Emotional working memory load selectively increases negativity bias

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Abstract

Cognitive resources are needed for successful executive functioning; when resources are limited due to competing demands, task performance is impaired. Although some tasks are accomplished with relatively few resources (e.g., judging trustworthiness and emotion in others), others are more complex. Specifically, in the face of emotional ambiguity (i.e., stimuli that do not convey a clear positive or negative meaning, such as a surprised facial expression), our decisions to approach or avoid appear to rely on the availability of top-down regulatory resources to overcome an initial negativity bias. Cognition-emotion interaction theories (e.g., dual competition) posit that emotion and executive processing rely on shared resources, suggesting that competing demands would hamper these regulatory responses towards emotional ambiguity. Here, we employed a 2×2 design to investigate the effects of load (low versus high) and domain (non-emotional vs. emotional) on evaluations of surprised faces. As predicted, there were domain-specific effects, such that categorizations of surprise were more negative for emotional than non-emotional loads. Consistent with prior work, low load (regardless of domain; i.e., domain-general) was associated with greater response competition on trials resulting in a positive categorization, showing that positive categorizations are characterized by an initial negativity. This effect was diminished under high load. These results lend insight into the resources supporting a positive valence bias by demonstrating that emotion-specific regulatory resources are important for overriding the initial negativity in response to emotional ambiguity. However, both domain-general and domain-specific loads impact the underlying processes.

Keywords: cognitive load, task interference, emotional ambiguity, valence bias, negativity bias

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Humans readily make judgments about others based on limited information (e.g., judging trustworthiness, attractiveness, and emotion; Bar et al., 2006; Said & Todorov, 2011; Todorov, et al., 2008; Cloutier et al., 2008; Brooks et al., 2019; Carroll & Russell, 1996). For example, we spontaneously sort information, including facial expressions, into valence categories which are crucial for guiding social behavior (e.g., approach-avoidance; Krieglmeyer et al., 2010; and group membership or affiliation; Tskhay & Rule, 2015, 2018). Although some facial expressions are easily categorized as positive (happy) or negative (angry), others (surprise) require more resources due to the nature of their valence ambiguity (Neta et al., 2009; Neta & Tong, 2016; Petro et al., 2018). Indeed, surprised expressions can predict both positive (e.g., winning the lottery) and negative (e.g., a car accident) outcomes, and without contextual information to disambiguate these expressions, there are individual differences in the tendency to categorize surprised faces as having a more positive or negative meaning (i.e., valence bias; Neta et al., 2013; Neta et al., 2009; Neta & Whalen, 2010).

Despite this variability in valence bias, there appears to be an initial negativity bias in categorizations of surprise across people (Neta et al., 2009, 2010, 2011; Petro et al., 2018). This 'initial negativity hypothesis' posits that positive categorizations rely on regulatory resources that help to override the initial negativity. Support for this model comes from studies using MouseTracker (Freeman & Ambady, 2010), which offers a rich insight into decision-making processes by indexing response trajectories as a measure of response competition (Calcagni et al., 2017; Freeman et al., 2011; Hehman et al., 2015). Specifically, previous work has demonstrated that, when categorizing the valence of surprised faces, response trajectories to the negative response option were more direct, whereas positive categorizations were characterized by greater attraction to the unselected (negative) response (Brown et al., 2017; Mattek et al., 2016; see also Neta et al., under review). Neuroimaging work has supported this initial negativity hypothesis, demonstrating that the amygdala—associated with bottom-up signals of emotion (Derryberry & Tucker, 1992)—and the vmPFC—a putative top-down regulatory region (Motzkin et al., 2015)—show inverse activity as a function of subjective categorizations of surprised faces (Kim et al., 2003). Specifically, individuals with a more negative valence bias show more amgydala and less vmPFC activity (Kim et al., 2003; Neta & Whalen, 2010), but the reverse was shown in individuals with a more positive bias (Kim et al., 2003). These findings support the notion that positive categorizations rely more on regulatory resources than do negative categorizations.

Despite the accumulating evidence of a role for regulatory resources in a more positive valence bias, the exact nature of these regulatory resources is less clear. Given that theories of cognition-emotion interactions (e.g., the dual competition model; Pessoa, 2009) posit that emotion and executive functions rely on a shared resource pool, concurrent task demands should hamper regulatory ability during categorizations of surprised faces (i.e., resulting in more negative categorizations). In other words, when resources are engaged with one task (e.g., maintaining emotional content in working memory), those resources are no longer available for a secondary task (e.g., regulating emotional responses to ambiguity). This insight is particularly useful for probing the nature of the resources underlying task performance (e.g., resolving ambiguity; Neta et al., 2009). Put another way, if performance of the first task impacts performance on the second task, then it is likely that at least some subset of resources needed for the first task are also needed for the second.

Given the initial negativity hypothesis, concurrent emotional task interference (i.e., a lack of available regulatory resources) should reduce the likelihood of seeing surprise in a positive light. Notably, one study to date has examined the effect of task interference on valence categorizations of surprised faces (Mattek et al., 2016). Although this study found no interference effect on valence bias, the manipulation was non-emotional (i.e., remembering a number sequence). As such, the resources that were engaged in the first task (maintaining non-emotional content in working memory) may not have been required for overriding the initial negativity bias in response to ambiguity. Therefore, an open question remains as to whether or not a domain-specific (emotional) interference per se will tax the resources putatively required for a positive bias, resulting in more negative categorizations.

The present study

In the present study we explored task interference effects on responses to emotional ambiguity as a function of load (low versus high) and domain (non-emotional versus emotional), using a standard working memory paradigm (e.g., Ahmed, 2018). To do this, we manipulated both the amount and domain of material that participants needed to remember while they categorized the valence of facial expressions. Using MouseTracker software (Freeman & Ambady, 2010), we examined two distinct components of responses to ambiguity: the product of the responses (proportion of positive versus negative categorizations of surprised faces) and underlying processes (response trajectories). Regarding the response products, we expected to replicate previous work showing no effect of domain-general load (low versus high) on categorizations (Mattek et al., 2016). However, we did expect a domain-specific effect, such that emotional load would result in more negative categorizations than non-emotional load, suggesting that emotional load interferes with the resources that are useful for seeing ambiguity in a positive light. Further, we predicted domain-general load effects on the response processes, such that there would be greater response competition for positive than negative categorizations under low load, consistent with previous work (Brown et al., 2017; Mattek et al., 2016), and that this effect would be mitigated under high load (Mattek et al., 2016).

Methods

Participants

Fifty-nine participants ($M(SD)_{age}$ = 19.03(1.70) years, 49 female) were recruited from the undergraduate research pool at the University of Nebraska-Lincoln. The data from nine participants were excluded due to technical difficulties that prevented data from being saved. The final sample included the remaining 50 participants ($M(SD)_{age}$ = 18.82(1.19) years, 41 female), which an a priori power analysis determined a sufficient sample size for detecting a moderate to large within-subjects effect at an alpha level of .05 and with 95% power (η_p^2 = .06, total sample size required = 36; G*Power 3.1; Faul et al., 2009). All participants identified as White/Caucasian without Hispanic/Latinx ethnicity to control for potential effects of cross-race judgments. Further, they all provided written informed consent in accordance with the Declaration of Helsinki and all procedures were approved by the University of Nebraska-Lincoln

Institutional Review Board (Approval #20141014670EP). Each participant received course credit for completing the study.

Stimuli

A total of 288 scenes (72 positive, 72 negative, and 144 neutral) were selected from the International Affective Picture System (IAPS; Lang et al., 2008) for use in image matrices. An additional set of 63 IAPS images were used as memory probe foils (i.e., they never appeared in the image matrices). Only 36 of these 63 images were randomly selected for each participant, so that performance was not dependent on the features of the specific foils, and this subset varied across participants. For the matrices with emotional images, there were an equal number of positive and negative images within a matrix to avoid priming effects on the subsequent face ratings (e.g., Flexas et al., 2013; Payne et al., 2005), as previous work has shown categorizations of surprised faces are sensitive to valence priming (Kim et al., 2004; Neta et al., 2011). Notably, these positive and negative images did not differ in arousal after testing with a Wilcoxon signed-rank test (Z = -0.23, p = .82). There was also no significant difference in valence for the images in the non-emotional versus emotional images (Z = -0.12, p = .90).

The face stimuli included images from the NimStim (Tottenham et al., 2009) and Karolinska Directed Emotional Faces (Lundqvist et al., 1998) stimulus sets, as in previous work (Brown et al., 2017; Neta et al., 2009). The faces consisted of 34 unique identities—some showing all three expressions and others showing only a subset of the expressions—for a total of 12 angry, 12 happy, and 24 surprised expressions presented pseudorandomly.

Procedure

The task was conducted using MouseTracker software (Freeman & Ambady, 2010) and was structured to closely resemble the cognitive load task used by Mattek, Whalen, Berkowitz, and Freeman (2016), which used a single digit (low load) or seven digit sequence (high load) followed by a one digit memory probe. Participants initiated each trial at their own pace by clicking the “start” button at the bottom of the screen. After initiating the trial, a fixation cross appeared (1000 ms), then participants viewed an image matrix consisting of 2 or 6 images (low or high load, respectively) with either emotional or non-emotional properties (equal number of trials) for 4000 ms (Figure 1). Participants were instructed to remember these images for the duration of the trial (i.e., until the memory probe at the end of the trial). After the image matrix, a happy, angry, or surprised face appeared for 1000 ms, and participants categorized the face as positive or negative using the computer mouse. Finally, participants initiated the memory probe trial by clicking the “start” button and a fixation appeared for 1000 ms, followed by a single image probe (5000 ms). Participants used the computer mouse to indicate whether the image probe was present in the previous image matrix by clicking either yes (i.e., the image was present) or no (i.e., the image was not present). The experimenter guided participants through a practice face rating and memory probe trial, after which they completed a total of 72 trials while their mouse movements were recorded. Notably, in two-choice designs, maximum deviations from a straight-line response trajectory are often conceptualized as a measure of response competition, and can quantify the extent to which trial-wise ratings are characterized by an attraction to the competing (unchosen) response (Calcagni et al., 2017; Freeman et al., 2011;

Hehman et al., 2015).

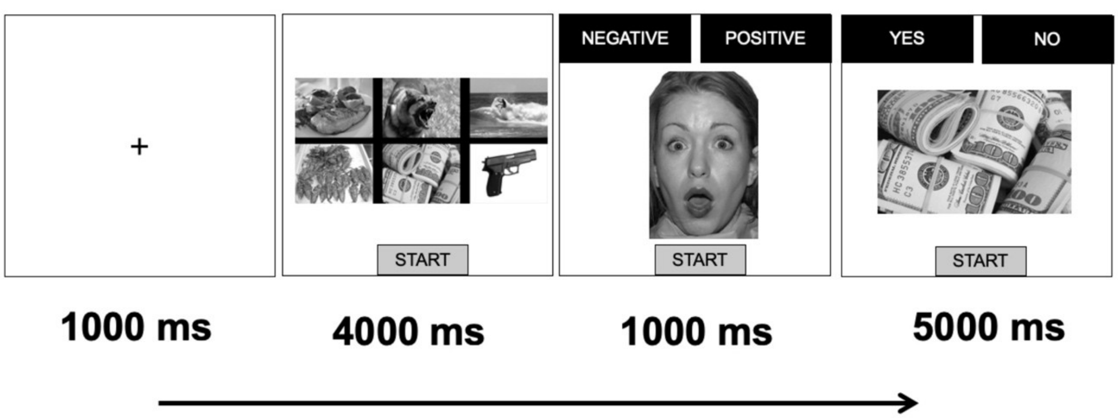

Figure 1: Example of a single trial in the emotional high load condition. Each trial begins with the presentation of a fixation cross, followed by an image matrix consisting of 2 (low load) or 6 (high load) images with either non-emotional or emotional properties. Participants were instructed to remember these images for the duration of the trial. Then, a happy, angry, or surprised face appeared, which the participants were instructed to categorize as positive or

negative using the computer mouse. Finally, participants see a fixation cross, followed by a single image probe, which they indicate as having been present (yes) or not (no) in the previous matrix.

Data analysis

We used R (Version 3.6.0; R Core Team, 2019) for all our analyses and analysis scripts are available at https://osf.io/cmx8w/. Data preprocessing, analysis, and plotting were completed in R using the mousetrap (Kieslich et al., 2019), lme4 (Bates et al., 2015), lmerTest (Kuznetsova et al., 2017), emmeans (Lenth et al., 2020), and ggplot2 (Wickham, 2016) packages. While it is possible that trials in which participants responded incorrectly to the memory probe indicated a manipulation failure (i.e., the participant was not maintaining the images in memory), we included all trials regardless of accuracy due to the lack of an objective method for determining if participants were attempting to remember the images in the matrix. Note that we also ran all analyses after removing incorrect trials for comparison purposes (the results were qualititavely similar throughout). Our primary dependent measures focused on surprised face trials, and included valence bias, calculated as percent negative categorizations, and maximum deviation, or the extent to which a response trajectory deviated or was attracted to the competing—unselected—response option. For the main test of our hypotheses, we examined effects of load (low, high) and domain (non-emotional, emotional) in a 2×2 design, and explored the effects of these four conditions and trialwise categorizations (positive and negative) on maximum deviation.

We used a repeated measures Analysis of Variance (ANOVA) approach, but also capitalized on the flexibility of linear mixed models to account for missing data in our analyses based on categorization (e.g., some participants rated surprise as negative on all trials). Zero summed contrasts were used to test the effects of experimental conditions (load: low versus high, and domain: non-emotional versus emotional) on categorizations, maximum deviations, reaction time, and memory probe accuracy in a linear mixed model with a Gaussian error distribution. This approach demonstrated better model fit than alternative options (i.e., gamma distribution), and is robust to violations of normality (Knief & Forstmeier, 2018) evidenced in our data by Shapiro-Wilks tests (p's $< .001$). Estimated marginal means were used to estimate mean differences across levels of the factors. To account for the repeated measures in these data, random intercepts for both the subject and the interaction of subject and any fixed effects were included in the model. Denominator degrees of freedom were calculated using the Sattherwaite method in the lmerTest package (Kuznetsova et al., 2017). All models used full information maximum likelihood estimation to account for any missing data (e.g., if a participant did not rate any surprised faces as positive or negative).

Results

Subjective categorizations of ambiguity (products of the response)

A Load (low versus high) × Domain (non-emotional versus emotional) repeated measures ANOVA revealed the predicted significant effect of Domain ($F(1, 100) = 28.32$, $p < .001$), such that categorizations of surprised faces under an emotional load (*M(SD)* = 74.04(24.63)) were more negative than those under a non-emotional load (*M(SD)* = 65.01(27.42)). There was no significant effect of Load ($F(1, 50) = 0.56$, $p = .46$); low load: *M(SD)* = 68.86(25.92); high load: *M(SD)* = 70.20(26.97)), nor was there a significant Domain × Load interaction ($F(1, 100) = 0.33$, $p = .57$; see Table 1 for descriptive statistics).

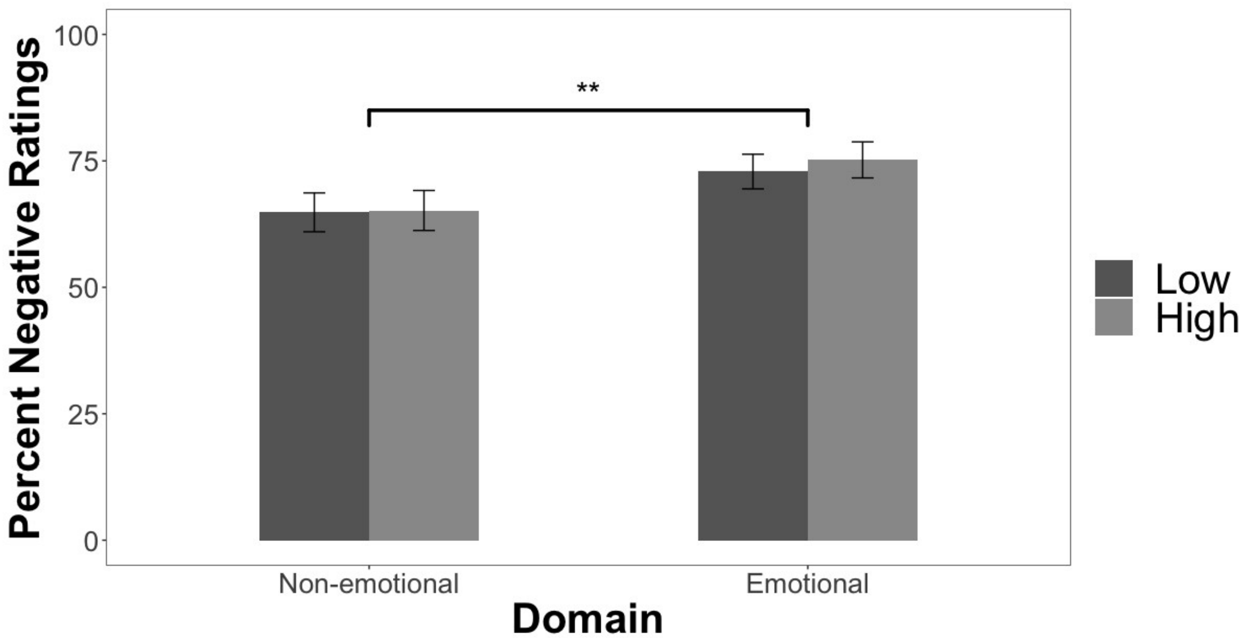

Figure 2: Percent negative ratings across conditions. Surprised faces were categorized as negative more frequently during emotional than non-emotional load trials ($F(1, 100) = 28.32$, $p < .001$), but there was no effect of Load (low versus high) on ratings ($F(1, 50) = 0.56$, $p = .46$). Error bars represent the standard error of the mean. $^{**}p \leq .001$.

Table 1. Descriptive statistics for all dependent variables per condition.

Rating	Load	Non-emotional *M*	Non-emotional *SD*	Emotional *M*	Emotional *SD*
		Percent Negative Categorizations			
N/A	**Low**	64.83	27.16	72.89	24.21
N/A	**High**	65.20	27.96	75.19	25.23
		Maximum Deviations			
Positive	**Low**	0.47	0.47	0.56	0.50
	High	0.31	0.29	0.52	0.37
Negative	**Low**	0.27	0.23	0.32	0.32
	High	0.44	0.28	0.40	0.28

		Reaction Time			
Positive	**Low**	1979.48	455.16	2066.12	758.32
	High	1720.16	338.96	1924.07	557.88
Negative	**Low**	1788.45	361.90	1880.24	398.97
	High	1811.83	363.16	1813.67	322.56
		Memory Probe Accuracy			
N/A	**Low**	98.18%	5.41%	98.83%	3.54%
N/A	**High**	96.70%	6.30%	88.33%	11.50%

Maximum deviation (processes underlying the response)

Next, we examined the effect of our experimental manipulation and trial-wise surprise categorizations (positive versus negative trials) on maximum deviation. A Load (low versus high) × Domain (non-emotional versus emotional) × Rating (positive versus negative categorizations of surprise) repeated measures ANOVA revealed a significant main effect of Rating ($F(1, 51) = 4.42$, $p = .04$), such that maximum deviations were larger for positive (*M(SD)* = 0.46(0.42)) than negative trials (*M(SD)* = 0.36(0.29)). There was also a significant Load × Rating interaction ($F(1, 228) = 13.28$, p < .001; Figure 3). This revealed that, as expected, maximum deviations were larger for positive (*M(SD)* = 0.51(0.48)) than negative categorizations (*M(SD)* = 0.30(0.28); $t(91) = -3.71$, $p < .001$; Bonferroni corrected significance for these analyses $p < .013$) on low load trials, but not on high load trials (positive: *M(SD)* = 0.40(0.34); negative: *M(SD)* = 0.42(0.28); $t(94) = 0.10$, $p = .92$). Specifically, maximum deviations for negative trials were larger on high than low load trials ($t(108) = -2.85$, $p = .005$), and although maximum deviations did not differ for positive trials on high than low load trials, the effect approached conventional levels of significance ($t(132) = -1.72$, $p = .09$).

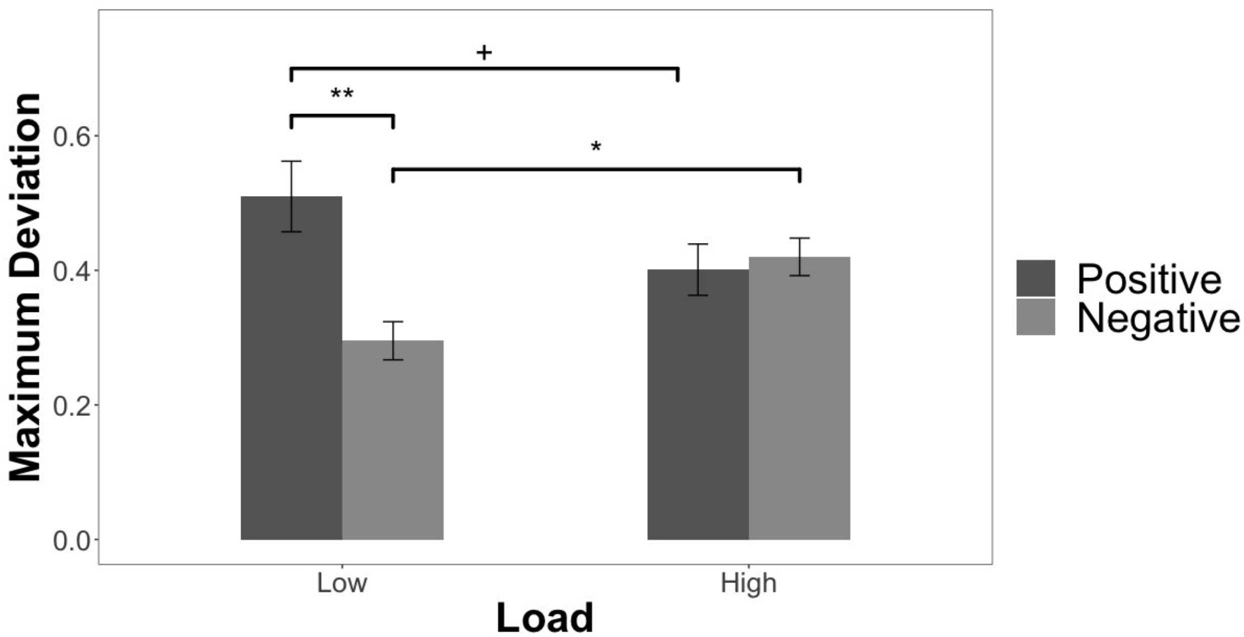

Figure 3: Response competition as a function of load and categorization. There was greater response competition, operationalized as maximum deviation, for positive than negative categorization, but only under low load ($t(91) = -3.71$, $p < .001$). Response competition under high load increased for negative categorizations ($t(108) = -2.85$, $p = .005$) and marginally decreased for positive categorizations ($t(132) = -1.72$, $p = .09$). Error bars represent the standard error of the mean. +$p \leq .06$, *$p < .05$, **$p \leq .001$.

This analysis also revealed some effects that were not predicted: there was a main effect of Domain (F (1, 228) = 6.22, p = .01), which revealed that maximum deviations were larger for emotional (*M(SD)* = 0.44(0.38)) than non-emotional load trials (*M(SD)* = 0.37(0.34)) as well as an interaction of Doman × Rating (F (1, 228) = 5.13, p = .02). The interaction revealed that maximum deviations were larger for positive (*M(SD)* = 0.54(0.44)) than negative (*M(SD)* = 0.36(0.30)) categorizations on emotional load trials (*t*(99) = -2.91, *p* = .005), but not for non-emotional load trials (*t*(86) = -0.63, *p* = .53; positive *M(SD)* = 0.39(0.40); negative *M(SD)* = 0.35(0.27)). In other words, maximum deviations on positive trials were reduced on non-emotional compared to emotional load trials (*t*(236) = 3.18, *p* = .002), but there was no domain-related difference for negative categorizations (*t*(217) = 0.17, *p* = .86).

Reaction time (processes underlying the response)

To further explore the processes underlying the response, we examined the effect of our experimental manipulation and trial-wise surprise categorizations (positive versus negative trials) on reaction time. A Load (low versus high) × Domain (non-emotional versus emotional) × Rating (positive versus negative categorizations of surprise) repeated measures ANOVA revealed results that nicely parallel the effects of maximum deviation. Specifically, there was a main effect of Rating which approached, but did not reach, conventional levels of significance (*F*(1, 48) = 3.83, *p* = .06), with marginally longer reaction times for positive (*M(SD)* = 1915.77(547.01)) than negative trials (*M(SD)* = 1823.96(361.51)). There was also a significant Load × Rating interaction (*F*(1, 223) =6.98, p = .009), with the effect of Rating evident on low load trials (positive (*M(SD)* = 2018.21(607.15); negative (*M(SD)* = 1835.28(382.09); *t*(108) = -3.17, p = .002) but not on high load trials (positive: *M(SD)* = 1808.27(455.23); negative: *M(SD)* = 1812.76(341.49); *t*(111) = 0.01, *p* = .99). Finally, as with maximum deviation, there was also a significant main effect of Domain (*F*(1, 223) = 6.28, *p* = .01), such that RTs were slower under emotional (*M(SD)* = 1910.70(518.26)) than non-emotional load (*M(SD)* = 1825.20(390.94).

Memory probe accuracy

As a manipulation check, we examined accuracy on the memory probe in a Load (low versus high) × Domain (non-emotional versus emotional) repeated measures ANOVA. There was a significant main effect of Load ($F(1, 150) = 44.38$, $p < .001$), such that accuracy was greater under low (*M(SD)* = 98.51(4.56)%) than high load (*M(SD)* = 91.78(10.03)%), suggesting the load manipulation was successful. There was also a significant main effect of Domain ($F(1, 150) = 9.57$, $p = .002$), with greater accuracy for probes following non-emotional (*M(SD)* = 96.70(6.30)%) than emotional loads (*M(SD)* = 93.58(9.97)%). There was also a significant Load × Domain interaction ($F(1, 150) = 14.01$, $p < .001$), revealing that the accuracy was greater for non-emotional loads than emotional loads, but only when load was high ($t(150) = -4.83$, $p < .001$; i.e., there was no significant domain difference for low loads ($t(150) = 0.46$, $p = .65$).

Finally, we explored the extent to which memory probe accuracy – one potential, albeit inconclusive, indicator of successfully maintaining the working memory load – was driving the reported effects. For example, one alternative explanation of the findings is that emotional load trials resulted in more negative categorizations because participants were more accurate at remembering the negative than positive probes, and these negative images primed more negative categorizations of surprise. A paired sample t-test of memory probe accuracy on emotional load trials revealed that there was not a significant difference in performance on trials with a negative (*M(SD)* = 93.52(0.06)%) versus positive probe (*M(SD)* = 91.55(0.06)%; $t(49) = -1.77$, p = .08).

Discussion

Here we explored the nature of the regulatory resources supporting positive categorizations of emotional ambiguity by manipulating the resources available for the categorization task (i.e., loads with either non-emotional or emotional properties). We explored effects on the products and processes of these responses and found that the products were susceptible only to domain-specific interference, whereas the underlying processes were susceptible to both domain-specific and domain-general interference. More generally, these results highlight the importance of considering the domain of task demands when assessing interference effects for concurrent task performance, as this can shed important insight on the overlapping resources required for the tasks. We discuss these results in the context of the initial negativity hypothesis and domain-general cognitive control below.

Effects on the categorization products

The initial negativity hypothesis posits that positive categorizations of ambiguous stimuli rely on regulatory resources that override an initial negativity bias (Neta et al., 2009; Petro et al., 2018). Here, we used a standard working memory paradigm (Ahmed, 2018) to explore the effects of both non-emotional and emotional task interference on valence categorizations of emotional facial expressions. Consistent with previous work, we found that non-emotional load does not affect categorizations of surprised expressions (Mattek et al., 2016). Further, we found the predicted effects of emotional load, such that participants categorized surprised faces as more negative only under an emotional load. This finding suggests that this type of load taxed the emotion-related resources required for a positive interpretation. Indeed, increased cognitive load that has an emotional component has been associated with increased activity in the vmPFC and decreased activity in the amygdala (Kompus et al., 2009), a pattern of activity that has also been linked to emotion regulation (Ochsner et al., 2002; Quirk & Beer, 2006) and to a more positive valence bias (Kim et al., 2003; Petro et al., 2018). Altogether, this pattern of results suggests that the same resources are recruited for both active maintenance of emotional stimuli and a positive valence bias, and that these resources are limited in that engagement in the memory task hampers regulatory performance in the valence categorization task.

Effects on the categorization processes

While subjective categorizations of ambiguity were susceptible only to domain-specific interference, the *processes* of ambiguity resolution (response competition) was vulnerable to both domain-general and domain-specific interference. Specifically, previous work has shown that positive categorizations of surprised faces are associated with greater response competition (i.e., more attraction to the competing – negative – response) and longer reaction times than negative categorizations (Brown et al., 2017; Neta et al., 2009). Here we demonstrate that this difference is mitigated when task demands are high (i.e., high load), irrespective of emotional properties. This effect was driven by increased response competition for negative categorizations under high compared to low load, whereas positive categorizations showed a marginal trend towards decreased competition under high load. At least for the former, this effect parallels work showing that high load increases distractor processing (Lavie & De Fockert, 2005) and response competition measured with mouse-based response trajectories (Bundt et al., 2018).

Previous work has shown that this valence categorization task recruits a set of regions in the cingulate and anterior insula that are central to a domain-general task control network called the cingulo-opercular network (Neta et al., 2013). Indeed, these regions are recruited in response to many types of ambiguity (Neta et al., 2014; Sterzer et al., 2002; Thompson-Schill et al., 1997). Though speculative, it could be that the domain-general task demands in the present study taxed these domain-general cingulo-opercular resources. Indeed, some work has demonstrated that these regions show reliable activitation during cognitively demanding tasks, such as those requiring increased attention and control (Duncan & Owen, 2000; Dosenbach et al., 2006; Nee et al., 2007). As such, the demands induced during high load, regardless of the domain, likely relied on these regions.

Alternatively, these domain-general load effects may represent an interference with resources needed for motor processing. Indeed, working memory loads reliably interfere with the planning and successful execution of motor movements (e.g., temporal control of discrete movements; Maes et al., 2015; anti-saccades; Mitchell et al., 2002), which may account for the increased response competition for negative categorizations of surprise. However, high load also resulted in decreased response competition for positive categorizations, which is not consistent with this account. Future work is needed to disentangle these differential interference effects as a function of categorizations.

In addition to the domain-general interference, there was unexpected domain-specific effect on the response processes as well. In other words, similar to the decrease in response competition (i.e., more direct trajectories and faster reaction times) for positive categorizations that we found in response to high versus low load, the pattern emerged also in response to non-emotional versus emotional load. Although speculative, it could be that more difficult trials (those with higher load or a load of non-emotional images that may be more difficult to hold in memory) encourage participants to make a more decisive categorization (direct trajectory) in order to get to the memory probe portion of the trial.

Limitations and future directions

There are a few limitations to the present study. First, although accuracy was higher for low than high load trials (indicating a successful load manipulation), overall accuracy on the memory probe task was quite high, suggesting that the cognitive resources were not taxed heavily. Relatedly, participants may have been able to rely on recognition (rather than active working memory maintenance) for the memory probes, which renders the task easier (Shepard, 1967). In the present study, each image appeared within only one image matrix and each matrix was only presented once, perhaps facilitating participants' ability to recognize the image during the memory probe. Future work could address these limitations by increasing the task difficulty, either by using more than six images in the high load matrix, re-using some images across trials making it more difficult to remember if the image probe was presented on that specific trial, or making the probe task more difficult (e.g., identifying the location of the image in the previous matrix rather than a present/not judgment).

Further, it is important to note that our matrices contained an equal number of positive and negative images within a matrix to avoid priming effects on the subsequent face ratings (e.g., Flexas et al., 2013; Payne et al., 2005), as previous work has shown categorizations of surprised faces are sensitive to valence priming (Kim et al., 2004; Neta et al., 2011). Although these positive and negative images did not differ in arousal, it is difficult to determine if participants deployed more attention to the negative than positive images in each matrix, and whether this may have impacted their face categorizations. One interesting avenue for future work is to incorporate eye tracking to explore which images are prioritized within a matrix. This would offer insight into which critical features/images draw attention and whether this moderates the categorization of surprised faces. Some evidence against this interpretation is that participants were not significantly more accurate for negative than positive probes, but future work using eyetracking will help to rule out a priming explanation. Eyetracking would allow us to determine at a trial-level which images were being attended and how this impacted subsequent memory and face categorizations.

Conclusions

Here we have provided both a conceptual replication and a novel extension of previous work assessing task interference effects on categorizations of ambiguity (Mattek et al., 2016). Notably, these findings illuminate the processes putatively underlying positive categorizations by demonstrating that these positive categorizations are less likely under emotional load (i.e., the regulatory resources are taxed during concurrent emotion-related processing). As such, these findings lend further support for the initial negativity hypothesis by suggesting that positivity (more so than negativity) relies on additional emotion-specific resources. We also demonstrated a domain-general effect of load on response competition, which is likely related to the domain-general demands of high load within the cingulo-opercular network. Future work should explore the underlying neural mechanisms of these processes. Notably, elucidating the neural mechanisms through which individuals become more negative would offer insight into a range of clinical disorders characterized by negativity bias (e.g., anxiety, depression). Further, this work may even shed light on mechanisms through which those in cognitively and emotionally demanding positions (e.g., healthcare workers) experience negativity related to workplace burnout.

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