Domain-specific working memory loads selectively increase negative interpretations of surprised facial expressions

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| Nicholas R. Harp1 & Maital Neta1 |
| 1 University of Nebraska-Lincoln |
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# Author note

Correspondence concerning this article should be addressed to Nicholas R. Harp. E-mail: [nharp@huskers.unl.edu](mailto:nharp@huskers.unl.edu)

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# Introduction

Facial expressions are important social signals; they communicate emotion between individuals and even spark emotional responses in others (Frith, 2009). Indeed, humans readily make judgments about personality traits (e.g., trustworthiness), aesthetics (e.g., attractiveness), and emotions/dispositions from faces (Carroll & Russell, 1996; Bar, Neta, & Linz, 2006; Said & Todorov, 2011; Todorov, Baron, & Oosterhof, 2008). One of the most important aspects of perceiving facial expressions is determining the valence (i.e., the inherent positive or negative emotional value of a stimulus) of such expressions. Valence has long been believed to be a core component of emotional experience (Russell, 1980), and perceptions of valence guide social (i.e., approach-avoidance) behavior (Krieglmeyer, Deutsch, De Houwer, & De Raedt, 2010) and even influence person construal in social group categorization tasks (e.g., political affiliation or sexual orientation; Taskhay & Rule, 2015; Tskhay & Rule, 2018).

While most people can accurately differentiate the emotional valence of facial expressions, such as consistently interpreting angry faces as negative and happy faces as positive, there are individual differences in valence judgments of emotionally ambiguous facial expressions, like a surprised face (Neta et al., 2009; Petro, Tong, Henley, & Neta, 2018 ). This difference in valence interpretations of surprised expressions is attributable to this expression’s predictive value for both positive (e.g., winning the lottery) and negative (e.g., a car accident) outcomes. This individual difference in interpretations of emotionally ambiguous stimuli is known as one’s *valence bias*, and a growing body of work has used both facial expressions and emotional scenes to better understand this bias (Neta, Kelley, & Whalen, 2013; Neta et al., 2009; Neta & Whalen, 2010). The valence bias represents an important individual difference, as these two equally valid but alternative interpretations likely lead to different downstream behaviors (e.g., Krieglmeyer et al., 2010). For instance, individuals that interpret ambiguous expressions negatively may avoid the expresser, and vice versa, given the relevance of emotional valence in approach-avoidance behaviors (Bradley, 2009; Frijda, 1986; Lang, 1985).

Despite individual differences in valence bias, the initial response to ambiguity appears to be negativity for most people (Neta, Davis, & Whalen, 2011; Neta et al., 2009; Neta & Whalen, 2010; Petro et al., 2018). Under this framework, which is known as the *initial negativity* hypothesis, positive interpretations rely on the implementation of some emotion regulation strategy in order to override the initial negativity. Several studies provide evidence to support this hypothesis. For instance, images containing only low spatial frequency information, which is processed faster than high spatial frequency information, are rated more negatively than their high spatial frequency counterparts (Neta & Whalen, 2010). Additionally, surprised facial expressions are more quickly detected in an emotional oddball paradigm among happy (positive) than angry (negative) faces (Neta et al., 2011), suggesting that surprised expressions are more readily perceived as similar to angry faces than happy faces.

Conversely, other research supports the notion that positive interpretations rely on a regulatory process. For instance, reaction time data show that individuals with a more positive bias take longer to reach a valence judgment for surprised expressions than those with a more negative bias (Neta et al., 2009), suggesting a more time-intensive (regulatory) process for positive interpretations. A recent study demonstrated that instructions to delay responding during valence judgments of surprised expressions resulted in a shift towards positivity for those with a negative baseline bias (Neta & Tong, 2016). Neuroimaging work has shown that ventromedial prefrontal cortex, a putative regulatory region, and amygdala actively are inversely correlated, and that participants with a more negative valence bias showed greater amygdala activity while more positive participants showed greater ventromedial prefrontal cortex (vmPFC) activity (Kim, Somerville, Johnstone, Alexander, & Whalen, 2003). More recently, Petro, Tong, Henley, & Neta (2018) found that participants with a more positive valence bias showed greater activity for surprised faces in brain regions recruited during an explicit emotion regulation (cognitive reappraisal) task. Taken together, initial responses to ambiguity appear to be negative, and positive interpretations rely on regulatory processes, perhaps through an emotion regulation mechanism including cognitive reappraisal. However, given the cognitive cost of regulatory strategies (Richards & Gross, 2000; Sheppes & Meiran, 2008), concurrent cognitive demands will likely interfere with individuals’ ability to effectively implement regulatory strategies in the face of ambiguity.

## Cognitive loads and task interference

In daily life, cognitive resources are limited, which can lead to difficulty in effortful self-regulation of cognitive and affective processes (Baumeister & Heatherton, 1996; Kahneman, 1973; Storbeck, 2012; Scalf, Torralbo, Tapia, & Beck, 2013). For example, imagine a student attending a lecture while engaging in a text message conversation with a friend. The student will be distracted by notifications, thus directing cognitive resources towards the conversation and away from the lecture. In turn, the student’s ability to understand and remember the lecture material will suffer. Directing cognitive resources between different tasks in this manner taxes an already limited pool of cognitive resources (Baumeister & Heatherton, 1996; Kahneman, 1973). Indeed, cognitive resource competition leads to a phenomenon known as cognitive load, which negatively impacts executive processes (Lavie, Hirst, Fockert, & Viding, 2004; Murphy, Groeger, & Greene, 2016). High levels of cognitive load alter performance on cognitively demanding tasks, including those in both cognitive and emotional domains (Jiaping et al., 2017; Kron, Schul, Cohen, & Hassin, 2010; Nagamatsu et al., 2011; Pontari & Schlenker, 2000; Thomas, Donohue-Porter, & Stein Fishbein, 2017; Mather & Knight, 2005; Knight et al., 2007). For instance, reducing cognitive load (e.g., through integration of diagrams and text information to reduce split-attention) facilitates learning of complex topics (e.g., geometry, physics, and anatomy) which already have intrinsic cognitive demands (Chandler & Sweller, 1991). The affective qualities of cognitive load also matter, as performance on a deductive reasoning task, in which participants assessed the logic of a conclusion given some provided premises, was worse when the premises included emotional words (e.g., there are torturers who are introverts, introverts do not hurt people, no torturers hurt people) rather than emotionally neutral words (e.g., the sky is blue, blue is not green, the sky is green; Trémolière, Gagnon, & Blanchette, 2016). These studies highlight the susceptibility of cognitive processes to cognitive load, as well as the importance of load characteristics (i.e., emotional vs. non-emotional qualities)

Further, cognitively demanding tasks often interact with concurrent affective processes (e.g., face categorization, subjective emotional experience), perhaps as a result of a shared resource pool for these processes (Ahmed, 2018, Blair et al., 2007; Muraven, Tice, & Baumeister, 1998; Mather & Knight, 2005; Knight et al., 2007). For instance, Ahmed (2018) showed that performance on a facial expression categorization task suffers when participants are under high cognitive load. Additionally, cognitive load has been linked to changes in emotional responses (Blair et al., 2007; Van Dillen, Heslenfeld, & Koole, 2009). For example, higher loads during a working memory task (Van Dillen et al., 2009) and increased cognitive demands (Blair et al., 2007) reduce subjective emotional experience, as well as brain responses to emotion (i.e., amygdala and inferior frontal gyrus activation). Additionally, there is evidence that behavioral performance of a cognitively demanding task (i.e., Stroop task) suffers during trials with emotional distractors (Blair et al., 2007). Other work has demonstrated the negative effects of cognitive load on affective bias in older adults, showing that cognitively demanding tasks (e.g., distraction during memory encoding) reduces age-related positivity bias (Mather & Knight, 2005; Knight et al., 2007). Together, these effects suggest an overlap between cognitive demands and emotional processes, with high cognitive demands interfering with typical emotion processing.

Given the initial negativity hypothesis, cognitive load, specifically one which taxes the same resources used for emotion regulation, should result in a more negative valence bias. Previous work has revealed, in contrast, no effect of load on subjective interpretations of surprised expressions, but participants did show altered response (computer mouse) trajectories, such that mouse movements were less drawn towards their modal response option (e.g., positive ratings for individuals with a positive bias; Mattek, Whalen, Berkowitz, & Freeman, 2016). That is, the cognitive load did not interfere with the tendency to interpret surprised expressions as positive or negative, but instead interfered with the cognitive-motor dynamics of *how* one arrived at a response.

One potential explanation for the null effect of load on ratings is the domain-specificity of the cognitive load. In other words, some research has shown that one task (i.e., Stroop task) can recruit different brain regions depending upon the emotional properties of the task and stimuli (i.e., gender judgments of neutral faces vs. expression judgments of emotional faces), highlighting the dissociable processing of emotional and non-emotional stimuli within similar tasks (Egner, Etkin, Gale, & Hirsch, 2008). Critically, Mattek and colleagues (2016) used non-emotional stimuli (i.e., number sequence) in their manipulation of cognitive load during interpretations of surprised facial expressions. The cognitive demand required for maintaining emotional (but perhaps not non-emotional) information in working memory may be necessary for taxing resources used for emotion regulation.

## The present study

In the present study we tested the effect of high cognitive load on valence bias, and directly compare the effects of load that carries emotional versus non-emotional properties. In other words, we manipulated the emotional properties as well as the amount of material that participants needed to maintain in working memory while concurrently making valence judgments of facial expressions. First, we predict a null effect of load on valence bias (i.e., ratings of surprised faces will not differ under low versus high load), replicating Mattek and colleagues (2016). Notably, we expect to find a main effect of content type (emotional versus non-emotional) on interpretations of surprise, such that interpretations made under emotional load are more negative than those made under non-emotional working memory loads. This would suggest that emotional loads tap into the same processes that are used during resolution of emotional ambiguity (e.g., regulatory resources used for positive interpretation may be engaged with the memory load leaving them unavailable for the valence judgment). Further, we predict an interaction effect, such that high emotional working memory load will result in more negative interpetations than low emotional working memory load.

# 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. 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). 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 and procedure

After arriving at the lab, participants provided informed consent prior to completing the task. Participants then completed the task, which included 144[[1]](#footnote-1) trials in which an image matrix, face, and single image memory probe were presented. The experimenter guided participants through a practice face rating and memory probe trial. The trials were self-initiated; that is, the participant 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 which the participants were instructed to remember for the duration of the trial (i.e., until the memory probe portion of the trial). The image matrices were designed to induce either low (two images) or high (six images) cognitive load with either non-emotional or emotional properties (Figure 1). A total of 288 scenes (72 positive, 72 negative, and 144 neutral) were selected from the International Affective Picture System (Lang, Bradley, & Cuthbert, 2008) for use in the matrices, and the positive and negative images did not differ in arousal (Z = -0.23, p = 0.82). For the matrices with emotional properties, there were an equal number of positive and negative images within a matrix. Disambiguating the effects of positive and negative valence loads would prove difficult as these valence effects could result in priming effects (e.g., Flexas, Rosselló, Christensen, Nada, La Rosa, & Munar, 2013), and previous work has shown that participants’ valence bias shifts towards the valence of more frequently occurring stimuli when surprised expressions are consistently preceded and followed by either angry or happy faces, (Neta et al., 2011).

After the image matrix, either a happy, angry, or surprised face appeared for 1000 ms and the participants rated the face by clicking on either the positive or negative response option. face selections fromAfter the face rating, a single image probe appeared (5000 ms), and participants indicated 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 task was completed using MouseTracker software (Freeman & Ambady, 2010) and participants responded with the mouse to indicate the appropriate response for both the face ratings and the memory probe. Mouse trajectories are a rich source of insight into the continuous cognitive-motor dynamics underlying decision-making (Freeman, Dale, & Farmer, 2011), and i

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## Figure 1: Instructions for the working memory and valence bias task and sample images.

## Data analysis

We used R (Version 3.6.0; **???**) for all our analyses. Data preprocessing, analysis, and plotting were completed in R using the mousetrap (**???**), lme4 (???), and ggplot2 (???) packages. First, trials were screened for reaction time outliers (i.e., > three standard devations above the mean) and subsequently removed. Additionally, we removed the preceding face rating trial for any incorrect memory probe trials, as these trials can be considered a manipulation failure. Next, percent negative ratings were calculated for happy, angry, and surprised faces across all trial types, as well as a percent correct score for the memory probe trials.

For the main test of our hypothesis, we tested for differences in valence bias among the different working memory load conditions. Additionally, we assessed mouse trajectories among these same conditions, while also testing for differences as a function of subjective rating (i.e., positive or negative). In order to account for the interdependence among measurements from the repeated measures design, we used a multilevel modeling approach. The intraclass correlation was .19, meaning that, as expected, there was statistical dependency among the measurements for any given subject. This provided additional support for the decision to use mixed-effects modeling. Prior to completing the analyses, all rating and mouse data were assessed for normality using Shapiro-Wilks tests. The results of all four tests were highly significant (p’s < .001) for the rating data, as ratings of ambiguity are typically negatively skewed. As such, we assessed alternative distributions for use in a generalized linear mixed model; however, the model fit of the traditional linear mixed model with a gaussian error distribution fit better than alternative model options (i.e., gamma distribution). Notably, other work has shown that linear mixed models are robust to violations of normality (Knief & Forstmeier, 2018). We employed the model building approach suggested by Raudenbush and Bryk (2001), assessing model fit using *X*2 difference tests for any random parameters added to the model. All model comparisons were completed with full information maximum likelihood estimation to account for any missing data (e.g., if a participant did not rate any images as positive).

# Results

## Subjective ratings

First, a random intercept-only model was tested and the likelihood ratio test results supported the decision to model the intercept randomly across individuals (p < .001), suggesting that individuals varied randomly in percent negative ratings at baseline (i.e., low, non-emotional cognitive loads).After, a fixed component for the effect of content type (i.e., non-emotional vs. non-emotional), load (i.e., low vs. high) and their interaction were added to the model uncentered at level one. The effect of content type significantly contributed to the model (ß10 = 8.62, S.E. = 2.46, *t*(147) = 3.51, p < .001), such that the emotional load ratings were more negative than the non-emotional load ratings. The effect of load did not significantly contribute to the model (ß20 = -.18, *t*(147) = -.07, S.E. = 2.46, p = .943). Additionally, the interaction of the conditions was also non-significant (ß30 = 3.45,*t*(147) = .99, S.E. = 3.48, p = .323). Nested model comparisons demonstrated that the addition of a random effect to the content type and load slopes did not improve model fit (both p’s > .400). Altogether, these results suggest that load did not differentially affect ratings, but that content type did affect ratings.

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

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**Figure 2: Percent negative ratings across the working memory load conditions. Ratings during loads with emotional properties were more negative than ratings during loads with non-emotional properties, but there was no difference between ratings under low or high cognitive load. Error bars represent the standard error of the mean.**

**Maximum deviation**

Next, we tested for differences in maximum deviation across the working memory conditions, as well as by subjective rating (i.e., positive and negative ratings). First, a random intercept-only model was tested for absolute maximum deviation of mouse trajectories, 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., low, non-emotional cognitive loads).After, fixed parameters for the effect of domain (i.e., non-emotional vs. emotional), load (i.e., low vs. high), rating (i.e., positive or negative), and their interactions were added to the model. There were two significant interactions. The first, a Rating x Load interaction (β = .31, *t*(310) = 3.29, S.E. = .09, p = .001; Figure 3), showed that positive ratings had larger maximum deviations than negative ratings (*t*(321) = 3.969, S.E. = .049, p < .001; Bonferroni corrected significance p < .004) during low load trials. However, this difference was not present during the high load conditions (*t*(324) = .562, S.E. = .050, p = .575), suggesting that greater cognitive demands mitigate differences in the draw towards competing responses across positive and negative judgments. Additionally, there was a trend towards greater maximum deviations during negative ratings under high load compared to low load (*t*(315) = -2.538, S.E. = .046, p = .012), but this did not reach statistical significance after correcting for multiple comparisons.

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**Figure 3: The interaction of Rating and Load for maximum deviations shows the influence of high cognitive load on cognitive-motor dynamics for surprised expressions interpreted as negative. These results are averaged across the content type factor. Error bars represent the standard error of the mean.**

Additionally, there was a significant three-way interaction of Rating x Load x Domain (β70 = -.29, *t*(311) = -2.07, S.E. = .14, p = .040; Figure 4). Pairwise comparisons showed that positive ratings under high load had smaller deviations for neutral compared to emotional load trials (*t*(323) = -3.092, p = .002; Bonferrroni corrected significance p < .004). There were also several trending results. For instance, for trials with low load and non-emotional working memory content, positive ratings showed a trend towards larger deviations than negative ratings (*t*(318) = 2.800, p = .005). A similar pattern was seen on trials with low load and emotional content, such that positive ratings tended to have larger maximum deviations (*t*(322) = 2.819, p = .005). Several other comparisons approached significance, with positive ratings showing marginally greater deviations than negative ratings in the high load and emotional content condition (*t*(324) = 2.383, S.E. = .074, p = .018), as well as a treand for larger deviations during high load than low load for negative ratings with non-emotional working memory content (*t*(316) = -2.51, S.E. = .066, p = .013). These results demonstrate that mouse trajectories of positive interpretations are affected by the emotional properties of high cognitive loads, such that emotional loads resulted in greater attraction towards the negative response.

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

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**Figure 4: Maximum deviations by working memory load condition and subjective rating. Larger maximum deviation indicates greater response competition and attraction towards the unselected response. Error bars represent the standard error of the mean.**

# Discussion

Here we tested the effects of cognitive loads with either emotional or non-emotional properties on valence bias. As predicted, interpretations of surprise were more negative under cognitive loads with emotional properties than loads with non-emotional properties. This result extends previous work testing the effects of cognitive load on valence bias (Mattek et al., 2016), and aligns with literature demonstrating that the emotional properties of cognitively demanding tasks affect both task performance and the neural systems engaged during tasks (Egner et al., 2008). We also found evidence that maximum deviations varied across the working memory conditions and subjective ratings. Previous work has shown that negative interpretations of ambiguous facial expressions are more direct than positive interpretations (Brown et al., 2017), and here we demonstrate that this difference is mitigated under high cognitive load. This parallels other work showing that high cognitive load increases distractor processing (Lavie & De Fockert, 2005) and that increased cognitive control demands (i.e., incongruent trials within a Stroop task) increase response competition measured with mouse-based response trajectories (Bundt, Ruitenberg, Abrahamse, & Notebaert, 2018). Additionally, maximum deviations for positive interpretations varied during high load trials depending on the emotional properties of the cognitive loads. Cognitive loads with emotional properties resulted in an increased attraction towards the negative response, revealing a bias towards negativity in the dynamics of the decision-making that accompany the shift towards negativity seen in the subjective ratings. We discuss these results in the context of the initial negativity hypothesis below.

**Domain-specific effects**

The initial negativity hypothesis posits that positive interpretations of ambiguous stimuli rely on regulatory resources (Neta et al., 2009; Petro et al., 2018). We used a standard working memory paradigm (Ahmed, 2018; Burnham, 2010; Lavie & De Fockert, 2005) to induce high cognitive load with either emotional or non-emotional properties while participants made valence judgments of surprised facial expressions. As expected, participants interpreted surprise as more negative during cognitive loads with emotional properties, suggesting that these loads specifically taxed the resources required for positive interpretations of ambiguity. While there was no effect of high cognitive load on subjective interpretations, mouse trajectories of positive interpretations varied between the emotional and non-emotional domain when cognitive load was high. In other words, active working memory maintenance of emotional images resulted in a greater attraction towards the negative response option for trials where surprise was ultimately interpreted as positive. Taken together, these results show that domain-specificity of emotional content matters more than the load demands for altering subjective interpretations of ambiguity, but that the cognitive-motor dynamics of the decision are only susceptible to domain-specificity when cognitive load is high. These findings highlight the importance of domain-specificity when considering the effects of cognitive demands on both the subjective response and cognitive-motor dynamics underlying affective decision-making.

Previous work supports the idea that emotional properties of tasks or stimuli recruit neural processes associated with emotion processes (Etkin et al., 2006; Neta et al., 2011). For instance, Neta and Whalen (2011) found that performing an emotional expression-based n-back task recruited greater amygdala activation when compared to an identity-based task. Given the initial negativity hypothesis’ prediction that positivity relies on regulation, it may be that working memory loads with emotional properties interfered with regions known to regulate amygdala activity. One such region, the anterior cingulate cortex, is known to correlate positively with amygdala during emotional face processing (i.e., increases in anterior cingulate and amygdala activity occur together) in youth and young adults with higher levels of anxiety (Kujawa, Wu, Klumpp, Pine, Swain, Fitzgerald, Monk, & Phan, 2017). Indeed, the emotional Stroop task differentially activates anterior cingulate cortex when compared to a non-emotional Stroop task (i.e., gender judgment; Etkin et al., 2006), suggesting that the working memory loads with emotional properties may have done so as well. Taken together, we interpret this effect of content type on interpretations of ambiguity as evidence that regulatory resources needed for positive interpretations of ambiguity are susceptible to domain-specific cognitive load demands, and that domain-general cognitive resources are less critical for regulating subjective interpretations of emotional ambiguity.

**Domain-general effects**

While subjective interpretations of ambiguity were susceptible to the content type of cognitive loads, the underlying cognitive-motor dynamics (i.e., maximum deviations) of these decisions were more susceptible to differences in domain-general cognitive load demands. That is, maximum deviations varied as a function of low compared to high cognitive load, but also as the emotional properties of the memory load changed (see the above findings). Specifically, there was evidence that high cognitive loads of any type mitigate the more direct trajectories characteristic of negative interpretations of emotional ambiguity (Brown et al., 2017). In other words, while positive judgments typically result in trajectories showing greater response competition, there was no difference between the maximum deviations of positive and negative judgments when individuals maintain more demanding working memory loads. This replicates previous work showing that the cognitive-motor dynamics underlying the valence bias task are susceptible to increases in cognitive demands generally, but that final interpretations are not (Mattek et al., 2016). One interpretation of these differences in maximum deviations is that the tendency for individuals to be drawn towards an unselected response may reflect a type of distraction effect (Spivey, Grosjean, & Knoblich, 2005). This mirrors effects seen in the cognitive load literature, where high cognitive loads lead to deficits in the ability to filter out task-irrelevant information (Lavie, Hirst, de Fockert, & Vidling, 2004). At the least, high cognitive load appears to interfere with typical mouse-based response trajectories during resolution of emotional ambiguity.

Previous work has shown that emotional ambiguity resolution relies on a domain-general task control network called the cingulo-opercular network (Neta et al., 2013); though speculative, the cognitive loads may have taxed these resources, as this network is recruited in response to many types of ambiguity (Neta et al., 2013; Neta et al., 2014; Sterzer, Russ, Preibisch, & Kleinschmidt, 2002; Thompson-Schill, D’Esposito, Aguirre, & Farah, 1997). Other neuroimaging work supports the notion that cognitive loads would preoccupy resources in the cingulo-opercular network; for instance, regions in the network (i.e., anterior cingulate cortex and anterior insula) regularly show activity increases during cognitively demanding tasks, such as those requiring increased attention and control (Duncan & Owen, 2000; Nee, Wager, & Jonides, 2007). As such, the demands induced during high cognitive load, regardless of the emotional properties of the load, likely increased demands in this network. Ultimately, this increase in demands for this domain-general network are one explanation for the observed increase in response competition (i.e., maximum deviations) during high cognitive loads.

**Limitations and conclusions**

However, the present study is subject to limitations. For instance, despite the effect of content type on subjective interpretations of ambiguity and the effect of high load on response trajectories, working memory performance was near ceiling across all conditions (i.e., greater than 90% correct). This suggests that the high cognitive load may not have taxed resources to the fullest extent possible, perhaps weakening some effects. Indeed, participants may have been able to rely on recognition, rather than active working memory maintenance, for the memory probes, as humans are readily able to identify previously seen images after exposure to a large amount of material (i.e., 600 images) at high accuracy (Shepard, 1967). Future work could address this by increasing the demands of the task, either through larger sets of image matrices (e.g., eight, ten, or more), increasing the number of trials so that participants view the same images across several matrices, or relying on a different stimulus type altogether (e.g., emotional or non-emotional words). 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.

Here we have provided both a conceptual replication and a novel extension of previous work which tested the effects of high cognitive load on subjective interpretations of ambiguity (Mattek et al., 2016). Notably, the previous work did not include working memory demands intended to recruit neural resources related to the processing of emotional stimuli, and as such did not show an effect on interpretations of ambiguity. In other words, only cognitive loads which tax emotion-related processing will lead to more negative interpretations of ambiguity, highlighting the importance of domain-specificity in cognitive demands. We posit that this effect relies on taxing neural resources related to ambiguity resolution and results in an increase in negativity as a result of a mitigated ability to employ regulatory processing, which is in line with our initial negativity hypothesis. We also demonstrated a domain-general effect of cognitive load on mouse trajectories, which could be further understood in future studies, but is likely related to the domain-general demands of high cognitive load within the cingulo-opercular network. Future work should explore these effects to verify the neural processes underlying these behavioral phenomena. Improving the field’s understanding of 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) and may even shed light on mechanisms through which those in cognitively and emotionally demanding positions (e.g., physicians) experience negativity related to workplace burnout.

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1. Some participants only completed 142 trials due to a programming error. [↑](#footnote-ref-1)