Emotional working memory load selectively increases negativity bias

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**Abstract**

Cognitive resources are needed for successful executive functioning; when resources for a particular task are limited due to cognitive load, task performance is impaired. 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 rely heavily on domain-specific emotion resources. Specificially, previous work has shown that the default response to surprised faces is negative, and that positive categorizations are thought to require top-down regulatory resources. Here, we employed a 2x2 design to investigate the effects of load (low versus high) and domain (non-emotional vs. emotional) on evaluations of emotional ambiguity (i.e., positive or negative categorizations). As predicted, a mixed effects model revealed 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, but this effect was diminished under high load. These results suggest emotional load depletes the regulatory resources necessary for positive categorizations of emotional ambiguity, but that greater domain-general load impacts the process underlying the subjective categorizations.

Keywords: cognitive load, depletion, emotional ambiguity, valence bias

**Emotional working memory loads selectively increase negativity bias**

The availability of cognitive resources is necessary for employing adaptive processes in everyday life, including strategies for attentional deployment (Franconeri et al., 2013), decision-making (Deck & Jahedi, 2015; Whitney et al., 2008), cognitive control (Deveney & Pizzagalli, 2008), and emotion regulation (Johns et al., 2008; Richards & Gross, 2002). Engagement in a task that taps a cognitive resource (i.e., a cognitive load) often results in a state of depletion, which leads to impaired performance on concomitant or subsequent tasks that rely on those depleted resources (Richeson & Trawalter, 2005; Baumeister & Heatherton, 1996; Franconeri et al., 2013; Kahneman, 1973; Storbeck, 2012). On a larger scale, cognitive depletion can have widespread societal implications, such as burnout and absenteeism (Diestel & Schmidt, 2011). For instance, in emotionally demanding occupations (e.g., healthcare positions), cognitive depletion is associated with worse job performance (Ihle et al., 2015; Motowidlo et al., 1986) and increased job-related stress that can have adverse downstream effects on executive functioning (Privitera et al., 2014).

Although cognitive load interferes with a broad range of control (e.g., attention; Lavie et al., 2004) and regulatory processes (Ward & Mann, 2000), the domain of the load can modulate these effects. In other words, when cognitive load does not deplete the specific resources needed for a concomitant or subsequent task, performance on the latter task may be unaffected. These domain-specific divisions of cognitive resources have been well-studied at the level of loads on verbal and visuospatial processes (Brooks, 1967; Logie, 1995), and there is accumulating evidence for domain-specific divisions of load effects as a function of the load’s emotional properties. For instance, when asked to remember the emotional expression of a face, participants were less accurate on a subsequent task that required pairing emotional concepts (e.g., couple-happy) compared to pairing perceptual properties (e.g., lemon-yellow; Vermeulen et al., 2014). Neuroimaging and lesion studies suggest a mechanism for these findings, as resolving conflicting emotional cues (i.e., a happy face with an incongruent label, such as “fear”; Egner et al., 2008; Maier & di Pellegrino, 2012) or inhibiting responses to task-irrelevant emotional information (i.e., emotional expressions during an identity-based n-back task; Neta & Whalen, 2011) reliably elicit activity in rostral anterior cingulate cortex. This region is critical for exercising cognitive control in tasks with emotional content (Bush et al., 1998; Whalen et al., 1998), and is located more ventrally in prefrontal cortex than other regions implicated in domain-general cognitive load (e.g., dorsolateral prefrontal cortex; Neta & Whalen, 2011). In other words, when resources are engaged with an emotional load—regardless of whether or not the emotional content is task-relevant—those resources are no longer available to regulate other emotional processes. In turn, regulatory performance on these tasks will likely be impaired, meaning that the effect of load on a concomitant or subsequent task can illuminate the underlying resources engaged during that task. This insight is particularly useful for tasks which rely on cognitive resources (e.g., resolving ambiguity; Neta et al., 2009).

**Resources used for categorizing emotional ambiguity**

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 in categorizations of surprise across people (i.e., *initial negativity hypothesis*; Neta et al., 2009, 2010, 2011; Petro et al., 2018). Under this framework, positive categorizations rely on emotion regulation 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 the decision-making process by quantifying the shape of response trajectories (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 are more direct, whereas positive categorizations were characterized by greater attraction to the unselected (negative) response (Brown et al., 2017; Mattek et al., 2016). Neuroimaging work has also supported this initial negativity hypothesis, demonstrating that the amygdala—associated with bottom-up signals of emotion (Aggleton & Saunders, 2000; Adolphs et al., 1994; LeDoux, 2000)—and the ventromedial prefrontal cortex (vmPFC)—a putative top-down regulatory region (Motzkin et al., 2015)—show inverse activity as a function of subjective categorizations of surprised expressions (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 heavily on regulatory resources than do negative categorizations. Given this reliance on regulatory resources, we would predict that a cognitive load that depletes emotion-related regulatory resources would interfere with the likelihood of seeing ambiguity in a positive light. Notably, one study to date has examined the effect of load on valence categorizations of surprised faces (Mattek et al., 2016). Although this study found no such effect of load, the load manipulation was non-emotional (i.e., remembering a number sequence). Therefore, an open question remains as to whether or not a domain-specific (emotional) load per se will deplete the resources putatively required for a positive bias, resulting in more negative categorizations.

## The present study

In the present study we tested the effect of cognitive load on responses to emotional ambiguity as a function of load (low versus high) and domain (non-emotional versus emotional). 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 (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 the process (response trajectories). Regarding the response products, we expected to replicate previous work showing no effect of domain-general load (high versus low) 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 depletes the resources that are useful for seeing ambiguity in a positive light. Further, we predicted domain-general load effects on the response process, 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*age = 19.03 years, *SD* = 1.70 years, 49 female) were recruited from the undergraduate research pool at the University of Nebraska-Lincoln, which an a priori power analysis determined a sufficient sample size for detecting moderate to large within-subjects effect at an alpha level of .05 and with 80% power (*d* = .5, total sample size required = 34; G\*Power 3.1; Faul et al., 2009). 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*age = 18.82 years, SD = 1.19 years, 41 female), and all identified as White/Caucasian without Hispanic/Latinx ethnicity to control for potential effects of cross-race judgments. All subjects 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 probes, but never appeared in the image matrices – only 36 of these 63 images were randomly selected for each participant, 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), as previous work has shown categorizations of surprised faces are sensitive to valence priming (Neta et al., 2011). Notably, the positive and negative images used in these matrices did not differ in arousal after testing with a Wilcoxon signed-rank test (*Z* = -0.23, *p* = 0.82).

The face stimuli included images from the NimStim (Tottenham et al., 2009) and Karolinska Directed Emotional Faces (Lundqvist et al., 1998) stimuli sets, as in previous work (Brown et al., 2017; Neta & Whalen, 2010). 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) memory 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 the 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 single image probe appeared (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).

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## Figure 1: Example of a single trial in the emotional high load condition. At the start of each participant-initiated trial, a fixation cross appeared (1000 ms), 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 for 1000 ms, which the participants were instructed to categorize as positive or negative using the computer mouse. Finally, participants initiated the probe portion of the trial by pressing the start button again which presented another 1000 ms fixation followed by a single image probe appeared (5000 ms). Then participants used the computer mouse to indicate whether the image probe was present (yes) or not (no) in the previous image matrix.

## Data analysis

We used R (Version 3.6.0; R Core Team, 2019) for all our analyses. Data preprocessing, analysis, and plotting were completed in R using the mousetrap (Kieslich et al., 2019), lme4 (Bates et al., 2015), 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. 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 2x2 design, and explored the effects of these four conditions and trialwise categorizations (positive and negative) on maximum deviation.

We used a mixed effects modeling approach to account for both the interdependence among measurements due to the repeated measures design and the missing data in our analyses based on categorization (i.e., some participants rated surprise as either negative or positive on all trials). Additional justification for the mixed effects modeling approach comes from tests of statistical dependency among the measures for any given subject, which was revealed through an intraclass correlation (ICC) of .75 for ratings of surprised faces and .17 for maximum deviations.

To test the effects of experimental conditions (load: low versus high, and domain: non-emotional versus emotional) on categorizations and maximum deviations, we used 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). All model building was completed using 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)

First, a random intercept-only model was tested and likelihood ratio test results supported the decision to model the intercept randomly across individuals (*p* < .001). This indicates individual variance in valence bias at baseline (i.e., even under low, non-emotional loads) that is best modeled as a separate intercept for each subject.Next, fixed effects for Load (low versus high), Domain (non-emotional versus emotional), and their interaction were added to the model. There was a significant effect of Domain, such that categorizations of surprised faces following an emotional load (*M* = 74.0, *S.E.* = 3.49) were more negative than those following non-emotional loads (*M* = 65.0, *S.E.* = 3.49; ß = 9.03, 95% CI [5.58, 12.50], *t*(153) = 5.17, *p* < .001). There was no significant effect of Load (low load: *M* = 68.9, *S.E.* = 3.49; high load: *M* = 70.2, *S.E.* = 3.49; ß= 1.34, 95% CI [-2.11, 4.79], *t*(153) = .77, *p* = .45), nor was there a significant Domain × Load interaction (ß30 = 1.93, *S.E.* = 3.46, 95% CI [-4.89, 8.76], *t*(150) = .56, *p* = .58).

**Mixed Model:** Percent Negative Ratingsti = (β00 + r0i) + β10\*(Domainti) + β20\*(Loadti) β30\*(Domainti \* Loadti) + eti

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**Figure 2: Percent negative ratings across conditions.** Surprised faces were categorized as negative more frequentlyduring emotional than non-emotional load trials (*t*(153) = 5.17, *p* < .001), but there was no effect of Load (low versus high) on ratings (*t*(153) = .77, *p* = .45). Error bars represent the standard error of the mean. \*\*p ≤ .001.

**Maximum deviation (process underlying the response)**

Next, we examined the effect of our experimental manipulation and trial-wise surprise categorizations (positive versus negative trials) on maximum deviation. First, a random intercept-only model was tested for maximum deviation, and a likelihood ratio test supported this decision to model the intercept randomly (*p* < .001). This means that individuals differed in their average maximum deviations at baseline (i.e., under low, non-emotional loads), and that the best fitting model includes an intercept for each subject individually.Next, fixed effects of Load (low versus high), Domain (non-emotional versus emotional), Rating (positive versus negative categorizations of surprise), and their interactions were added to the model. A significant Load × Rating interaction (β50 = .32, *S.E.* = .09, 95% CI [.14, .50], *t*(314) = 3.55, *p* < .001; Figure 3) revealed that, as expected, maximum deviations were larger for positive (*M* = .50, *S.E.* = .04) than negative categorizations (*M* = .30, *S.E.* = .04; β=.21, *S.E.* = .05, 95% CI [.11, .30], *t*(325) = 4.39, *p* < .001; Bonferroni corrected significance for these analyses *p* < .013) on low load trials. However, this difference was not present on high load trials (positive: *M* = .41, *S.E.* = .04; negative: *M* = .42, *S. E.* = .04; β = -.01, S.E. = .05, 95% CI [-.11, .08], *t*(327) = -.31, *p* = .76), supporting our hypothesis that high load would diminish the attraction towards the ‘negative’ response. Specifically, maximum deviations for negative trials were larger on high than low load trials (β *=* -.13*, S.E.* = .05, 95% CI [-.22, -.04], *t*(320) = -2.81, *p* = .005), and there was a trend for smaller maximum deviations for positive trials on high than low load trials (β= .10, *S.E.* = .05, 95% CI [.00, .19], *t*(324) = 1.93, *p* = .06).

**Mixed Model:** Maximum Deviationti = (β00 + r0i) + β10\*(Loadti) + β20\*(Domainti) + β30\*(Ratingti) + β40\*(Loadti)\*(Domainti) + β50\*(Loadti)\*(Ratingti) + β60\*(Domainti)\*(Ratingti) + β70\*(Loadti)\*(Domainti)\*(Ratingti) + eti



**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*(325) = 4.39, S.E. = .05, *p* < .001). Response competition under high load increased for negative categorizations (*t*(320) = -2.81, S.E. = .05, *p* = .005) and tended to decrease for positive categorizations (*t*(324) = 1.93, *p* = .06). Error bars represent the standard error of the mean. +*p* < .06, \**p* < .05, \*\**p* ≤ .001.

**Memory probe accuracy**

Next, we explored the extent to which memory probe accuracy – one potential indicator of successfully maintaining the working memory load – was driving the reported effects. Specifically, if emotional load was more effective at changing categorizations because it was a more effective manipulation, we might expect greater accuracy on trials with an emotional load (which result in more negative categorizations) compared to non-emotional load. Although there was a significant effect of Domain on accuracy (*F*(1, 49) = 10.49, *p* = .002), accuracy was higher for non-emotional than emotional load. Further, if high load was more effective at modulating response trajectories because it was a more effective manipulation, we might expect greater accuracy on trials with a high load (which modulate response trajectories) compared to those with low load. Although there was a significant effect of Load on accuracy (*F*(1, 49) = 50.28, *p* < .001), accuracy was higher for trials with low than high load.

Another alternative explanation related to memory probe accuracy is that, on the emotional load trials, participants were more accurate at remembering the negative than positive probes, which primed more negative categorizations of surprise. A paired sample t-test of memory probe accuracy on emotional load trials revealed that there was no significant difference in performance on trials with a negative versus positive probe (*t*(49) = -1.77, p = .08).



**Discussion**

Here we tested the effects of cognitive load with either non-emotional or emotional properties on responses to emotional ambiguity. We explored effects on the products of these categorizations and found, as predicted, that categorizations of surprise were more negative under emotional than non-emotional load. As in previous work, higher non-emotional load did not affect categorizations (Mattek et al., 2016), but here we demonstrate that these categorizations are susceptible to load effects when the load depletes emotion-specific resources. This result aligns with literature demonstrating that the emotional properties of cognitively demanding tasks impact both behavioral and neural responses during those tasks (Egner et al., 2008), and suggests a role for emotion-specific regulatory resources in overriding initial negativity in the face of ambiguity. More generally, these results highlight the importance of considering the domain of the load when interpreting the impact of load on subsequent processing, as not all loads deplete the same resources.

We also explored the effects on the process (response competition) of categorization and found evidence that response trajectories were modulated by domain-general cognitive load (i.e., across both domains) as a function of trial-by-trial categorizations. 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) than negative categorizations (Brown et al., 2017), and here we demonstrate that this difference is mitigated under higher domain-general load. Specifically, negative categorizations were associated with increased response competition under high load compared to low load, whereas positive categorizations showed a trend towards decreased competition under high load. This parallels other 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). We discuss these results in the context of the initial negativity hypothesis below.

**Domain-specific effects**

The initial negativity hypothesis posits that positive categorizations of ambiguous stimuli rely on regulatory resources that override an initial negativity (Neta et al., 2009; Petro et al., 2018). Here, we used a standard working memory paradigm (Ahmed, 2018; Burnham, 2010; Lavie & De Fockert, 2005) to induce high cognitive load with either non-emotional or emotional properties while participants made valence judgments of surprised facial expressions. As expected, participants categorized surprise as more negative under emotional loads, suggesting that this type of load depleted the emotional 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; Jackson et al., 2003; Urry et al., van Reekum et al., 2007) and to a more positive valence bias (Kim et al., 2003).

These results also corroborate evidence that resource depletion is associated with a greater reliance on bottom-up emotional responses and weaker top-down responses. For example, some work has shown depletion was associated with greater amygdala (bottom-up) and less prefrontal (top-down) activity in response to negative images (Wagner & Heatherton, 2013). In the context of surprised faces, this pattern of activity is linked with more negative categorizations (Kim et al., 2003; Neta & Whalen, 2010; Petro et al., 2018). Taken together, these findings – in association with previous work using emotional load and resource depletion – lend support for the initial negativity hypothesis.

**Domain-general effects**

While subjective categorizations of ambiguity were susceptible only to domain-specific load, the process of ambiguity resolution (response competition) was instead vulnerable to domain-general load demands. 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., 2013; Neta et al., 2014; Sterzer et al., 2002; Thompson-Schill et al., 1997). Though speculative, it could be that the domain-general cognitive loads in the present study taxed these domain-general cingulo-opercular resources. Indeed, some work has demonstrated that these regions show reliable activitation during other cognitively demanding tasks, such as those requiring increased attention and control (Duncan & Owen, 2000; 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 effect of load interfering with cognitive 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, 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 effects of load as a function of categorizations.

**Limitations and future directions**

There are a few limitations to the present study. First, acuracy on the memory probe task – even under high load – was high, suggesting that the cognitive resources were not depleted 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 in 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 just a present/not judgment).

Here, we attempted to use a similar working memory task that could directly compare loads with non-emotional versus emotional properties. Thus, unlike previous work that used numerical sequences that could be rehearsed using verbal working memory, our task likely relies more on visual working memory (Baddeley, 1998). One interesting avenue for future work with visual working memory is to incorporate eye tracking to explore which images participants attended to the most within a matrix, offering insight – beyond that of our accuracy analyses –into which images may be most likely to be held in working memory. In turn, this would allow testing on a trial-by-trial basis, such that attention towards either positive or negative emotional images could be quantified and explored in the context of subsequent ratings of surprised expressions.

**Conclusions**

Here we have provided both a conceptual replication and a novel extension of previous work which tested the effects of cognitive load 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. 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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