during intergroup conflict (McDonald et al., 2012). Varying the gender of the faces in our crowds would provide a clear test of the role of stimulus content on bias, and potentially a test of the role of affordance-to-commit-harm on the strength of our effect, too. We ran a pilot study and found evidence that men's faces induced a stronger anger bias than women's faces overall (see the online supplemental materials), supporting these predictions, but our stimulus set was limited and our design did not include measures of participants' attitudes about gender. We thus propose that future work should examine this topic more comprehensively. Another potential direction for content effects on crowd bias includes examining judgments of ingroup and outgroup members, especially because the presence of anger is known to eliminate the outgroup homogeneity bias (Ackerman et al., 2006). A third contextual direction could include examining how dynamic interactivity, or even entitativity, modulates the strength of anger bias in crowd judgments. Perception of dynamic, whole-body crowd interaction is important for perception of, and reaction to, panic (Huis in 't Veld & De Gelder, 2015). Additionally, perceivers afford individuals less of a mind when they are part of a large, cohesive, and entitative group (Morewedge et al., 2013). It is reasonable that a crowd with shared goals and values should react and engage with a perceiver more as a group, potentially exaggerating anger bias. Future research should examine how the extent to which perceivers think that a crowd has a "group mind" influences biases in judgment about their collective affect.

Fifth, and finally, the affective bias we have shown here could potentially be moderated by a perceiver's internal characteristics, like anxiety or aggression. People with social anxiety tend to attribute a higher emotional cost to interacting with groups than individuals (Douilliez et al., 2012). They also tend to interpret ambiguous information as being hostile (Bell et al., 2011; Yoon & Zinbarg, 2008), and are faster to push "away" (using a joystick) in response to images of crowds when the number of angry members increases (Lange et al., 2008). To our knowledge, just one study has examined biased evaluations of crowds among people with social anxiety (Yang et al., 2013), but the authors used emotionally heterogeneous crowds of full-intensity expressions of happiness and anger, which makes comparison with our results difficult. Aggressive individuals also have a tendency to infer hostile intent in others' behaviors (Dodge, 2006) and are especially biased to report that ambiguously emotional faces are angry (Schönenberg & Jusyte, 2014). New research examining how biases may contribute to the maintenance of anxiety and aggressive behavior in clinical populations is thus important to consider.

Alternative Explanations

Recent work shows that extreme members of a set tend to dominate and amplify ensemble evaluations of sets and crowds, both for judgments of shape size (Kanaya et al., 2018) and a crowd's emotional expressions (Goldenberg et al., in press), but not a crowd's attractiveness (Ying et al., 2019). This phenomenon occurs presumably because larger objects "pop out" or because emotional faces, particularly angry faces, are fixated longer during brief viewing. Our crowds were homogeneous in terms of expressivity and thus should not have depended on this same mechanism. Additionally, the unique pattern of increased sensitivity (i.e., higher d' values) for high-intensity expressions hints that the crowd judgments in our experiments may even reflect an effect of probability summation rather than pure ensemble integration (Blake et al., 1980). Our data also do not allow us to determine that the process of sampling, integrating, and then averaging (or pooling) information across the faces in crowds occurred in our experiments. Thus, we cannot draw conclusions about the operation of ensemble coding, nor was this our objective. Our findings nonetheless add an important complementary piece to the growing crowd-perception literature, which has largely focused on sensitivity or discrimination ability rather than bias in perception of facial expressions.

Our results are unlikely to be attributable to differences in the deployment of visual attention, different patterns of fixation across our conditions, or engagement of a visual search process. We acknowledge that because we did not use an eye tracker, we cannot be sure that observers always maintained fixation at the center of the screen. Given the short presentation time we used in most of our experiments, this should not be a concern. Single faces and crowds were always displayed for 100 ms (in Experiments 1–5), a duration too brief for observers to have made deliberate saccades to individual faces (Findlay & Walker, 1999) in either condition. Moreover, in Experiments 1–4 the faces within any given crowd were always identical to one another, so attending to (or searching for) different faces, even randomly or unintentionally, would not have imparted any benefit to observers. Finally, faces in the single condition were always placed near fixation, so initiation of rapid, longer-distance saccades on these trials was not necessary. The amplified liberal bias in the crowd condition thus appears to be rooted in an effect of numerosity and not issues related to peripheral presentation or visual acuity.

Spatial uncertainty was higher in the single-face condition than in the crowd condition. That is, the location of the target on a single-face trial could never be predicted, whereas the locations of the faces were always predictable on crowd trials. However, we consider it very unlikely that this uncertainty could have been responsible for our results, for example, biasing responses toward neutral interpretations on single-face trials. First, the other two sources of uncertainty in our experiments—expressive uncertainty and low visibility—moved bias in the opposite direction, toward endorsements of anger. Second, estimates of the starting bias parameter did not differ between the single-face and crowd conditions in Experiment 6. And even though this experiment featured long presentation times, spatial uncertainty was still greater for single faces than crowds at least at the start of each trial, which is precisely when starting bias is measured.

Conclusion

We demonstrated a bias to report anger on faces when visual information is scarce or ambiguous, and we showed that this bias is amplified when perceivers evaluate crowds relative to individuals. Our findings complement the many examples of biased processing of threat when it is more conspicuous, for example in terms of prioritized attention (Dominguez-Borras & Vuilleumier, 2013), access to visual awareness (Capitão et al., 2014), or during visual search (Gilbert et al., 2011; Huang et al., 2011). More generally, our work illustrates the value of considering bias in addition to sensitivity, especially for understanding how people see and understand information at the crowd level.

Context Paragraph

One of the primary research foci at the Visual Perception, Emotion, and Cognition Laboratory is ensemble coding and crowd perception. This investigation expands on this body of research and takes a complementary approach by focusing on bias, rather than sensitivity, during perception of crowds. The authors conceived of this project while they were investigating a potential relationship between crowd perception and concomitant facial mimicry. Dr. Timothy Sweeny, a vision scientist, and Diana Mihalache, a clinical doctorate student, are particularly interested in bridging vision science research with other areas and disciplines of psychology. For example, we have established a collaboration with a clinical psychologist to extend this work to children and parents with anxiety. Dr. Sweeny and Ms. Mihalache collaborate with psychologists from other areas (e.g., social, cognitive, and clinical), including Dr. Sarah Lamer, and experts from other disciplines (e.g., engineering) within the University of Denver and at other institutions, as well as academic medical centers, and we hope that this initial research will provide the foundation for further collaborations.

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