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Working Memory Capacity is Associated with Optimal Adaptation of Response Bias to Perceptual Sensitivity in Emotion Perception

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Abstract

Emotion perception, inferring the emotional state of another person, is a frequent judgment made under perceptual uncertainty (*e.g.,* a scowling facial expression can indicate anger or concentration) and behavioral risk (*e.g.,* incorrect judgment can be costly to the perceiver). Working memory capacity (WMC), the ability to maintain controlled processing in the face of competing demands, is an important component of many decisions. We investigated the association of WMC and anger perception in a task in which "angry" and "not angry" categories comprised overlapping ranges of scowl intensity, and correct and incorrect responses earned and lost points, respectively. Participants attempted to earn as many points as they could; adopting an optimal response bias would maximize decision utility. Participants with higher WMC more optimally tuned their anger perception response bias to accommodate their perceptual sensitivity (their ability to discriminate the categories) than did participants with lower WMC. Other factors that influence response bias (*i.e.*, the relative base rate of angry vs. not angry faces and the decision costs & benefits) were ruled out as contributors to the WMC-bias relationship. Our results suggest that WMC optimizes emotion perception by contributing to perceivers' ability to adjust their response bias to account for their level of perceptual sensitivity, likely an important component of adapting emotion perception to dynamic social interactions and changing circumstances.

Keywords

working memory capacity, emotion perception, decision making, signal detection theory, optimality

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During social interactions, people make inferences about what their social partners are feeling, an example of emotion perception. Emotion perception judgments are seemingly made rapidly, automatically, and effortlessly. Judgments in one moment (e.g., that a social partner is angry) guide the perceiver's behavior in the next moment (e.g., to allay the perceived anger). A person's ability to perceive the feelings of others is necessary for normal social functioning. A deficit in emotion perception is a defining feature of almost every class of mental disorder and might constitute a transdisorder vulnerability to psychopathology (Phillips, Drevets, Rauch, & Lane, 2003). Emotion perception abilities change with chronological development and aging (Isaacowitz et al., 2007; Horning, Cornwell, & Davis, 2012), and are impaired in almost all neurodegenerative disorders.

Outside the laboratory, emotion perception is frequently performed under *perceptual uncertainty* and *behavioral risk*. Perceptual uncertainty means that a given set of facial movements can mean different things in different contexts. Behavioral risk means that there are costs to being wrong about the meaning of facial actions. Because of uncertainty and risk, inferring a person's emotional state from his or her facial expression is not simply a matter of accurately decoding the structural information of a facial expression. Context, including the decision environment and the perceiver's internal state, is crucial to disambiguating alternative interpretations of a given facial expression (for a review see Wieser & Brosch, 2012). For example, both affectively-charged background imagery presented with a face and the perceiver's own behavioral inhibition/activation tendencies can interact to influence how intense a facial depiction of fear needs to be before it is judged as fearful (Lee, Choi, & Cho, 2012).

The importance of correctly accounting for context suggests that aspects of executive function, such as working memory capacity (WMC), may have a role in effective emotion perception. Working memory capacity measures the capacity for "controlled processing" of items in working memory (Barrett, Tugade, & Engle, 2004). This notion of processing capacity is distinct from working memory size or storage capacity (e.g., how many items can be remembered simultaneously). Controlled processing is one's ability to maintain goal-oriented performance in conditions characterized by interference with, and competing demands on, focusing on what is relevant and suppressing extraneous, irrelevant stimuli or thoughts (Kane & Engle, 2002). For example, accomplishing tasks in a context that requires inhibition of habitual or typical responses utilizes WMC (*e.g.*, Kane & Engle, 2003). As such, WMC influences performance across a variety of domains, such as reading comprehension (*e.g.*, Daneman & Merikle, 1996), following directions (*e.g.*, Engle, Carullo, & Collins, 1991), and effective reasoning about novel or changing problems (*e.g.*, Conway, Cowan, Bunting, Therriault, & Minkoff, 2002). Breakdown of controlled processes permits responses that are less relevant to current goals to emerge, causing performance decrements (reviewed by Barrett et al., 2004). Fatigue, drug use, and mental illness are all associated with state-like variation in the ability to maintain controlled processing, and produce short-term fluctuations of otherwise trait-like variation among people (reviewed by Engle, 2010). Although high WMC has been associated with optimal decision making under economic risk (*e.g.*, Cokely & Kelley, 2009), WMC has received little attention in emotion perception, a domain in which risk and perceptual uncertainty can interact.

Many of the functional characteristics typical of tasks shown to involve WMC likely apply to emotion perception. For example, effective emotion perception requires perceivers to discriminate emotion categories by their physically similar, and sometimes shared, facial actions. Higher WMC is associated with more effective visual target identification in the presence of distracting information that is physically similar to target information (Tuholski, Engle, & Baylis, 2001). Furthermore, maintaining effective emotion perception across different social contexts (*e.g.,* talking with peers *vs.* superiors) may require perceivers to adapt their expectations about the risks of misperception, and higher WMC is associated with more successful adaptation of behavioral strategies to changing conditions (Schunn & Reder, 2001).

While WMC has not been examined as an individual difference in emotion perception, operating under working memory load interferes with self-regulation of emotional expression (Schmeichel, Volokhov, & Demaree, 2008) and interpretation of non-verbal social cues (Phillips, Tunstall, & Channon, 2007), including categorization of facial expressions in verbal labeling tasks (Phillips, Channon, Tunstall, Hedenstrom, & Lyons, 2008) and categorization of ambiguous facial expressions (Lim, Bruce, & Aupperle, 2014). For example, Phillips, et al. (2008) used a verbal working memory load in a dual-task design with a facial emotion labeling task. They found that working memory load

decreased accuracy of emotion perception. In addition, Lim, et al. (2014) used a spatial working memory load in a dual-task design with an ambiguous facial emotion categorization task. They found that interference with working memory by emotion-word distractors led perceivers to more frequently categorize the faces as "fearful," but only for the more intense depictions of fear. Taken together, these findings suggest that individual differences in WMC may influence how effectively people discriminate and/or respond to the emotions of others: Working memory capacity may interact with environmental context, such as the perceptual similarity of one emotion category to another (Lim et al., 2014), to influence the functionality of emotion perception (Phillips et al., 2008).

Emotion perception research often focuses on categorization *accuracy* (proportion of trials correctly answered). In addition, studies typically employ a balanced base rate and undifferentiated decision payoffs. *Base rate* refers to the probability of occurrence of different emotional categories. A balanced base rate means that no one category is encountered more often than another (for example, when different emotion categories are presented with equal frequency in an emotion perception task). *Payoff* refers to reinforcing and/or punishing feedback following correct or incorrect categorization judgments, respectively. For undifferentiated payoffs, the magnitude of reward for correct judgments does not differ from the magnitude of punishment for incorrect judgments (for example, the feedback statements "That was correct" and "That was incorrect" are assumed to have the same magnitude). However, signal detection theory (SDT; Green & Swets, 1966; Macmillan & Creelman, 1991) recognizes that accuracy decomposes into two factors (e.g., Lynn & Barrett, 2014; Lynn, Hoge, Fischer, Barrett, & Simon, 2014). One factor is *perceptual sensitivity*, a perceiver's ability discriminate *targets* (*e.g.,* faces depicting one emotion category, such as anger) from *foils* (*e.g.,* faces depicting an alternative emotion). Perceivers with high sensitivity attain high accuracy because they experience less uncertainty about what the correct answer is, and so make fewer mistakes. The other factor is *response bias*, a perceiver's tendency to favor answering with one category over another. With the typically-employed balanced base rate, perceivers who do not intrinsically favor one answer over another, called *neutral* bias, attain high accuracy because they match their use of an answer to the probability of its being the correct answer (the base rate). It remains unaddressed whether WMC's influence on emotion perception may be in part attributable to an effect on perceiver sensitivity, bias, or both.

Moreover, perceivers may attempt to *optimize* their decision making, seeking to maximize the payoff accrued over a series of decisions (e.g., Lynn, Zhang, & Barrett, 2012). In SDT, when perceivers seek to optimize decision making, three parameters influence their bias: base rate, payoff, and the perceivers' own sensitivity (*e.g.,* Lynn & Barrett, 2014). Under balanced base rate and undifferentiated payoffs, neutral bias is optimal: No answer is more likely to be correct than another, and any costs of incorrect responses are offset by benefits of correct responses (see Lynn & Barrett, 2014; Lynn et al., 2014). However, when base rate or payoffs do specify a non-neutral optimal bias, the perceiver's sensitivity becomes a third biasing parameter (Figure 1B, and see *e.g.,* Stretch & Wixted, 1998; Lynn et al., 2012). For example, effectively avoiding obstacles in conditions of poor visibility requires more cautious behavior than in conditions of good visibility. The increase in cautiousness (more extreme bias) under poor visibility is called for, not because obstacles are more common (an increase in base rate) or more costly to hit (a change in payoffs), but because they are harder to discriminate from open space (a decline in perceiver sensitivity). To achieve the optimal blend of correct and incorrect judgments, given their benefits, costs, and likelihoods, perceivers with low sensitivity must adopt a more extreme bias than perceivers with high sensitivity (Lynn & Barrett, 2014).

In sum, working memory is associated with accuracy in emotion perception tasks (e.g., Phillips et al., 2008). In the presence of uncertainty and risk, which likely characterizes emotion perception outside the laboratory, SDT decomposes accuracy into sensitivity and bias. We can, then, recognize three hypotheses by which WMC might influence emotion perception under uncertainty and risk: (1) high WMC promotes sensitivity, which produces high accuracy (Lynn & Barrett, 2014); (2) high WMC promotes neutral response bias, which, under the unbiased designs typical of many emotion perception experiments, produces high accuracy (e.g., Lynn et al., 2014); and (3) high WMC promotes the perceiver's ability to optimize his or her bias to one of the three parameters that influence bias, (i) base rate, (ii) payoff, and (iii) the perceiver's own sensitivity. Prior experiments measuring accuracy are unable to distinguish these three alternative hypotheses, and experiments that impose a neutral bias cannot distinguish hypothesis 2 from 3, because in such experiments neutral bias *is* optimal bias. Here,

we implemented tasks capable of distinguishing these three hypotheses. Identifying the correct mechanism by which WMC influences decision is important for programs seeking to improve decision making or to understand differences in the effectiveness of decision making across individuals.

The Current Study

Our research question was: What is the role of WMC in emotion perception under perceptual uncertainty and behavioral risk? To address this question we examined the association between individual differences in WMC and emotion perception by manipulating levels of uncertainty and risk in an anger perception task. Uncertainty was implemented by "angry" and "not angry" categories comprised of shared morphed facial scowl intensities. Risk was implemented by points earned or lost for correct and incorrect responses, respectively. Participants attempted to earn as many points as they could by categorizing faces as angry or not angry (Figure 1). We can distinguish hypotheses 1-3 by comparing the influence of WMC on sensitivity and bias. We can distinguish hypotheses 3i-iii by systematically manipulating the three parameters that influence bias. On a first visit to the laboratory, all participants completed a mildly conservatively biased "baseline" version of the task. On a return visit to the laboratory, participants completed a "contrast" version of the task that differed from baseline by the manipulation of one of the three parameters that influence bias. Relative to baseline, the contrast task demanded either (i) more conservative bias due to high base rate of angry faces, (ii) more liberal bias due to costly missed detection mistakes, or (iii) more conservative bias due to low sensitivity.

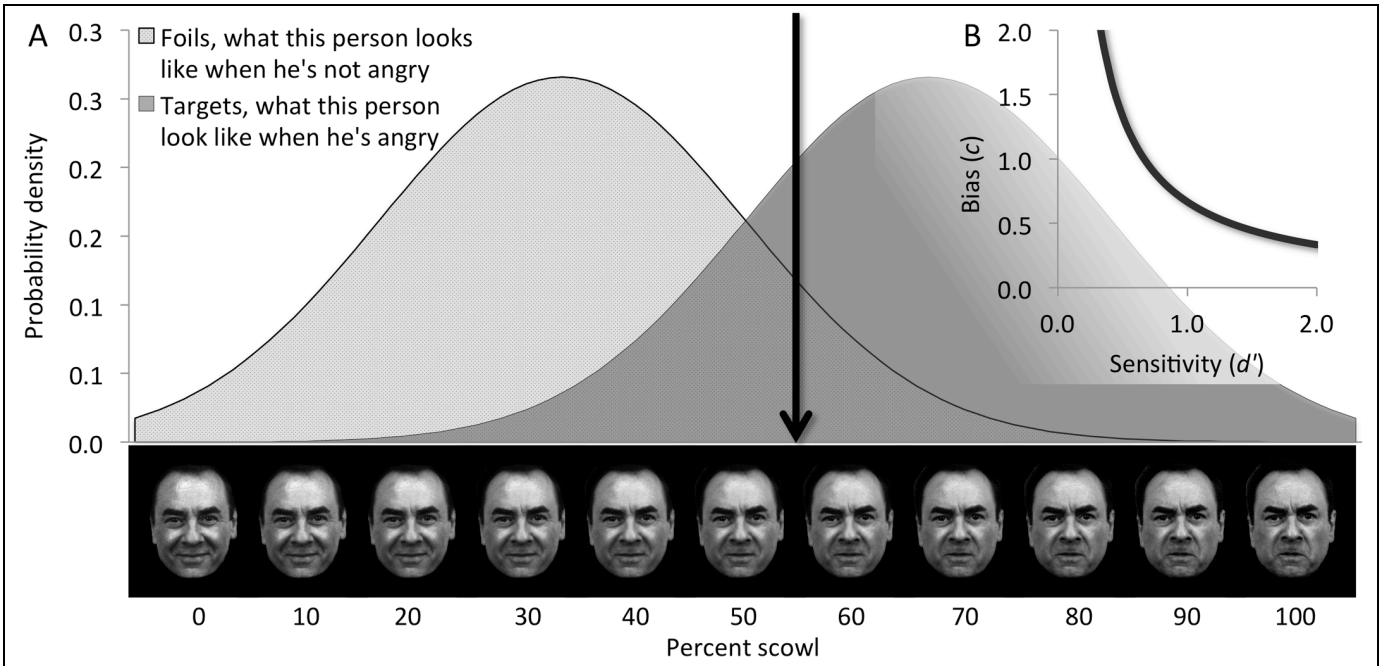

Figure 1. Emotion perception as a signal detection issue. (A) Signals (instances of facial emotion), arise from two categories: targets (e.g., anger) and foils (e.g., not-anger). Signals from either category vary over a perceptual domain, from weak to strong cues of the emotion categories (e.g., scowl intensity as a cue of anger, on the x-axis). Here, the perceiver responds to faces above (to the right of) his or her decision criterion (arrow) as if they are angry, and to faces below criterion as if they are not angry, yielding four possible outcomes: An above-criterion angry face is a correct detection, an above-criterion not-angry face is a false alarm mistake, a below-criterion angry face is a missed detection mistake, and a below-criterion not-angry face is a correct rejection. Three mathematical parameters describe the decision environment: the perceptual similarity of the target and foil categories (described here by Gaussian distribution means and standard deviations), payoffs accrued for each category judgment (benefits and costs associated with the four outcomes), and the base rate of encountering signals from the target vs. the foil category. Measures of perceptual sensitivity, depicted as overlap of targets and foils, characterize the amount of perceptual uncertainty in the environment or experienced by a perceiver. Measures of response bias characterize the decision criterion's location on the

perceptual domain. Response bias is described as conservative (rightward, categorizing only strong signals as angry), liberal (leftward, categorizing even weak signals as angry), or neutral (in the middle). By combining these parameters, signal detection theory's expected value function estimates the optimal criterion location for a given set of parameter values (e.g., Lynn & Barrett, 2014): Responding to all faces right of this criterion as "angry" will maximize expected value. (B) The combination of base rate, payoffs, and perceived similarity of targets vs. foils determines a "line of optimal response" (LOR, curve plotted on inset graph; see Lynn & Barrett, 2014). The LOR relates a perceiver's sensitivity (*x* axis) to the amount of bias (*y* axis) that will optimize the perceiver's decision making. Lower perceptual sensitivity, visualizable as higher standard deviations of the Gaussian distributions in panel A, requires a more extreme decision criterion location to maximize net benefit over a series of judgments. Panels A and B depict conditions in the baseline emotion perception task described in Method.

Method

Participants

One hundred thirty-two participants were recruited via fliers posted on and around an urban college campus. Participants were 18-54 years old years (median = 19 years 75th percentile at 23 years), 62% women, 58% Caucasian, 11% African-American, 23% Asian, and 6% Hispanic. Exclusion criteria were self-assessed, and comprised lifetime psychiatric diagnosis, severe unstable medical illness, history of seizure disorder, current use of psychiatric medications, recreational drug use in the prior two weeks, and, at the second laboratory visit, alcohol or caffeine consumption in the prior 12 hours. All participants gave informed consent in accordance with the policies of the Northeastern University Institutional Review Board, which approved all procedures. Participants visited the laboratory on two occasions, to complete the baseline and contrast emotion perception tasks, respectively. Median time between visit 1 and visit 2 was seven days. Participants were compensated with cash at the end of each visit and earned $15-$20 at visit 1 and $20-$25 at visit 2.

Emotion Perception Tasks

Four stimulus sets were created, two male and two female, using males 22 and 211 from the Color 2D Facial Emotional Stimuli (Gur et al., 2002), female 23 from Karolinska Directed Emotional Faces (Lundqvist, Flykt, & Ohman, 1998), and female 6 from the NimStim Set of Facial Expressions (Tottenham et al., 2009). The face images were converted from color to grey scale, rescaled to have equal distance between left and right auricular notches, and placed on a black background. For each photographic model, we created a continuum of facial scowl intensity by digitally blending (FantaMorph 4, Abrosoft) his or her happy and angry facial expression depictions to generate a series of 11 "morphs" that ranged from 0% to 100% scowling in 10% increments. The set of 11 morphed images comprised a stimulus set (Figure 1A depicts one such set). Viewed on an LCD computer monitor from approximately 0.6 m distance, the faces subtended approximately 11˚ horizontally x 15˚ vertically. This experiment was part of a larger study on perception of social threat, and that focus was the motivation for our use of smiling vs. scowling facial expressions.

The values for target:foil base rate, perceptual similarity, and payoffs controlled details of stimulus presentation and response feedback (see Table 1). The target:foil base rate specified the proportion of "angry" to "not angry" trials. On each trial, a computer program determined whether that trial would show an angry face (i.e., a stimulus to be drawn from the target distribution) or not-angry face (i.e., a stimulus to be drawn from the foil distribution), guided by the base rate. The stimulus to be shown on a particular "angry" trial or a "not angry" trial was randomly drawn from the respective Gaussian signal distribution imposed on the 11-item stimulus continuum (Figure 1A). Mean and variance of the distributions controlled perceptual similarity of the target (angry) and foil (not-angry) categories. All 11 stimuli on the continuum had some likelihood of being shown as an exemplar of both the target and foil categories; that likelihood was determined by the respective signal distributions. There was, thus, a correct answer for each of these signal-drawn trials but participants experienced uncertainty as to what the correct answer was. Payoffs for correct and incorrect categorization of a face as angry or not angry were implemented as points earned or lost following each judgment. The uncertainty is a defining feature of a signal detection problem; it is literally impossible to achieve 100% accuracy. However, the

probability density functions that characterized the target and foil categories and the base rate of encountering those categories create statistical regularities in the perceptual environment. Participants can learn these regularities, associating resultant benefits and costs with the particular stimulus that they just categorized. Participants were instructed to earn as many points as they could as they learned to categorize the faces. Neither response speed nor accuracy were mentioned in participant instructions.

Each trial began with a white fixation cross (300 ms duration) centered on a black screen, followed by a single face stimulus (500 ms duration). A response prompt ("Was that anger?") followed the face and remained on-screen until the participant responded by using his or her index fingers to press USB keyboard buttons labeled "Yes" and "No". Participants earned and lost points for correct or incorrect answers, and received immediate on-screen feedback ("That was correct." or "That was incorrect.", points earned or lost for the current trial, and total cumulative points). A 300 ± 100 ms inter-trial interval (black screen) followed the feedback. One thousand trials were presented. Participants received a rest break after trial 500. After trial 700, a final 190 regular trials were interspersed with 110 confidence-rated trials. On a confidence-rated trial, after the yes/no face categorization, a confidence rating screen replaced the regular feedback screen. Participants were asked to rate their confidence in the yes/no judgment they had just made on a 9-point scale. We elicited 10 confidence ratings for each of the 11 stimuli on the continuum. Confidence-rated trials were included for analysis of meta-cognitive awareness as part of the larger study. Confidence-rated trials were not drawn from the target and foil signal distributions so did not have correct answers, and these trials are not analyzed here. Sensitivity and bias were calculated over the 890 signal-drawn trials (Figure 1A). The task was preceded by 11 practice trials, including two confidence-rated practice trials. Participants finished the task in approximately 45 minutes. Stimulus set and response label locations (on the "z" and "/" buttons) were randomized across participants, with the exception that a different stimulus set was used for visit 1 and visit 2. The task was programmed in Matlab (The Mathworks, Inc.) with Psychophysics toolbox (Brainard, 1997).

At visit 1, all participants experienced the same baseline condition. This condition imposed a mildly conservative bias via unbalanced payoffs (the values for target:foil perceptual similarity, base rate, and payoffs are given in Table 1 and depicted in Figure 1). At visit 2, participants were assigned to one of three "contrast" conditions (Table 1). The *base rate contrast condition* (n=41) imposed more conservative bias than baseline by implementing a lower proportion of trials drawn from the "angry" distribution. The *payoff contrast condition* (n=47) imposed more liberal bias than baseline by implementing a greater loss of points for missed detection mistakes (i.e., responding to an angry trial as if it were a not-angry trial) and a lower loss of points for false alarm mistakes (i.e., responding to a not-angry trial as if it were an angry trial). The *sensitivity contrast condition* (n=44) imposed more conservative bias than baseline by increasing the target and foil distributions' standard deviations to cause a decrement in perceiver perceptual sensitivity (see Figure 1B).

Working Memory Capacity Task

We evaluated WMC with the Run Letter Span task (Broadway & Engle, 2010), an automated running memory span task (Unsworth, Heitz, Schrock, & Engle, 2005), administered in E-Prime 2 (Psychology Software Tools, Inc). Participants viewed letters on a computer screen one at a time (300 ms letter duration, 200 ms inter-letter interval). On each trial, m distractor letters preceded n target letters (m=0, 1, or 2; n=3, 4, 5, or 6). Participants attempted to report the target letters in order of appearance, and could leave blank any serial positions for which the letter could not be recalled. Number of targets was blocked, with the blocks randomly ordered. Number of distractors was randomized (without replacement) within blocks. Thus, there were m=3 trials in each of n=4 blocks, for 12 trials in all. Participants were informed of the target length prior to each block, and the response screen for each trial again prompted participants for the number of targets. Including delivery of instructions, this task lasts approximately 6 minutes and compares favorably with longer-duration complex-span tasks (Broadway & Engle, 2010). Excluding trials on which m=0 (short-term memory trials, for which WMC is assumed to be unnecessary), one point was scored for each letter correctly assigned to its serial position, for a maximum of 36 points possible. See Broadway & Engle (2010) for further details.

Table 1

Signal Parameter Values Defining the Experimental Conditions

Condition	Base rate	Payoffs				Perceptual similarity				Maximum expected performance	
						Targets		Foils			
		Correct detection	Correct rejection	False alarm	Missed detection	M	SD	M	SD	*c*	*d'*
Baseline	0.50	100	100	-120	-10	65%	15%	35%	15%	0.33	2.00
Base rate contrast	0.20	100	100	-120	-10	65%	15%	35%	15%	1.07	2.00
Payoff contrast	0.50	100	100	-10	-120	65%	15%	35%	15%	-0.33	2.00
Sensitivity contrast	0.50	100	100	-120	-10	65%	26%	35%	26%	0.61	1.15

Note. Payoffs are in units of points. Perceptual similarity mean and standard deviation are in units of percent scowl. *c* and *d'* are measures of response bias and perceptual sensitivity, respectively, from signal detection theory (Macmillan & Creelman, 1991).

Procedure

On visit 1, after informed consent, participants completed the baseline emotion perception task. Immediately following the emotion perception task we assessed WMC. The WMC task was followed by self-report questionnaires as part of the larger study. On visit 2, participants completed the contrast emotion perception task in addition to other tasks and self-report questionnaires as part of the larger study.

Analyses

Trials with a response time <250 ms were excluded from analysis due to the likelihood of their containing motor errors, resulting in exclusion of 0.1-5% of trials from 43% of participants. We calculated sensitivity (d') and bias (c) on the remaining trials (equations 1 and 7, respectively, of Stanislaw & Todorov, 1999). We calculated *bias optimality*, the degree to which a perceiver achieves the amount of bias that will maximize his or her expected point earnings over the series of trials, as d_O, the distance from the point defined by a participant's observed sensitivity and bias to the task's "line of optimal response" (LOR, Figure 1B; see equations 1 and 2 of Lynn & Barrett, 2014). Because d_O expresses a perceiver's bias relative to the bias that is optimal for environmental base rate and payoff values, it permits a measurement of whether a perceiver is too biased vs. not biased enough, taking into account the perceiver's sensitivity. Shorter distance-to-LOR reflects more optimal bias: For a given level of sensitivity, perceivers whose bias places them closer to the LOR will accrue more points over a series of decisions. Distance to the LOR as a measure of optimality can be confounded by the separate influences of sensitivity on utility (higher sensitivity produces higher point earnings) and on distance (higher sensitivity requires less extreme bias to achieve optimality) (Lynn et al., 2012). Accordingly, we controlled for sensitivity in all analyses of d_O by analyzing residual d_O after regression on d'.

We used multivariate regression (SPSS 21, IBM Corporation) to directly compare effect sizes of the associations between WMC and three dependent measures of performance: sensitivity, bias, and bias optimality. Multivariate regression, distinct from multiple regression, permits the simultaneous evaluation of the association between an independent variable (*i.e.*, WMC) and multiple dependent variables. Multivariate regression avoids the potential increase in experiment-wise error rate engendered by running individual analyses for each dependent variable. We analyzed the four experimental conditions in separate multivariate regressions. The level of statistical significance for all tests was set to *alpha*=0.05 (two-tailed).

Results

Mean WMC did not significantly differ among the three contrast conditions ($F[2,129]=1.7$, $p>0.18$). However, variance of WMC differed significantly among the groups (Levene's Test for Equality of Error Variances: $F[2,129]=7.1$, $p<0.002$). The sensitivity contrast condition possessed significantly higher variance than the base rate or payoff contrast conditions largely due to more thorough sampling of low WMC participants. Multivariate regression indicated no difference in the influence of WMC on task performance as measured by sensitivity, bias, or bias optimality for the either the baseline, base rate, or payoff conditions (baseline: $F[3,128]=1.2$, $p>0.32$, $\eta_p^2=0.03$; base rate: $F[3,37]=1.6$, $p>0.20$, $\eta_p^2=0.11$; payoff: $F[3,43]=0.21$, $p>0.89$, $\eta_p^2=0.01$). WMC also showed no significant associations with any individual dependent variables in those conditions (Table 2).

However, for the sensitivity contrast condition, the overall multivariate regression was significant ($F[3,40]=3.0$, $p<0.045$, $\eta_p^2=0.18$), indicating that the influence of WMC differed among the dependent variables when it was difficult to discriminate targets from foils. While WMC was not significantly associated with perceiver sensitivity, higher WMC was significantly correlated with more extreme bias and better bias optimality (Table 2, Figure 2). Participants with higher WMC were better able to adjust their bias to accommodate their sensitivity than were participants with lower WMC.

Table 2

Descriptive Statistics (M±SD) and Multivariate Regression Results for Individual Dependent Variables (Sensitivity, Bias, and Bias Optimality) with WMC as the Independent Variable

	Condition			
	Baseline	Base rate contrast	Payoff contrast	Sensitivity contrast
n	132	41	47	44
WMC	22.0±7.11	23±5.29	22.7±6.33	20.4±9.02
Sensitivity (*d'*)	1.5±0.23	1.4±0.24	1.4±0.24	0.8±0.19
F	0.0	0.7	0.3	1.8
p	0.93	0.40	0.57	0.19
η_p^2	0.00	0.02	0.01	0.04
Bias (*c*)	0.1±0.18	0.8±0.27	0±0.18	0.1±0.37
F	0.3	3.8	0.3	4.6
p	0.58	0.06	0.61	0.04*
η_p^2	0.00	0.09	0.01	0.10
Bias optimality (d_O)	0.4±0.18	0.6±0.21	0.5±0.17	0.6±0.31
F	0.0	5.3	0.3	5.3
p	0.99	0.11	0.59	0.03*
η_p^2	0.00	0.06	0.01	0.11

Note. n = number of participants, WMC = working memory capacity, *F*-test degrees of freedom = (1,*n*-2), and * indicates statistical significance.

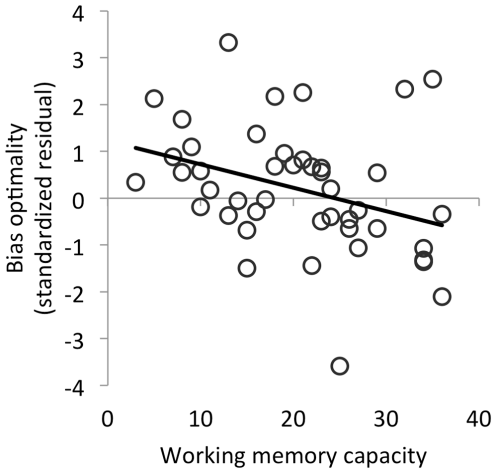

Figure 2. A scatter plot of the relationship between bias optimality (d_O controlling for perceptual sensitivity, *d'*) and working memory capacity in the sensitivity contrast condition. Shorter d_O is better, therefore higher working memory capacity was associated with better ability to adjust response bias to subjective perceptual sensitivity (r^2=.11).

In summary, we found support for the hypothesis that high WMC promotes a perceiver's ability to optimize his or her bias when bias is driven by the perceiver's own sensitivity (hypothesis 3iii). WMC did not improve emotion perception by increasing sensitivity (hypothesis 1); WMC was not associated with sensitivity in any of the four conditions. WMC did not affect emotion perception by promoting neutral response bias (hypothesis 2) because higher WMC was only associated with *less*-neutral (higher) response bias (in the sensitivity contrast condition and, marginally, in the base rate contrast condition). High WMC did not promote perceivers' abilities to optimize their bias when bias was driven by base rate (hypothesis 3i) or payoffs (hypothesis 3ii).

This pattern of results indicates that WMC does not strongly influence measures of performance when it is relatively easy to discriminate targets from foils, despite environmental pressure to adapt bias to base rate or payoffs. Instead, it was only in the condition demanding extreme bias due to low sensitivity that WMC was associated with bias. Alternative analyses of the three dependent variables as contrast-baseline difference scores and in multiple regressions controlling for baseline performance showed this same pattern of significant vs. null associations with WMC.

Discussion

Our results suggest that high WMC promotes optimizing judgments about the emotional state of others specifically by contributing to perceivers' ability to adjust their response bias to account for their level of perceptual sensitivity. WMC was not associated with perceivers' ability to adjust their response bias to base rate or payoffs. Response bias and sensitivity are not independent in perceivers: Under biased conditions, perceivers seeking to maximize expected value must tune their bias to their own level of sensitivity (Figure 1B). Perceivers must adjust their exposure to the four possible decision outcomes (correct detections, missed detections, false alarms, and correct rejections) as the likelihoods of those outcomes change concomitant with changes in perceptual uncertainty. Biased conditions arise when the perceiver's encounter rate with targets vs. foils is unequal and/or when the outcome payoffs, the benefits and costs accrued by the perceiver, do not cancel out. We believe that, outside the laboratory, most signal detection issues, including emotion perception, are biased in these ways.

Our data indicate that WMC is specifically linked to adapting bias to ideographic sensitivity. The adjusting of bias to account for sensitivity effectively constitutes a weighting on how base rate and payoffs influence behavior. Low sensitivity weights the influence of base rate and payoffs on behavior more strongly than high sensitivity. We speculate that adjustment of bias to account for sensitivity may be more cognitively demanding than adjustment of bias to either base rate or payoffs alone, or to acquiring sensitivity itself, revealing the WMC relationship. Executive functions, such as working memory, cognitive control, and attention, are integrated with perceptual judgments (e.g., Pessoa & Engelmann, 2010), including perception of facial emotion (e.g., Pessoa, Kastner, & Ungerleider, 2002; Rolls, 2007; Tottenham, Hare, & Casey, 2011). The integration of context (here characterized by the three signal detection parameters) as an aid to optimizing risky perceptual judgments over ambiguous percepts may be one function of that integration.

We tested participants under four conditions (Table 1). WMC influenced bias optimality in the sensitivity condition but not in the baseline, base rate or payoff conditions (Table 2). The critical feature distinguishing the condition in which WMC was influential from those in which it was not is the perceivers' ability to discriminate the ambiguous categories. This result suggests that WMC is particularly important when perceptual uncertainty is high. Nonetheless, WMC did not, itself, contribute to resolving the uncertainty, *i.e.,* to improving sensitivity. In no conditions was WMC associated with perceiver sensitivity. Rather, WMC appears to contribute to operating under the uncertainty–optimally tuning bias given the difficulty of the discrimination.

In the sensitivity contrast condition, participants, as a group, were not particularly successful at adjusting their bias (Table 2). Relative to the baseline condition, these participants exhibited very little change in raw bias (c) and the worst (highest value) bias optimality (d_O). Adapting bias to decreasing sensitivity appears to be difficult, something we have seen in prior work (Lynn et al., 2012). Could WMC, then, simply be taxed in situations in which it is difficult to adapt bias, regardless of the parameter demanding that adaptation? Results from the other conditions argue against this explanation. Participants in the base rate condition also did not achieve particularly optimal bias, despite a large overall change in raw bias relative to the baseline condition. In addition, participants in the liberal-going payoff condition did not achieve especially liberal raw bias, despite achieving the best bias optimality (adaptation of bias to payoffs is known to be difficult to accomplish, relative to adaptation to base rate [Bohil & Maddox, 2001; Maddox & Bohil, 2005]). Finally, we found no association between WMC and bias or bias optimality in the base rate or payoff conditions. Together, these results indicate that WMC is not associated with difficult bias adaptation per se.

Prior studies show another role for working memory in emotion perception: selecting the correct semantic label from alternatives (Phillips et al., 2007; Phillips et al., 2008). Phillips et al. (2008) used a dual-task design to show that accuracy on emotion labeling tasks decreased under working memory load imposed by a concurrent 2-back letter recognition task. The performance decrement was higher with more label options from which to choose, but still present for a two-label condition. Performance on a label-free same/different task was unimpaired under working memory load, indicating that the semantic aspect of label selection involves working memory. Our yes/no tasks implied two labels, "angry" and "not angry", which were explicitly referenced in the participant instructions. The contrast of positive vs. null results among our conditions show that any semantic aspects of our task cannot,

alone, be responsible for the effects we found (nor, likewise, for the effects shown by Lim et al., 2014], who also used a yes/no task over a range of facial expression intensity).

Our emotion perception task possesses functional characteristics analogous to those shown to be influenced by WMC in research outside affective science. These characteristics include the ability to adopt strategies in response to feedback (Schunn & Reder, 2001) and deciding among risky outcomes (Cokely & Kelley, 2009). Again, however, the contrast of positive vs. null results among our conditions suggests that these functional characteristics are not, alone, responsible for the effects we found. Only under conditions of substantial perceptual uncertainty did WMC emerge as a critical factor in performance. The interaction of perceptual uncertainty with these other characteristics is a relatively unexplored area in both decision making and working memory. Relevant to understanding this interaction, Lim, et al., (2014) showed an increased rate of categorizing intense expressions as targets with higher working memory load. This pattern could be interpreted as a greater reliance on prepotent responses under load, congruent with an association between low WMC and expression of prepotent response (Ilkowska & Engle, 2010). Whether prepotent responses are helpful or not is context dependent (e.g., Jamieson & Harkins, 2009), suggesting areas for future study.

Our emotion perception task differs from tasks that ask participants to choose which of several emotion words best matches a posed, exaggerated facial depiction (faces exemplified by the end points of continuum in Figure 1; e.g., Phillips et al., 2008) or to dichotomously categorize faces drawn from a continuum of expressive intensity in the absence of corrective feedback (e.g., Lee et al., 2012; Lim et al., 2014). Instead, we required participants to optimize their perceptual decisions by learning from the outcomes of their past decisions. As a learning experiment, our results suggest that WMC may promote perceivers' ability to optimally adapt their emotion perception to the differences in risk and uncertainty that characterize different social contexts. Using SDT as a conceptual model of emotion perception implies that switching social partners involves switching sets of signal parameter values. For example, interacting with a peer vs. a superior may involve adopting different sets of benefits and costs of correct and incorrect judgments. Likewise, meeting someone new may involve constructing target and foil signal distributions that describe what the new person looks like when he or she is experiencing different emotional states as well as estimating the base rate of encountering the new person in those states. WMC may aid perceivers' ability to effectively adapt their behavior to such changing or novel contexts.

As one example of the importance of understanding how WMC influences emotion perception (and mental state attribution more generally), Kleider et al. (2010) found that police officers with lower WMC exhibited lower sensitivity on a simulated shoot/don't-shoot task than officers with higher WMC. The effect was only observed among officers experiencing heightened negative arousal. The task was unbiased, involved a go/no-go response under time pressure, and induced high-arousal negative affect. The task thus differed from our anger perception task in several potentially important ways that suggest directions for future studies–affective state, amount of environmental bias, and time pressure may modulate how WMC influences decisions under perceptual uncertainty.

We used blends of smiling and scowling facial depictions framed as an anger detection task. Whether the association between WMC and optimal adjustment of bias to sensitivity generalizes to other social decisions or to non-social domains is an open question. Given the ubiquitous nature of signal detection issues in real-world decision making (*e.g.,* Swets, Dawes, & Monahan, 2000) and the importance of WMC across a diversity of human behavior (*e.g.,* Barrett et al., 2004), such generalizability seems likely.

One limitation of the present studies relevant to the generalizability of our results is that we did not manipulate WMC or test anger perception under working memory load. Therefore, our results do not establish a causal link between WMC and optimal adjustment of bias to sensitivity, a direction for future studies. Another limitation is the difference in WMC variance across our contrast conditions. Restricted range of an independent variable can be a cause of failure to find a relationship with the dependent variable when one in fact exists. In addition, it could be that low WMC is associated with difficulty adapting bias to any biasing factor. For these reasons, it is possible that our failure to detect a stronger association between WMC and bias optimality in the payoff and base rate conditions was due to a relative paucity of low WMC participants in those conditions. Arguing against these points, and supporting the contention that low sensitivity is a critical element, is the observation that the baseline

condition, which included all participants and permitted high sensitivity, found no relationship between WMC and bias optimality despite containing the complete range of WMC and a much larger sample size. Further research will be necessary to address these limitations.

Barrett and colleagues (Barrett et al., 2004; Barrett, 2008) hypothesized that WMC should affect the flexibility and effectiveness with which perceivers can utilize emotion knowledge. One circumstance in which the utilization of emotion knowledge manifests is emotion perception judgments. When inferring the emotional state of another person, a perceiver presumably applies his or her existing emotion knowledge to the situation, modifying a priori expectations based on knowledge about the current social context. Such knowledge may comprise representations of the likelihood of encountering the emotion, the benefits and costs of correct and incorrect judgments, and the similarity of associated facial expression cues–the parameters of signal detection. Our results suggest that WMC is particularly important to emotion perception, and perhaps decision in general, when judgments are made in contexts of perceptual uncertainty and behavioral risk.

References

Barrett, L. F. (2008). The science of emotion: what people believe, what the evidence shows, and where to go from here. In J. J. Blascovich & C. R. Hartel (Eds.), *Human Behavior in Military Contexts* (pp. 189-216). Washington, D.C.: National Academies Press.

Barrett, L. F., Tugade, M. M., & Engle, R. W. (2004). Individual differences in working memory capacity and dual-process theories of the mind. *Psychological Bulletin, 130*, 553-573.

Bohil, C., & Maddox, W. (2001). Category discriminability, base-rate, and payoff effects in perceptual categorization. *Attention, Perception, & Psychophysics, 63*, 361-376.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision, 10*, 433-436.

Broadway, J. M., & Engle, R. W. (2010). Validating running memory span: Measurement of working memory capacity and links with fluid intelligence. *Behavior Research Methods, 42*, 563-570.

Cokely, E. T., & Kelley, C. M. (2009). Cognitive abilities and superior decision making under risk: A protocol analysis and process model evaluation. *Judgment and Decision Making, 4*, 20-33.

Conway, A. R. A., Cowan, N., Bunting, M. F., Therriault, D. J., & Minkoff, S. R. B. (2002). A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence, 30*, 163-183.

Daneman, M., & Merikle, P. (1996). Working memory and language comprehension: A meta-analysis. *Psychonomic Bulletin & Review, 3*, 422-433.

Engle, R. W. (2010). Role of working-memory capacity in cognitive control. *Current Anthropology, 51*, S17-S26.

Engle, R. W., Carullo, J. J., & Collins, K. W. (1991). Individual differences in working memory for comprehension and following directions. *Journal of Educational Research, 84*, 253-262.

Green, D. M., & Swets, J. A. (1966). *Signal Detection Theory and Psychophysics*. New York: Wiley.

Gur, R. C., Sara, R., Hagendoorn, M., Marom, O., Hughett, P., Macy, L., . . . Gur, R. E. (2002). A method for obtaining 3-dimensional facial expressions and its standardization for use in neurocognitive studies. *Journal of Neuroscience Methods, 115*, 137-143.

Horning, S. M., Cornwell, R. E., & Davis, H. P. (2012). The recognition of facial expressions: An investigation of the influence of age and cognition. *Aging, Neuropsychology, and Cognition, 19*, 657-676.

Ilkowska, M., & Engle, R. W. (2010). Trait and state differences in working memory capacity. In A. Gruszka, G. Matthews & B. Szymura (Eds.), *Handbook of Individual Differences in Cognition* (pp. 295-320): Springer New York.

Isaacowitz, D. M., Lockenhoff, C. E., Lane, R. D., Wright, R., Sechrest, L., Riedel, R., & Costa, P. T. (2007). Age differences in recognition of emotion in lexical stimuli and facial expressions. *Psychology and Aging, 22*, 147-159.

Jamieson, J. P., & Harkins, S. G. (2009). The effect of stereotype threat on the solving of quantitative GRE problems: A mere effort interpretation. *Personality and Social Psychology Bulletin, 35*, 1301-1314.

Kane, M. J., & Engle, R. W. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review, 9*, 637.

Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to Stroop interference. *Journal of Experimental Psychology: General, 132*, 47-70.

Kleider, H. M., Parrott, D. J., & King, T. Z. (2010). Shooting behaviour: How working memory and negative emotionality influence police officer shoot decisions. *Applied Cognitive Psychology, 24*, 707-717.

Lee, T.-H., Choi, J.-S., & Cho, Y. S. (2012). Context modulation of facial emotion perception differed by individual difference. *PLoS ONE, 7*, e32987. Retrieved from journals.plos.org/plosone/article?id=32910.31371/journal.pone.0032987.

Lim, S.-L., Bruce, A. S., & Aupperle, R. L. (2014). The influence of a working memory task on affective perception of facial expressions. *PLoS ONE, 9*, e111074. Retrieved from journals.plos.org/plosone/article?id=111010.111371/journal.pone.0111074.

Lundqvist, D., Flykt, A., & Ohman, A. (1998). The Karolinska Directed Emotional Faces - KDEF, CD ROM: Department of Clinical Neuroscience, Psychology Section, Karolinska Institutet.

Lynn, S. K., & Barrett, L. F. (2014). "Utilizing" signal detection theory. *Psychological Science, 25*, 1663-1673.

Lynn, S. K., Hoge, E. A., Fischer, L. E., Barrett, L. F., & Simon, N. M. (2014). Gender differences in oxytocin-associated disruption of decision bias during emotion perception. *Psychiatry Research, 219*, 198-203.

Lynn, S. K., Zhang, X., & Barrett, L. F. (2012). Affective state influences perception by affecting decision parameters underlying bias and sensitivity. *Emotion, 12*, 726-736.

Macmillan, N. A., & Creelman, C. D. (1991). *Detection Theory: A User's Guide*. New York: Cambridge University Press.

Maddox, W. T., & Bohil, C. (2005). Optimal classifier feedback improves cost-benefit but not base-rate decision criterion learning in perceptual categorization. *Memory & Cognition, 33*, 303-319.

Pessoa, L., & Engelmann, J. B. (2010). Embedding reward signals into perception and cognition. *Frontiers in Neuroscience, 4*, Article 17. Retrieved from journal.frontiersin.org/article/10.3389/fnins.2010.00017.

Pessoa, L., Kastner, S., & Ungerleider, L. G. (2002). Attentional control of the processing of neutral and emotional stimuli. *Cognitive Brain Research, 15*, 31-45.

Phillips, L., Tunstall, M., & Channon, S. (2007). Exploring the role of working memory in dynamic social cue decoding using dual task methodology. *Journal of Nonverbal Behavior, 31*, 137-152.

Phillips, L. H., Channon, S., Tunstall, M., Hedenstrom, A., & Lyons, K. (2008). The role of working memory in decoding emotions. *Emotion, 8*, 184-191.

Phillips, M. L., Drevets, W. C., Rauch, S. L., & Lane, R. (2003). Neurobiology of emotion perception II: Implications for major psychiatric disorders. *Biological Psychiatry, 54*, 515-528.

Rolls, E. T. (2007). The representation of information about faces in the temporal and frontal lobes. *Neuropsychologia, 45*, 124-143.

Schmeichel, B. J., Volokhov, R. N., & Demaree, H. A. (2008). Working memory capacity and the self-regulation of emotional expression and experience. *Journal of Personality and Social Psychology, 95*, 1526-1540.

Schunn, C. D., & Reder, L. M. (2001). Another source of individual differences: Strategy adaptivity to changing rates of success. *Journal of Experimental Psychology: General, 130*, 59-76.

Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments, & Computers, 31*, 137-149.

Stretch, V., & Wixted, J. T. (1998). Decision rules for recognition memory confidence judgments. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 24*, 1397-1410.

Swets, J. A., Dawes, R. M., & Monahan, J. (2000). Psychological science can improve diagnostic decisions. *Psychological Science in the Public Interest, 1*, 1-26.

Tottenham, N., Hare, T. A., & Casey, B. J. (2011). Behavioral assessment of emotion discrimination, emotion regulation and cognitive control, in childhood, adolescence, and adulthood. *Frontiers*

in Psychology, 2, Article 39. Retrieved from journal.frontiersin.org/article/10.3389/fpsyg.2011.00039.

Tottenham, N., Tanaka, J. W., Leon, A. C., McCarry, T., Nurse, M., Hare, T. A., . . . Nelson, C. (2009). The NimStim set of facial expressions: Judgments from untrained research participants. *Psychiatry Research, 168*, 242-249.

Tuholski, S., Engle, R., & Baylis, G. (2001). Individual differences in working memory capacity and enumeration. *Memory & Cognition, 29*, 484-492.

Unsworth, N., Heitz, R. P., Schrock, J. C., & Engle, R. W. (2005). An automated version of the operation span task. *Behavior Research Methods, 37*, 498.

Wieser, M. J., & Brosch, T. (2012). Faces in context: A review and systematization of contextual influences on affective face processing. *Frontiers in Psychology, 3*, Article 471. Retrieved from journal.frontiersin.org/article/10.3389/fpsyg.2012.00471.