DYSPHORIA, DEPRESSIVE RUMINATION, AND WORKING MEMORY

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DYSPHORIA, DEPRESSIVE RUMINATION, AND WORKING MEMORY

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SUMMARY

Current research on depression and rumination has produced mixed and sometimes incongruent results. Some researchers have found evidence of general cognitive deficits, while others have found evidence of only mood-congruent cognitive deficits. Recent research on deficits in working memory (WM) has indicated that general WM deficits occurred in a reading span task after people suffering from depression were exposed to mood congruent stimuli in a modified reading span task (affective transfer, Hubbard et al. 2016). However, the precise nature of these WM deficits remains unclear. The present study examined these effects with the decomposition of a modified *n*-back task into its component parts: WM updating and focus switching. Whether depression, depressive rumination, and mood were predictive of updating and focus switching was assessed. This study employed 52 participants split into two groups: a control group who completed only non-emotional tasks over two sessions, and an experimental group, who completed first a set of emotional tasks, followed by a set of non-emotional tasks. In this way, performance in the set 2 tasks was compared based on whether the participants were in the emotional or non-emotional group in set 1. This, effectively, is an extension of the affective transfer effect of Hubbard et al. (2016) to see if updating costs or switch costs or both are the driving cause of affective transfer. Furthermore, this study examined whether there were general or mood congruent WM deficits in the emotional set 1 task for these updating and focus switch costs. Affective transfer should have occurred in at least one of WM updating or focus switching, for individuals with elevated depressive symptoms, especially those who concurrently tended to engage in depressive rumination. It did not. Furthermore, elevated depression and depressive

rumination were not predictive of general nor of mood-congruent deficits in WM updating or focus switching.

CHAPTER 1

INTRODUCTION

Major depression is a leading cause of disability in the United States, accounting for 3.7% of all disability-adjusted life years and 8.3% of all years lived with disability (US Burden of Disease Collaborators: The State of US Health, 2013). According to the Diagnostic and Statistical Manual of Mental Disorders (4th ed.; DSM-4; American Psychiatric Association, 2000), Major Depressive Disorder (MDD) requires the presence of five or more of the following symptoms, one of which must be depressed mood or anhedonia (the inability to derive pleasure from things or activities previously enjoyed): sad (depressed) mood, anhedonia, fatigue, difficulty concentrating, feeling worthless, and suicidal ideation. These symptoms must be pervasive to the point of occurring most of the time, result in a marked change from the individual's usual functioning, and be substantially distressing socially, occupationally, academically, etc. Symptoms of MDD, which include behavioral, affective, somatic, and motivational dysfunction, do not result from comparatively reasonable causes, such as the death of a loved one, medical conditions, medications, or other drug use. Note that while depression shares general negative affect with other psychological disorders, such as anxiety, it can be distinguished by the presence of anhedonia, whereas anxiety includes heightened physiological arousal (Clark & Watson, 1991), which is quite the opposite of the lowered energy frequently present in major depression.

A substantial body of research, focused on linking ruminative thinking to depression, typically operationally defines rumination as a response mechanism to depressive symptoms; in effect, depressive rumination: a passive, seemingly uncontrollable spiral of thoughts focused upon one's depression, as well as its causes and effects (e.g., Nolen-Hoeksema, 1991; Treynor, Gonzalez, & Nolen-Hoeksema, 2003; Nolen-Hoeksema et al., 2008). The ruminative responses scale (RRS; Nolen-Hoeksema & Morrow, 1991), a 22-item self-report questionnaire assessing the frequency with which one engages in repetitive thoughts focused on one's depressive symptoms, predicts the severity and duration of depressive episodes (Nolen-Hoeksema, 1991; Nolen-Hoeksema et al., 2008), as well as the occurrence and duration of suicidal ideation (Smith, Alloy, & Abramson, 2006).

Prolonged attention to sad emotional stimuli enhances dysphoria and prolongs depressive symptoms (Disner, Beevers, Haigh, & Beck, 2011; Elliott, Rubinsztein, Sahakian, & Dolan, 2002; Eugene, Joormann, Cooney, Atlas, & Gotlib, 2010; Gotlib and McCann, 1984). Elevated dysphoria predicts biased attention toward sad faces only after removing anxiety's effect, while anxiety predicts the avoidance of sad faces only after accounting for the effect of dysphoria (Oehlberg, Revelle, & Mineka, 2012). Individuals with elevated anxiety show an initial visual bias toward threatening stimuli (SOA < 500ms) but subsequently avoid such stimuli (SOA > 1000ms), whereas individuals with elevated dysphoria show biases toward mood-congruent stimuli in later stage elaborative processing (Mathews & MacLeod, 2005; de Raedt & Koster, 2010).

Cognitive Deficits in Depression

Both depression and depressive rumination have been linked to deficient inhibition of emotionally charged stimuli, especially when the stimuli are mood-congruent (Joormann, 2004, 2006, 2010, Joormann & Gotlib, 2008). Depressive rumination remains strongly bound to depression, even after removing items excessively analogous to those of the Beck Depression Inventory, the RRS remained focused on depression, with two dimensions: 1) a directed reflection on depressive symptoms and 2) a passive brooding upon these symptoms (Treynor, Gonzalez, and Nolen-Hoeksema, 2003). In a meta-analysis of studies of rumination and depression, Olatunji, Naragon-Gainey, & Wolitzky-Taylor (2013) found that brooding and emotion-focused rumination are most strongly associated with depressive symptoms, relative to other forms of rumination such as reflection (both brooding and reflection as defined within in the RRS by Traynor et al., 2003).

Depression and rumination frequently accompany inhibitory deficits, especially for emotional material (Goeleven, De Raedt, Baert, & Koster, 2006; Gotlib & McCann, 1984; Joormann, 2004, 2006, 2010; Joormann & Gotlib, 2008; Zetsche & Joormann, 2011). However, the precise nature of rumination's relationship with major depression and dysphoria remains unclear, as does the precise nature of the attentional deficits that have been observed in congruence with depression and rumination. For example, in a pair of relatively recent studies on dysphoric individuals with emotional variants of the antisaccade task, De Lissnyder and colleagues found evidence of a general deficit in switching in depression, regardless of whether stimuli were negative or neutral, but only depressive ruminators showed evidence of inhibitory deficits restricted to negative information (De Lissnyder, Koster, Derakshan, De Raedt, 2010). However, in their 2011 study, they found no relationship between general depression symptoms and deficits in cognitive control, but did find evidence that those disposed to depressive rumination showed "impaired inhibition of non-emotional material" (De Lissnyder, Derakshan, De Raedt, & Koster, 2011, p. 894).

De Lissnyder and colleagues (2011) found that impairments to cognitive control specifically occurred with depressive rumination, rather than to more general symptoms of depression, in the form of saccade latency differences, but not in error rates, in an antisaccade task. The antisaccade task may be a more robust measure of cognitive control, specifically for individuals with depression, as more traditional RT tasks are probably confounded with overall response slowing in depression (Joormann et al., 2007), which makes it difficult to isolate deficits in cognitive control from motor response deficits. De Lissnyder et al. (2011) compared the antisaccade performance of dysphoric and nondysphoric individuals, assessed via the Beck Depression Inventory II (BDI-II, Beck, Steer, & Brown, 1996), and whether any observed cognitive control deficits were actually resultant from depressive rumination. Depressive rumination (brooding, according to Treynor, Gonzalez, and Nolen-Hoeksema, 2003) is a cognitive symptom and risk factor of depression, and is distinguished from reflection, its more adaptive sibling on the ruminative responses scale (RRS, Nolen-Hoeksema & Morrow, 1991). Thus, while switching, as assessed by the antisaccade task, may be generally impaired in depression, inhibitory deficits may be limited to negative rumination (De Lissnyder et al., 2010), with no deficits observed when stimuli are neutrally-valenced, rather than negative (De Lissnyder et al., 2011).

Zetsche and Joormann (2011) conducted a cross-sectional study of interference control, depressive symptomatology, and ruminative thinking. Specifically, they measured the relationship between symptoms of depression, rumination, and performance on an emotional flanker task and two negative affective priming (NAP) tasks, one with faces and the other with words. Differences in negative priming performance at initial testing predicted depression and rumination at a six-month follow-up, while differences in the flanker task did not. The influence of previous information, as in the NAP task, is more affected by depressive symptoms, such as depressive rumination, than is the influence of immediate information, as in the flanker task. This is in line with the idea that regulating the contents (especially emotional information) of working memory is more affected by rumination and other symptoms of depression than are more immediate, lower-level attentional processes.

Furthermore, while higher ruminative tendencies predicted better goal maintenance performance on a modified (75% congruent, 25% incongruent) Stroop task, higher dysphoria predicted worse performance. Conversely, trait-level ruminative tendencies corresponded to more errors in a letter naming measure of goal shifting ability (Altamirano, Miyake, and Whitmer, 2010).

Depressed individuals show task-switching deficits only if they are currently ruminating (Whitmer, A.J., and Gotlib, I.H., 2012), with the greatest deficits observed in depressed individuals currently engaged in depressive rumination. In contrast, trait rumination was related to deficits in inhibiting previous tasks, but not to general, non-inhibitory deficits in task switching.

Reviewing 29 studies, Peckham, McHugh, and Otto (2010) evaluated differences between depressed and nondepressed individuals on emotional Stroop and dot probe tasks. They found evidence of a marginal difference between depressed and non-depressed individuals (Cohen's $d = 0.17$, $p = .06$, 95% CI = -0.01, 0.34) in 16 emotional Stroop studies. The 9 included dot probe studies (with a total of 12 tasks) showed a significant difference between depressed and nondepressed individuals, with depression increasing the size of the dot probe effect (Cohen's $d = 0.52$, $p = .001$, 95% CI = .30, .74). This is somewhat unusual, given that the dot probe task is not noted for being consistently reliable (Schmukle, 2005).

Deficits in attention and inhibition may continue through periods of remission, and worsen with each subsequent episode of major depression (Kessing, 1998; Hasselbalch, Knorr, Hasselbalch, Gade, & Kessing, 2012), whereas memory deficits seem to be more isolated to periods of depression (Hasselbalch et al., 2012). Biasing attention toward negative material may result in excessively elevated negative mood, as well as a heightened stress response, relative to the induced bias away from negative material (MacLeod, Rutherford, Campbell, Ebsworthy, and Holker, 2002).

Overall, currently engaging in depressive rumination during a concurrent episode of major depression seems to be the most consistent predictor of cognitive deficiency, rather than depression or rumination alone. However, this relationship can be enhanced or obscured by task-specific conditions, such as the choice of independent variable.

Working Memory Deficits in Depression

Recent literature suggests that working memory may be a more likely location for deficits due to depression and rumination, relative to earlier, more basic forms of attention. Alderman et al. (2015) found an effect of depressive rumination in major depression on conflict monitoring in an Eriksen flanker arrow task, but not in attentional allocation in an attentional blink task. How people attend to their feelings relates to depressive symptomatology in two seemingly contradictory ways (Salguero, Extremera, & Fernández-Berrocal, 2013). Higher emotional attention predicts higher emotional clarity, which in turn predicts improved emotional repair and consequently lowered depressive symptomatology. Conversely, increased emotional attention corresponds to increased depressive rumination, which, in turn, predicts increased depressive symptomatology. Which of these pathways takes precedence may depend on individual differences in such things as attention, WMC, or WM updating, as well as the intensity of any triggering emotions or experiences.

In non-dysphoric individuals, better ability to update working memory (WM) predicts reduced negative affect, as indexed by facial expression, self-report, and corrugator electromyography (EMG), when utilizing distancing-focused cognitive reappraisal as the coping mechanism (Hendricks & Buchanan, 2015).

Hubbard, Hutchison, Hambrick, and Rypma (2016) observed what they dubbed "affective transfer" (p. 209) from an emotionally valenced reading span task (depressive span; Hubbard et al. 2015) to a traditional non-emotional reading span task in dysphoric individuals. Nondysphoric individuals showed no such decrement, and dysphoric individuals' performance was only worse than nondysphoric individuals when reading span followed depressive span; otherwise, their performance was not different. This indicates that dysphoric mood induction is an ideal component to maximize cognitive deficits in dysphoric individuals.

Complex Span Tasks

Complex span tasks, including the modified reading span task from Hubbard et al. (2015 and 2016), interleave a simple STM task with an additional task, such as performing simple mathematics operations (the operation-span task) or reading brief passages (the reading-span task). In this way, complex span tasks assess both storage and processing (Redick & Lindsey, 2013). Performance on complex span tasks correlates positively with a wide range of cognitive abilities, from the ability to comprehend reading, listening, and language to reasoning (Engle, 2010; Redick & Lindsey, 2013).

N-back Tasks

Although complex span tasks (Unsworth and Engle, 2007a, 2007b) and *n*-back tasks require the updating of WM's contents, they are, individually, at most modestly positively correlated (r = .20, *95% CI*: .16 to .24; Redick and Lindsey, 2013). However, at the latent variable level, their correlation increases to .69 between complex span (comprised of reading span, counting span, and rotation span) and *n*-back (numeric and spatial) latent factors

(Schmiedek, Lovden, and Lindenberger, 2014). Thus, there is substantial commonality between these two WM measurement tools after accounting for specific task characteristics.

Both *n*-back and complex span tasks require adding items to and removing items from WM, but differ in when these processes must occur for successful task performance. For *n*-back tasks, the participant must continually add to the item list, while simultaneously discarding no longer relevant items, making a memory judgment as each item is presented. Whereas for complex span tasks, the participant must continually add items to the list, then retrieve these items in the correct order, and only afterward remove all items from that list. For *n*-back tasks, the participant must compare each item as it appears to the current memory list, simultaneously discarding items that are no longer useful. For complex span tasks, the participant accrues items in their list, but does not evaluate nor discard items until a test phase at the end of that set of trials. This perhaps implies that successful *n*-back performance requires more rapid adjustment of the contents of WM than does successful complex span task performance. Additionally, complex span tasks require recall of items, whereas *n*-back tasks merely require item recognition. As noted by Redick and Lindsey, WM is not a "monolithic construct", but rather "a multifaceted system that relies on multiple processes (encoding, maintenance, recall, recognition, familiarity, updating, temporal ordering, binding, attention, and inhibition" (pg. 110).

N-back Decomposition

Price, Colflesh, Cerella, and Verhaeghen (2014) used three variants of a columnized *n*-back task to isolate individual processes within working memory; specifically, random search, forward search, and WM updating. WM updating was most amenable to improvement (in the form of faster response times) through repeated practice, and that predictable forward search allowed the focus of attention to expand from 1 to 5; even after extended practice, the focus maintained a maximum capacity of 1 item during random search. The current study adapts this columnized *n*-back to a row-based format to accommodate word lengths vs. single digits, and borrows the *n*-back decomposition to isolate WM updating costs and WM switch costs. I elected to focus on random-order search switch costs, as random-order search is less predictable than forward-order search and should therefore be more difficult and more likely to show deficiency in depression and depressive rumination.

The two main goals of this study were to see if affective transfer (Hubbard et al., 2016) occurred in a modified *n*-back task, and to examine the specifics of possible deficits in working memory in depression and rumination using an effects decomposition of this modified *n*-back task. Recall that affective transfer is the worsening of working memory performance on a non-emotional task after the completion of a mood-congruent emotionally valenced task, in participants with depression or depressive symptoms.

As such, participants completed an initial set of *n*-back tasks that, depending on the condition to which the participants were randomly assigned, either had a mixture of negative and neutral words or purely neutral words. In the first instance, participants had to judge whether the current word had the same valence (negative or neutral) as a previously to-be-remembered word. In the second instance, participants had to judge whether the current word fell into the same category as a previously to-be-remembered word (specifically, whether the word could refer to a living thing). After this first set of *n*-back tasks, participants completed a second set of the emotionally neutral task, in which they again judged whether the words could refer to living things. Following these modified *n*-back tasks, participants completed a set of questionnaires to assess depressive symptoms and rumination.

Hypotheses

If affective transfer occurs in this modified *n*-back paradigm, then I expect that participants who first completed the emotionally-valenced set 1 task set will have worse performance on the set 2 neutrally-valenced task only if they also have elevated depressive symptoms. If there is a worsening of performance on set 2 following the emotional task in set 1 that does not depend on the presence of elevated depressive symptoms, then this would be a simple mood induction from the negatively-valenced stimuli in the set 1 emotional condition. Furthermore, I expect enhanced affective transfer to occur in individuals who typically engage in depressive rumination, in addition to having elevated depressive symptoms.

Given the somewhat inconsistent findings in the literature of general vs. mood-congruent WM deficits in depression, I also examined whether performance in the set 1 emotional condition was worse for negatively-valenced stimuli than for neutrally-valenced stimuli as a function of depressive symptoms. I expect to find at least some evidence of worse performance on these negative stimuli for people with elevated depressive symptoms. Finally, I also assessed whether depressive rumination plays a part in affective transfer and in WM deficits within the emotional modified *n*-back task from set 1.

CHAPTER 2

METHOD

Participants

Participants were recruited from the Georgia Tech School of Psychology's online research pool via Sona Systems (https://gatech-psych.sona-systems.com). The study took approximately two hours to complete, and participants were compensated with two credit hours for their participation. To achieve a minimum power of approximately .80, a minimum of 125 participants were to be included in the study (G*Power version 3.1, Faul, Erdfelder, Lang, & Buchner, 2007). A total of 338 participants signed up for the study, of which 257 participants completed the study. Five participants were dropped from the dataset due to errors in recording response times. Within these 252, there was a noticeable subset of participants with both remarkably fast RT and accuracy no better than chance. As such, I established joint criteria for excluding these participants who "button-mashed" rather than actively engaged with the modified *n*-back tasks.

Participants were excluded from analysis if their accuracy fell below 0.66 on the simplest form of the modified *n*-back (i.e., the $n = 1$ forward order task that did not include an updating component, which I refer to as FN for forward no updating) and if their median RTs were below 500ms on any of the 20 trial types within the modified *n*-back tasks. The accuracy criterion reduced the sample size to N = 89, and the RT criterion further reduced this sample size to N = 52. The included subset of participants did not differ from the excluded subset on any of the survey measures (all *p*-values > .05). These criteria are admittedly ad hoc; I tried different combinations of accuracies and RT and this set of criteria left me with a reasonably large number of participants while still excluding unengaged participants. See the results section for a binomial logistic regression predicting whether participants were excluded based on their survey responses. The participants' self-reported demographics are shown in Table 1.

Table 1. Sample demographics.

	Original Sample (n)	Final Sample (n)
Female	122	26
Male	134	25
Other	1	1

Asian	105	14
White	93	29
Black	27	3
Hispanic	23	3
Other	9	3
High School	73	7
Some College	163	43
Bachelor's Degree	21	2

Materials

Mood, depressive symptoms, ruminative tendencies, anxiety, and stress were assessed with a battery of self-report measures. WM function was assessed with computer-administered modified *n*-back tasks.

PANAS

The Positive and Negative Affect Schedule (PANAS; Watson, Clark, and Tellegan, 1988) uses 20 self-report items to assess current (i.e., state), or recent (i.e., trait: in the past week), self-reported positive and negative emotions and feelings. While designed to assess two dimensions of emotion, some debate exists in the literature regarding whether a 3-factor model better explains observed data: a recent study (Galinha, Pereira, and Esteves, 2013) suggests that separate factors, comprising positive affect, negative affect, and, additionally, a third, cross-loading factor assessing degree of excitement, best fit data collected with the PANAS. Furthermore, the PANAS shows good trait stability, at least over a two-month interval, even when administered in its state format (Galinha et al., 2013). As it was not central to this study, I opted to use the standard 2-factor interpretation of negative and positive affect. To assess mood before and after each major stage of the study, the PANAS was administered three times: just before the two sets of *n*-back tasks, after these *n*-back tasks but before the other survey measures, and then after the other survey measures at the end of the study.

Depression Assessment: CESD-R

The Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977) is a brief, 20-item, self-report measure of depressive symptoms designed for research conducted on the general population. Items included in the CES-D were selected from established depression measures, including the BDI and the Minnesota Multiphasic Personality Inventory (MMPI; Hathaway and McKinley, 1951). Specifically, the CES-D assesses frequency of depressive symptoms during the past week. The CES-D has good internal consistency, with Cronbach's α of .85 and .90 for general and clinical populations, respectively (Radloff, 1977), and is highly positively correlated with the BDI-II ($r = .89$, $p < .001$; Hicks and McCord, 2012).

Depression Assessment: DASS-21

The Depression, Anxiety, and Stress Scales (Lovibond and Lovibond, 1995a, 1995b) is a 42-item self-report questionnaire designed to differentiate between symptoms of depression and symptoms of anxiety. Both the full and short (DASS-21; Lovibond and Lovibond, 1995a) versions have acceptable psychometric characteristics, assessed with traditional metrics as well as more modern IRT methods, even when the DASS-21 is administered online (Wardenaar, Wanders, Jeronimus, & de Jonge, 2017; Weiss, R. B., Aderka, I. M., Lee, J. L., 2015). In this study, the DASS-21 was administered. The DASS-21 assesses depression, anxiety, and stress (i.e., its three subscales) as related but separable components of a more general negative affect factor (Henry and Crawford, 2005).

Rumination Assessment: RRS

To assess rumination, both the ruminative responses scale (RRS; Nolen-Hoeksema & Morrow, 1991) and the perseverative thinking questionnaire (PTQ; Ehring, Zetsche, Weidacker, Wahl, Schönfeld, and Ehlers, 2011) were administered. The preeminent assessment of depressive rumination is the ruminative responses scale (RRS; Nolen-Hoeksema & Morrow, 1991). This 22-item self-report questionnaire measures the self-reported frequency of thoughts, attitudes, and actions, in response to depressive symptoms. Treynor, Gonzalez, and Nolen-Hoeksema (2003) used factor analysis to remove items which were indistinguishable from those of the Beck Depression Inventory, resulting in two subscales: 1) directed, and, perhaps, in the long-run adaptive, active reflection about depressive symptoms and 2) passive, consistently maladaptive brooding.

Rumination Assessment: PTQ

The perseverative thinking questionnaire (PTQ; Ehring, Zetsche, Weidacker, Wahl, Schönfeld, and Ehlers, 2011) is a 15-item self-report measure of rumination focused on how frequently one engages in ruminative thinking about negative events. Participants rate the general frequency of each item on a Likert scale from 0 to 4 (where 0 is never and 4 is almost always). The PTQ consists of three subscales, including core items, items related to unproductivity, and items related to mental capacity. The PTQ and its subscales have high internal consistency, high test-retest reliability, and good validity with other measures of negative ruminative thinking (Ehring et al., 2011).

Modified N-back Tasks

The current study utilized a transposed version of the columnized *n*-back from Price et al. (2014). Three variations of this transposed *n*-back were used to isolate the WM processes of updating the contents of WM and focus switching: Forward stimulus presentation with updating (FU), forward stimulus presentation without updating (FN), and random stimulus presentation without updating (RN). These modified *n*-back tasks assessed working memory using either emotional or non-emotional words as stimuli, with a category judgement about each presented word.

Task Stimuli

As the Affective Norms of English Words (ANEW; Bradley & Lang, 2010) database simply did not have enough words, stimuli were drawn from the BRM emotional word database collected and normed by Warriner & Brysbaert (2013). In this database, each word's emotional valence was rated from 1 to 9, with 1 the most negative and 9 the most positive. For the current study, to ensure that I had enough negative and neutral words to avoid repeating words across all task variants, I assigned words with affective ratings between 4 and 6 to the neutral category, and words with ratings below 4 to the negative category. Example words are in Table 2.

Table 2. Example words from the BRM database.

Word	Valence Mean	Valence SD	Arousal Mean	Arousal SD	Dominance Mean	Dominance SD	Valence Category
pedophile	1.26	0.65	5.05	3.21	3.37	2.04	Negative
rapist	1.3	0.73	6.33	2.39	2.21	2.19	Negative
AIDS	1.33	0.8	5	2.6	3.55	2.77	Negative
torture	1.4	0.82	5.09	2.55	2.76	2.05	Negative
leukemia	1.47	1.39	5.75	2.38	2.83	2.35	Negative
guillotine	1.63	0.9	5.64	2.73	3.39	2.07	Negative
alcoholism	2	1.61	5	2.45	3	2.53	Negative
attack	2	0.97	7.05	2.11	3.39	2.57	Negative
comatose	2	1	3.15	2.21	3.4	2.21	Negative
excrement	2	1.33	4.64	1.73	3.38	1.88	Negative
aging	3	1.41	3.8	2.88	3.06	2.54	Negative

Word	Valence Mean	Valence SD	Arousal Mean	Arousal SD	Dominance Mean	Dominance SD	Valence Category
ailment	3	1.37	3.68	2.25	3.14	2.12	Negative
allergic	3	1.86	5.4	2.44	3.81	2.43	Negative
annoying	3	1.71	5.55	2.04	3.28	1.28	Negative
arsenic	3	1.82	4.7	1.84	3.46	1.79	Negative
bait	4	1.83	3.5	2.02	5.95	2.32	Neutral
borderline	4	1.51	4.39	2.57	4.84	1.83	Neutral
brig	4	1.8	3.29	2.31	3.5	1.65	Neutral
bugler	4	1.97	4.15	2.68	4.24	1.64	Neutral
calculus	4	2.26	2.73	1.86	4.41	2.59	Neutral
corny	5	1.9	3	1.98	4.94	2.07	Neutral
council	5	1.65	3.86	1.68	5.21	2.57	Neutral
coworker	5	1.2	3.57	1.91	4.55	2.26	Neutral
credit	5	2.47	4.38	3.02	5	2.63	Neutral
cubby	5	1.46	3.71	2.08	5.65	1.82	Neutral
acrobat	6	1.3	4.9	2.14	5.42	2.24	Neutral
action	6	1.64	6.19	2.56	6.17	2.01	Neutral
adolescence	6	1.65	5.1	2.53	4.44	2.34	Neutral
aerobics	6	1.11	5.1	2.17	5.7	2.4	Neutral
airport	6	2.14	5.5	2.78	5.79	2.84	Neutral

Experimental Conditions

Participants were randomly assigned to either a control (i.e., non-emotional stimuli) or an experimental (i.e., emotional stimuli) condition. Both the control and experimental conditions included two sets of tasks. In the control condition, participants completed two sets of non-emotional tasks; in the experimental condition, participants completed one set of emotional tasks followed by one set of non-emotional tasks (see Table 3).

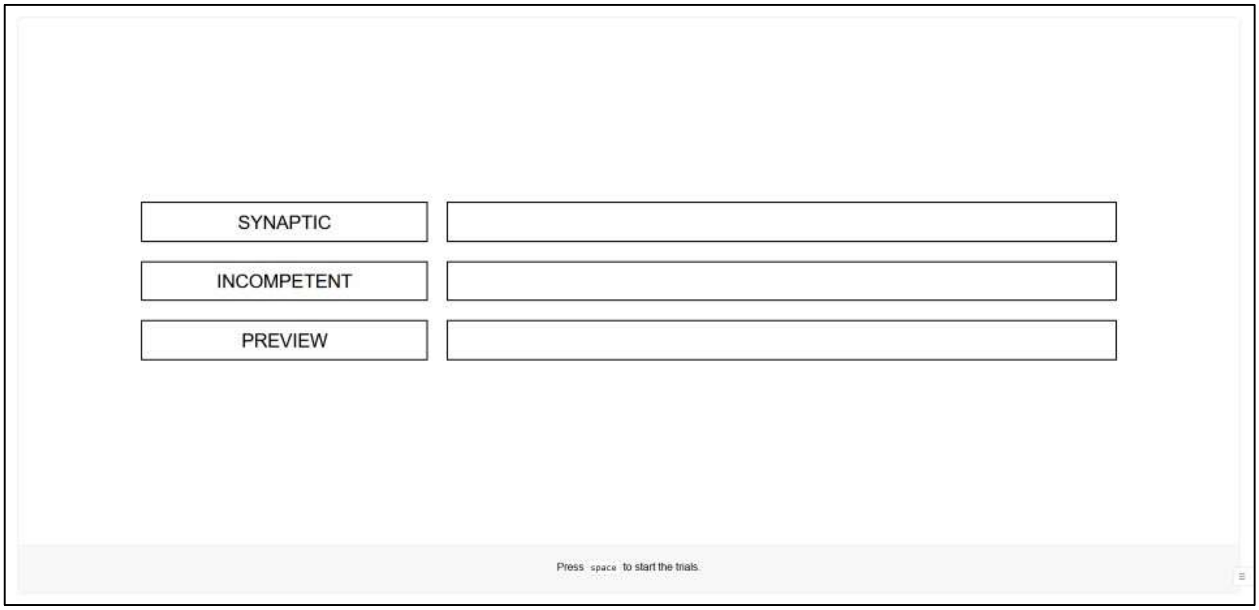
Table 3. Conditions in experimental design.

	Set 1	Set 2
Experimental Condition	Emotional *n*-back tasks	Non-emotional *n*-back tasks
Control Condition	Non-emotional *n*-back tasks	Non-emotional *n*-back tasks

In the non-emotional tasks, participants had to identify whether the current word stimulus could refer to a living thing. In the emotional tasks, participants had to decide whether the current word stimulus was negatively-valenced or emotionally neutral. In both emotional and non-emotional tasks, participants compared whether the category of the current stimulus matched the category of a previously presented stimulus.

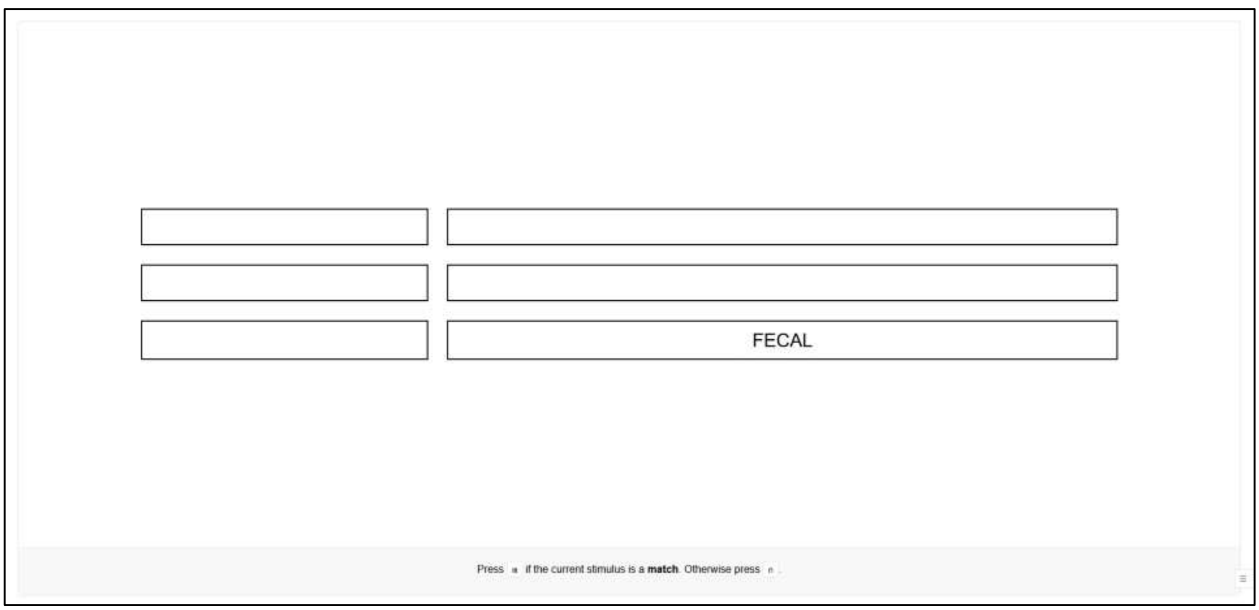
Trial Details

Each trial consisted of an encoding stage and subsequent retrieval probes. In each trial, participants viewed one to three to-be-encoded stimuli, presented simultaneously with one stimulus appearing in the box to the left of each row. Retrieval probes, presented one at a time in each row on the screen, appeared following the encoding stimuli for each trial. In the updating condition, each probe stimulus must be compared to the previous stimulus appearing in the same location (i.e., the same row), while the non-updating condition probes were always compared to the originally encoded stimulus in the same row for that trial set. Participants judged whether the current stimulus shared the same category as the originally encoded stimulus for that row (non-updating conditions) or whether the current stimulus shared the same category as the stimulus last presented in that same row (updating) within that trial set. See Figure 1 for an example of an encoding screen and a probe screen from an emotional 3-back trial. On each encoding screen, participants need to (a) decide to which category each word belongs (e.g., whether the word is negative or neutral) and (b) encode that category selection into memory. On each probe screen, participants need to (a) decide to which category the probe word belongs and (b) compare that category decision to either that trial's originally encoded word in the same location or, in the updating condition, to the last word in the same location. Additionally, and only in the updating condition, participants need to replace the prior word decision with the latest one.



Encoding Screen

(a) Decide whether each word is negative or neutral.
(b) Encode that valence decision with the location (i.e., row) of each word.



Probe Screen

(a) Decide whether the probe word is negative or neutral.
(b) Compare that with the valence decision from that row in the encoding stage (no updating) or with the valence decision from the last word in the same row.

Figure 1. Example encoding and probe screens from an emotional 3-back trial.

Procedure

Participants first completed the PANAS questionnaire. Next, participants completed the first and second sets of *n*-back tasks. By comparing performance in set 2 based on whether the participant was in the control or experimental condition in set 1, we assessed whether affective transfer occurs from affective to non-affective variants of the *N*-back task. The experimental group (henceforth referred to as the emotional condition) of participants completed the affective *n*-back tasks, followed by the non-affective *n*-back tasks, while the control group completed the non-affective *n*-back in set 1, followed by another affective *n*-back, with different words, in set 2.

After the two sets of *n*-back tasks, participants completed the PANAS a second time, followed by the PTQ, the RRS, the CESD-R, and the DASS. I elected to administer the questionnaires with dysphoric content after the WM tasks (as opposed to the task order of Hambrick et al., 2016, who administered all questionnaires prior to WM tasks) in an effort to avoid priming dysphoria. Finally, participants completed the PANAS a third and final time, allowing me to assess mood prior to the study, after the *n*-back tasks (one of which contained dysphoric content), and finally after the depression and rumination questionnaires. Thus, I can assess participants' baseline mood, whether the dysphoric WM tasks induced negative affect, and whether the dysphoric content questionnaires induced negative affect.

N-back Practice Task

Before completing the first set of main *n*-back tasks, participants practiced with a simplified version of the modified 2-back task, which used letters for the stimuli. The encoding phase of the practice trials presented 2 letters at the left of 2 rows. After manually progressing past this encoding screen, participants received 10 retrieval probe letters, each presented sequentially and separated by 250ms intertrial intervals. On each retrieval probe screen, participants had up to 5,000ms to decide whether the currently presented letter was the same as the letter presented in the same row during the encoding phase of the practice.

Main N-back Tasks

The tasks in each of the two main sets were presented in the following order: RN with n = 2, RN with n = 3, FN with n = 1, FN with n = 2, FN with n = 3, FU with n = 1, FU with n = 2, FU with n = 3 (see Table 4). The intertrial interval was the same as in the practice task (i.e., 250ms). As in the practice task, participants had up to 5,000ms to respond to each retrieval probe within each trial. Participants had as long as they wanted to study the words in the encoding stage of each trial. Again, the n-level represents the number of rows, so a task with n = 1 has only a single row, a task with n = 2 has two rows, and a task with n = 3 has three rows.

Table 4. *N*-back task order and trial details.

Set 1	Set 2	Trials (Encoding + Probes)	Probes
RN n = 2	RN n = 2	24	11
RN n = 3	RN n = 3	24	12
FN n = 1	FN n = 1	12	11
FN n = 2	FN n = 2	12	11
FN n = 3	FN n = 3	12	12
FU n = 1	FU n = 1	12	11
FU n = 2	FU n = 2	12	11
FU n = 3	FU n = 3	12	12

The RN task with $n = 2$ presented 24 trials. Each trial consisted of an encoding phase, with two words appearing at the left of each of the two rows, followed by 11 sequentially presented retrieval probes in one of those two rows. Which row the retrieval probe appeared in was randomized, allowing for the comparison of switch trials (where the next subsequent probe appears in a different row) with non-switch trials (where the next subsequent probe appears in the same row). Participants judged whether the word presented in each retrieval probe matched the category of the word originally presented in the same row during that stimulus's encoding phase (i.e., the last encoding phase the participant was to study). There were 24 sets of encoding and retrieval probes. In the emotional tasks, participants judged whether the words were sad or neutral, while in the non-emotional phase, participants judged whether the words represented living or non-living things.

The RN task with $n = 3$ presented 24 trials. Each trial consisted of an encoding phase with three words appearing in three rows, followed by 12 sequentially presented retrieval probes, each appearing in one of the three rows. Participants judged whether the word presented in each retrieval probe matched the category of the word originally presented in the same row during that encoding phase. Which row the retrieval probe appeared in was randomized. In the emotional tasks, participants judged whether the words were sad or neutral, while in the non-emotional phase, participants judged whether the words represented living or non-living things.

The FN task with $n = 1$ presented 12 trials. Each trial consisted of a set of encoding stimuli followed by 11 sequentially presented retrieval probes. In the encoding phase, 1 word appeared to the left of a central row; participants were instructed to remember this word. During the retrieval phase, participants judged whether the word presented in each retrieval probe matched the category of the word originally presented in the same row during that probe's encoding phase.

The FN task with $n = 2$ presented 12 trials. Each trial began with an encoding stage followed by 11 sequentially presented retrieval probes. The encoding phase presented two words, each to the left of the central rows. During the retrieval phase, participants judged whether the word presented in each retrieval probe matched the category of the word originally presented in the same row as the retrieval probe during that probe's encoding phase. The first retrieval probe for each encoding set appeared in the top row, with the second probe appearing in the bottom row. The third probe appeared in the top row, the fourth probe appearing in the bottom row, and so on (for $n = 2$, there are only two rows).

The FN task with $n = 3$ presented 12 trials, each with 1 set of encoding stimuli followed by 12 sequentially presented retrieval probes. In the encoding phase, one to-be-encoded word appeared to the right of each of three rows. The first retrieval probe for each encoding set appeared in the top (first) row, with the second probe appearing in the central (second) row, and the third probe appearing in the bottom (third) row. The fourth probe appeared in the first row, with the fifth probe appearing in the second row, and the sixth probe in the third row, and so on. For an encoding set, participants compared each retrieval probe to the original encoded word that appeared in the same row as that probe word.

The FU task with $n = 1$ presented 12 trials. Each trial consisted of a to-be-encoded word, appearing to the left of the single central row (since $n = 1$, there is only one row), followed by 11 sequentially presented retrieval probes. For each encoding and retrieval set, participants had to compare the current retrieval probe to the last stimulus that appeared in the same location (since this is $n = 1$, that is simply the last stimulus to appear). In this way, the first retrieval probe is compared to the encoded word, while the second retrieval probe is compared to the first retrieval probe, and the third retrieval probe is compared to the second retrieval probe, and so on. The presentation order is the same as in the FN tasks.

The FU task with $n = 2$ presented 12 trials. Each trial had a set of encoding stimuli, with one word appearing at the start of each row (here, there are two rows, so two words per set of encoding stimuli). Each encoding set was followed by 11 sequentially presented retrieval probes. Like in the FN tasks, the retrieval probes appeared from top-to-bottom, moving one row down until they reached the bottom row and began again in the top row (since there are only 2 rows for $n = 2$, the retrieval probes effectively alternate between the top and bottom rows). In this way, the first retrieval probe for an encoding set, which appears in the top row, is compared to the encoded word from the top row. The second retrieval probe appears in the second, or bottom, row and is compared to the encoded word from that same row. The third retrieval probe appears in the top row but is compared to the first retrieval probe (which also appeared in the top row). This is where updating is required: the current stimulus is compared to the last stimulus that appeared in the same location (i.e., the same row). The fourth retrieval probe appears in the bottom row and is compared to the second retrieval probe, which also appeared in the bottom row. Therefore, each retrieval probe requires that the participant update the word they are holding in mind for comparison (whereas in the tasks without updating, participants had to remember the encoded stimuli until the next encoding phase began).

FU with $n = 3$ again presented 12 trials, each consisting of encoding stimuli, with one word appearing to the left of each of the three rows. Each set of encoding stimuli was followed by 12 sequentially presented retrieval probes. The retrieval probes followed the same pattern as in the other forward order tasks, with the first probe appearing in the top row, the second probe in the second row from the top, the third probe in the bottom row. Participants had to compare each probe to the stimulus last appearing in the same row. This requires that the participant update the word they are holding in mind with each successive retrieval probe.

Planned Analyses

Affective transfer within the N-back tasks

Evidence of affective transfer within the *n*-back tasks will occur if performance on the non-affective *n*-back drops significantly for dysphoric individuals when preceded by the affective *n*-back, relative to when the non-affective *n*-back precedes its affective variation. This extension of the affective transfer effect seems plausible based on the latent level correlation of .69 between *n*-back and complex span observed by Schmiedek et al. (2014). Observing significant affective transfer between *n*-back paradigms would support the existence of affective transfer as a broader effect within WM, rather than as a more idiosyncratic effect within semantic complex WM span tasks.

Decomposition of the N-back Tasks

The *n*-back decomposition isolates the WM subcomponents of focus switching and updating by using subtractive logic on response times to stimulus probe trials. These processes are most readily interpretable based on response latencies to mismatched trials, as non-switch match probes (i.e., the same item repeats in the same location) probably benefit from repetition priming. As such, unique words were used for each encoding and each test stimulus. In other words, the valence could repeat, but the word itself did not.

In the present study, bin scores (Draheim, Hicks, & Engle, 2016) were computed to combine response latency and accuracy into a single measure. The reason for doing so is that costs in any one dimension – that is, latency or accuracy – might be contaminated with changes in speed-accuracy trade-offs. Combining both is one way to deal with this issue. To be thorough, analyses were also conducted in the traditional manner on response latencies, which discards inaccurate trials, as well as on the mean accuracy data.

Bin Score Computation

Bin scores were computed using R code provided by the Engle lab website (https://rdrr.io/github/EngleLab/englelab/man/bin_score.html) to combine response time and accuracy information into a single score. As per Draheim et al. (2016), bin scores ranged from 1 to 10, with inaccurate switch trials assigned a value of 20. In general, smaller bin scores indicate two things. First, that the participant was almost as fast on accurate switch, respectively updating trials as on non-switch, respectively non-updating trials, relative to other participants. This is indicative of little or no switch, respectively updating cost on switch, respectively updating trials. Second, that the participant was more accurate on switch, respectively updating trials relative to other participants. As such, smaller bin scores index better switch, respectively updating performance on a task, relative to other participants (Draheim et al., 2016).

Separate bin scores were computed for each participant's updating cost at the $n = 1$, $n = 2$, and $n = 3$ levels and switch cost at the $n = 2$ and $n = 3$ levels (recall that there is no switch cost calculable in the forward and random tasks without updating at the $n = 1$ level as there is only 1 possible location for each stimulus).

This R script conducts the following computations: First, it calculates mean RTs on accurate non-switch, respectively non-updating trials for each participant. Second, it subtracts the mean RT from the first step from the RT for each participant's accurate switch, respectively updating trial. Third, it rank-orders the scores from the second step and assigned to them a bin value from 1 to 10 (the fastest 10% of scores are ranked 1, the next fastest 10% of scores are ranked 2, and so on, until the slowest 10% of scores are ranked 10). Fourth, it assigns a bin value of 20 to inaccurate switch, respectively updating trials, regardless of RT. Fifth, it sums all of a participant's bin values to compute a single bin score for that participant.

I used the appropriate comparison between tasks, rather than strictly switch and non-switch, respectively updating and non-updating trials, for each difference score that would be analyzed in a traditional approach. For switch costs, I used the switch and non-switch trials from the random order task without updating (RN). For updating costs, I used trials from the forward order task with updating (FU) as my updating trials and trials from the forward order task without updating (FN) as my non-updating trials.

Utilizing this binning procedure for each level of n resulted in the following sets of data for each participant: updating cost at $n = 1$, updating cost at $n = 2$, updating cost at $n = 3$, switch cost at $n = 2$, and switch cost at $n = 3$. In this manner, bin scores were computed for the set 2 data, to investigate affective transfer, as well as for trial valence data from set 1, to investigate the presence of mood-congruent or general deficits in WM updating and switching. For set 2, this resulted in the above bin scores for each participant, split by whether they were in the emotional or non-emotional condition during set 1. For the analyses of set 1, this resulted in these bin scores, but split by whether the trials used in their calculation presented neutrally- or negatively-valenced stimuli. Table 5 summarizes the bin score WM costs that I calculated for each participant. For the supplemental analyses of median RT and mean accuracy data, I computed traditional difference scores for each of these switch and updating costs.

Table 5. Bin score WM costs calculated for each participant.

Set 2	Set 1: Neutral	Set 1: Negative
Updating cost, $n = 1$	Updating cost, $n = 1$	Updating cost, $n = 1$
Updating cost, $n = 2$	Updating cost, $n = 2$	Updating cost, $n = 2$
Updating cost, $n = 3$	Updating cost, $n = 3$	Updating cost, $n = 3$
Switch cost, $n = 2$	Switch cost, $n = 2$	Switch cost, $n = 2$
Switch cost, $n = 3$	Switch cost, $n = 3$	Switch cost, $n = 3$

Comparing bin score performance, where a smaller bin score indicates better performance, between the conditions within the modified *N*-back tasks allows me to isolate the WM processes of updating and focus switching, and, in turn, examine whether these processes are uniquely vulnerable to depressive rumination and dysphoria. As mentioned above, computing bin scores that index the performance difference between switch and non-switch trials within the random-without-updating task estimates the cost of focus switching in situations that are not predictable (e.g., random). Computing bin scores that index the performance difference between the forward-with-updating and forward-without-updating tasks estimates the cost of updating the contents of WM.

Rumination vs. Dysphoria

I expect higher trait-level rumination, as indexed by the RRS and PTQ, to correspond with lessened ability to update the contents of WM, as indexed by higher updating cost bin scores. In other words, people who tend to engage in depressive rumination are likely to show worse WM updating performance, relative to individuals who do not frequently ruminate about depression.

However, WM search processes should be relatively protected from trait-level depressive rumination, since these processes do not involve WM updating. Instead, WM search deficits should be at their worst when the depressed individual actively engages in depressive rumination (e.g., Whitmer & Gotlib, 2013). As such, I expect a combination of elevated negative mood, depressive symptoms, and depressive rumination to predict worse performance on WM search.

Data Collection

Data was collected online using Georgia Tech's Qualtrics platform. Using the resources provided by https://labjs.felixhenninger.com, I embedded the modified *n*-back tasks into Qualtrics and stored participant responses as embedded data for later extraction.

CHAPTER 3

RESULTS

Data Processing

The RStudio software program, version 1.2.5033, was used to extract the raw *n*-back task data from the embedded data in Qualtrics. Additional data processing was conducted using a combination of Microsoft Excel and RStudio to filter out extraneous information recorded by the programs.

Analyses

Data analyses were conducted using the Jamovi Project software package (version 2.2.5, 2021). Separate analyses were conducted on the data from set 1 and set 2. Recall that in set 1, participants were randomly assigned to either the emotional condition (n = 25) or to the non-emotional condition (n = 27). This emotional condition sets up the possibility of affective transfer to the non-emotional tasks in set 2. Half of the sample exceeded the cutoff for depressive symptoms on the CESD-R.

Principal Components Analysis on Survey Scores

A principal components analysis (PCA) with an oblimin rotation was used to group survey measures into separate domains using the full sample of N = 257. I selected components based on eigenvalues greater than one, resulting in three components: negative mood, positive mood, and rumination. This was supported by the scree plot in Figure 2. The observed separation of rumination and depression into different components is congruent with existing literature that indicates that rumination and depression are not a unitary concept (Brinker and Dozois, 2008). See Table 6 for the component loadings.

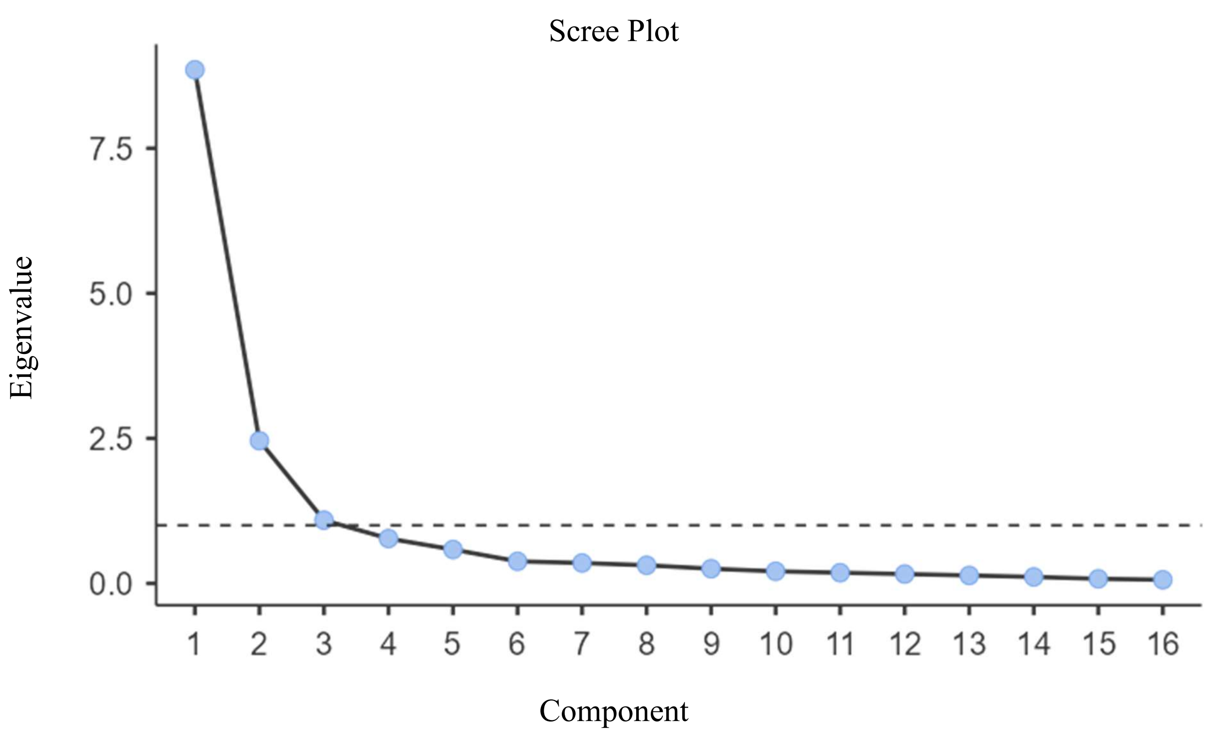


Figure 2. Scree Plot with Eigenvalue Cutoff from PCA.

Table 6. Component loadings from PCA with oblimin rotation.

Component Loadings

	Component			
	Negative Mood	Rumination	Positive Mood	Uniqueness
Positive PANAS 1			0.913	0.130
Negative PANAS 1	0.873			0.216
Positive PANAS 2			0.943	0.109
Negative PANAS 2	0.924			0.200
PTQ Core		0.882		0.244
PTQ Unproductive		0.867		0.290
PTQ Mental Capacity		0.760		0.376
RRS Depression		0.697		0.232
RRS Brooding		0.790		0.301
RRS Reflection		0.649		0.389
CESD-R	0.708			0.201
DASS-21 Stress	0.759			0.230
DASS-21 Anxiety	0.885			0.235
DASS-21 Depression	0.638		-0.328	0.247
Positive PANAS 3			0.936	0.082
Negative PANAS 3	0.941			0.116

Note. 'oblimin' rotation was used

Negative mood included the negative items from the three administrations of the PANAS, the brooding and reflection subscales of the RRS, the CESD-R, and all subscales from the DASS-21. Positive mood included only the positive items from the three administrations of the PANAS. Rumination included all subscales of the PTQ and the RRS. I used these component scores, rather than the individual survey scores, in the main analyses. Negative mood and rumination were positively correlated (r = .678), negative mood and positive mood were negatively correlated (r = -.228), and rumination and positive mood were negatively correlated (r = -.394)

Binomial Logistic Regression Predicting Attrition

I used these component scores in a binomial logistic regression to predict attrition from my previously-discussed criteria to remove button-mashing participants. Negative mood and rumination were not predictive of participant inclusion (p = .316 and p = .843, respectively), but positive mood was (coefficient = -0.37, p = .036). As such, people with higher positive mood were less likely to be included in the sample (i.e., more likely to button-mash). These estimates and odds ratios are shown in Table 7.

Table 7. Binomial logistic regression results for inclusion in sample.

Model Coefficients - Include

						95% Confidence Interval	
Predictor	**Estimate**	**SE**	**Z**	**p**	**Odds ratio**	**Lower**	**Upper**
Intercept	-1.4	0.16	-8.747	< .001	0.244	0.178	0.335
Negative Mood	-0.22	0.22	-1.002	.316	0.801	0.520	1.236
Rumination	-0.05	0.23	-0.198	.843	0.955	0.608	1.502
Positive Mood	-0.37	0.18	-2.095	.036	0.688	0.485	0.976

Note. Estimates represent the log odds of "Include = 1" vs. "Include = 0"

Affective Transfer: Set 2 ANOVA

The two main goals of this study were to see if affective transfer (Hubbard et al. 2016) occurs in a modified n-back task, and to examine the specifics of possible deficits in working memory in depression and rumination using an effects decomposition of this modified n-back task. Recall that affective transfer is the worsening of working memory performance on a non-emotional task after the completion of a mood-congruent emotionally valenced task, in participants with depression or depressive symptoms.

I examined this first, primary, question by comparing performance in set 2 based on whether participants were in the emotional or non-emotional condition in set 1. If affective transfer were to occur from set 1 to set 2, I would expect participants who were in the emotional set 1 condition to have worse performance in set 2 relative to participants who were in the non-emotional set 1 condition, and for this to depend on depression and/or rumination. If I observed a difference in set 2 performance based on set 1 condition that is unrelated to depression and/or rumination, then that difference would simply be due to mood induction rather than affective transfer. In the following ANOVAs, Negative Mood, Positive Mood, and Rumination were entered as covariates. CESD-R Threshold was a simple categorical variable.

Set 2 ANOVA Updating Costs: Bin Scores. There was a significant effect of *n*-level, $F(2, 84) = 11.57$, $p < .001$, , $\eta^2_p = .216$. Specifically, the $n = 3$ updating cost was greater than both the $n = 1$, $t(42) = 2.80$, $p_{\text{Tukey}} = .021$, and the $n = 2$, $t(45) = 4.04$, $p_{\text{Tukey}} < .001$, updating costs, although the mean differences were rather small, at 0.354 and 0.503, respectively. *N*-level did not interact significantly with negative mood, positive mood, rumination, condition, or CESD-R level (all $p > .05$). None of the three-way interactions, key for identifying affective transfer, were significant (all p > .05). The main effects of negative mood, positive mood, rumination, condition, and CESD-R threshold were all not significant (all $p > .05$). Furthermore, none of these main effects interacted significantly (all $p > .05$). These effects are in Table 8.

Table 8. Set 2 ANOVA bin score updating cost effects.

Within Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
***N*-Level**	**8.76**	**2**	**4.38**	**11.57**	**< .001****	**0.216**
N-Level ✻ Negative Mood	1.22	2	0.61	1.61	.206	0.037
N-Level ✻ Positive Mood	1.45	2	0.73	1.92	.153	0.044

N-Level ✻ Rumination	0.00	2	0.00	0.00	.998	0.000
N-Level ✻ Condition	0.86	2	0.43	1.13	.328	0.026
N-Level ✻ CESD-R Threshold	2.38	2	1.19	3.14	.049	0.070
N-Level ✻ Condition ✻ CESD-R Threshold	0.01	2	0.01	0.02	.983	0.000
N-Level ✻ Condition ✻ Negative Mood	0.21	2	0.11	0.28	.754	0.007
N-Level ✻ Condition ✻ Positive Mood	0.50	2	0.25	0.66	.520	0.015
N-Level ✻ Condition ✻ Rumination	0.63	2	0.31	0.83	.440	0.019
Residual	31.80	84	0.38			
Between Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*P*	η^2p
Negative Mood	2.85	1	2.85	0.51	.480	0.012
Positive Mood	0.67	1	0.67	0.12	.732	0.003
Rumination	1.99	1	1.99	0.36	.554	0.008
Condition	15.86	1	15.86	2.83	.100	0.063
CESD-R Threshold	0.02	1	0.02	0.00	.955	0.000
Condition ✻ CESD-R Threshold	15.46	1	15.46	2.76	.104	0.062
Condition ✻ Negative Mood	9.19	1	9.19	1.64	.207	0.038
Condition ✻ Positive Mood	1.26	1	1.26	0.23	.637	0.005
Condition ✻ Rumination	0.24	1	0.24	0.04	.838	0.001
Residual	235.29	42	5.60			

Note. Type 3 Sums of Squares

** $p < .01$, * $p < .05$

Set 2 ANOVA Switch Costs: Bin Scores. There was a significant interaction between *n*-level and condition, $F(1, 42) = 14.25$, $p < .001$, $\eta^2_p = .253$. Specifically, switch costs were higher at $n = 2$ in the emotional condition relative to the non-emotional condition (mean difference = 1.70, $p_{Tukey} < .001$), but this difference was not present at $n = 3$ ($p_{Tukey} = .729$). There was a significant interaction between condition and negative mood, $F(1, 42) = 4.73$, $p = .035$, $\eta^2_p = .101$. There was also a significant main effect of condition, $F(1, 42) = 5.65$, $p = .022$, $\eta^2_p = .119$, in which the switch cost was greater in the emotional condition than in the non-emotional condition (mean difference = 1.04, $p_{Tukey} = .004$). No other effects were significant (all $p > .05$). These effects are shown in Table 9. The interaction between *n*-level and condition is shown in

Figure 3. The interaction between condition and negative mood is examined in detail in the regression analysis section.

Table 9. Set 2 ANOVA bin score switch cost effects.

Within Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
N-Level	0.01	1	0.01	0.01	.927	0.000
N-Level ✻ Negative Mood	0.47	1	0.47	0.64	.428	0.015
N-Level ✻ Positive Mood	0.22	1	0.22	0.30	.585	0.007
N-Level ✻ Rumination	1.92	1	1.92	2.61	.114	0.059
***N*-Level ✻ Condition**	**10.48**	**1**	**10.48**	**14.25**	**< .001****	**0.253**
N-Level ✻ CESD-R Threshold	1.66	1	1.66	2.26	.140	0.051
N-Level ✻ Condition ✻ CESD-R Threshold	0.53	1	0.53	0.72	.402	0.017
N-Level ✻ Condition ✻ Negative Mood	0.04	1	0.04	0.05	.821	0.001
N-Level ✻ Condition ✻ Positive Mood	0.21	1	0.21	0.29	.595	0.007
N-Level ✻ Condition ✻ Rumination	0.35	1	0.35	0.47	.496	0.011
Residual	30.89	42	0.74			
Between Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
Negative Mood	4.33	1	4.33	1.43	.238	0.033
Positive Mood	1.07	1	1.07	0.35	.555	0.008
Rumination	1.07	1	1.07	0.35	.556	0.008
Condition	**17.07**	**1**	**17.07**	**5.65**	**.022**	**0.119**
CESD-R Threshold	0.37	1	0.37	0.12	.728	0.003
Condition ✻ CESD-R Threshold	6.74	1	6.74	2.23	.143	0.050
Condition ✻ Negative Mood	**14.29**	**1**	**14.29**	**4.73**	**.035***	**0.101**
Condition ✻ Positive Mood	0.53	1	0.53	0.17	.679	0.004
Condition ✻ Rumination	4.43	1	4.43	1.47	.233	0.034
Residual	126.86	42	3.02			

** $p < .01$, * $p < .05$
Note. Type 3 Sums of Squares

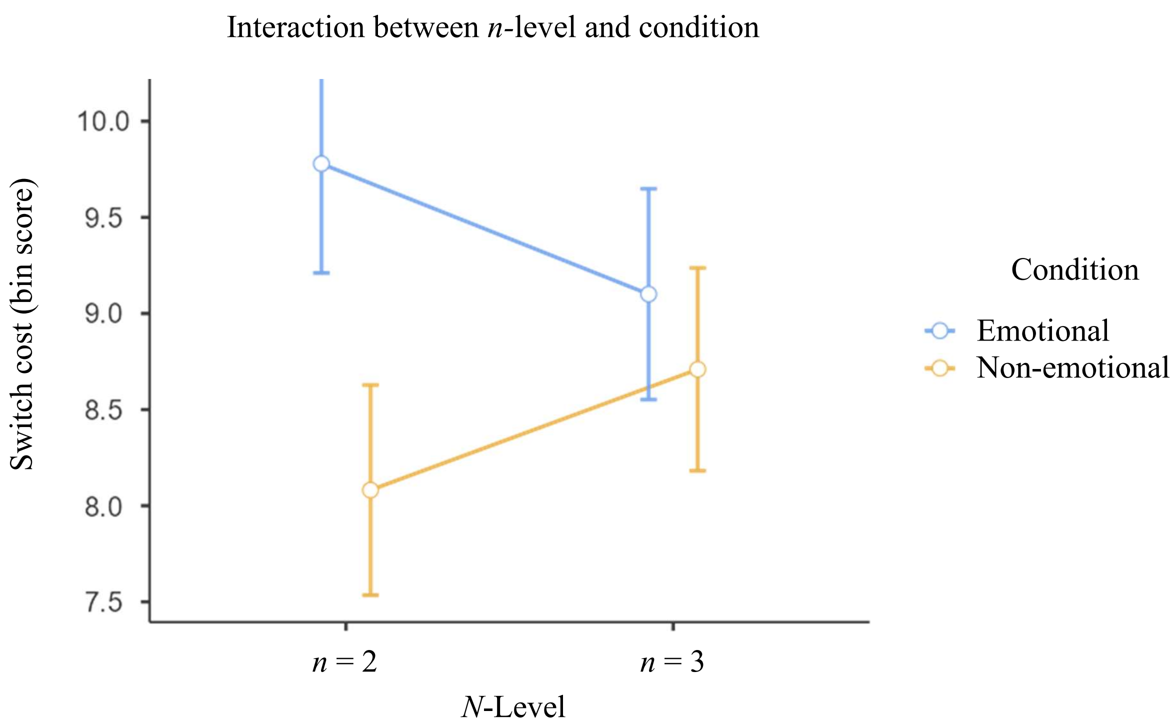


Figure 3. Interaction between condition and *n*-level on switch cost bin scores in set 2.

Set 2 ANOVA Updating Costs: Median RT Difference Scores. Since Mauchly's W = 0.83, $p = .023$, I report the Huynh-Feldt corrected results for the within-subjects effects. There was a significant interaction effect between *n*-level and condition, $F(1.78, 74.6) = 3.40$, $p = .044$, $\eta^2_p = 0.075$. Within the significant interaction, the median RT updating cost for the $n = 1$ non-emotional group was significantly lower than for the $n = 3$ non-emotional (mean difference = 132.67), $t(42) = 3.33$, $p = .021$; $n = 2$ non-emotional was significantly lower than $n = 3$ non-emotional (mean difference = 127.38), $t(42) = 3.94$, $p = .004$. Essentially, the non-emotional condition was unusually high at $n = 3$; this interaction is displayed in Figure 4. None of the other effects were significant (all *p*-values > .05). These effects are in Table 10.

Table 10. Set 2 ANOVA median RT updating cost effects.

Within Subjects Effects

	Sphericity Correction	Sum of Squares	df	Mean Square	F	p	$\eta^2 p$
N-Level	None	95733	2	47866	3.17	.047	0.070
	GG	95733	1.71	55944	3.17	.056	0.070
	HF	95733	1.78	53881	3.17	.054	0.070
N-Level ✻ Condition	**None**	**102805**	**2**	**51402**	**3.40**	**.038***	**0.075**
	GG	102805	1.71	60077	3.40	.046	0.075
	HF	**102805**	**1.78**	**57861**	**3.40**	**.044***	**0.075**
N-Level ✻ Negative Mood	None	4749	2	2375	0.16	.855	0.004
	GG	4749	1.71	2775	0.16	.822	0.004
	HF	4749	1.78	2673	0.16	.830	0.004
N-Level ✻ Positive Mood	None	24918	2	12459	0.82	.442	0.019
	GG	24918	1.71	14561	0.82	.426	0.019
	HF	24918	1.78	14024	0.82	.430	0.019
N-Level ✻ Rumination	None	1755	2	878	0.06	.944	0.001
	GG	1755	1.71	1026	0.06	.921	0.001
	HF	1755	1.78	988	0.06	.927	0.001
N Level ✻ CESD-R Threshold	None	31586	2	15793	1.05	.356	0.024
	GG	31586	1.71	18458	1.05	.348	0.024
	HF	31586	1.78	17777	1.05	.350	0.024
N Level ✻ CESD-R Threshold ✻ Condition	None	40627	2	20313	1.34	.266	0.031
	GG	40627	1.71	23741	1.34	.265	0.031
	HF	40627	1.78	22866	1.34	.266	0.031
N-Level ✻ Condition ✻ Negative Mood	None	44228	2	22114	1.46	.237	0.034
	GG	44228	1.71	25846	1.46	.239	0.034
	HF	44228	1.78	24893	1.46	.238	0.034
N-Level ✻ Condition ✻ Positive Mood	None	499	2	249	0.02	.984	0.000
	GG	499	1.71	291	0.02	.973	0.000
	HF	499	1.78	281	0.02	.976	0.000
N-Level ✻ Condition ✻ Rumination	None	24142	2	12071	0.80	.453	0.019
	GG	24142	1.71	14108	0.80	.436	0.019
	HF	24142	1.78	13588	0.80	.440	0.019
Residual	None	1.27E+06	84	15110			
	GG	1.27E+06	71.9	17660			
	HF	1.27E+06	74.6	17009			

** $p < .01$, * $p < .05$

GG = Greenhouse-Geisser, HF = Huynh-Feldt

Between Subjects Effects						
	Sum of Squares	df	Mean Square	F	p	$\eta^2 p$
Condition	48120	1	48120	1.20	.280	0.028
Negative Mood	7937	1	7937	0.20	.659	0.005
Positive Mood	67740	1	67740	1.69	.201	0.039
Rumination	84234	1	84234	2.10	.155	0.048
CESD-R Threshold	942	1	942	0.02	.879	0.001
CESD-R Threshold ✻ Condition	7865	1	7865	0.20	.660	0.005
Condition ✻ Negative Mood	32088	1	32088	0.80	.377	0.019
Condition ✻ Positive Mood	15322	1	15322	0.38	.540	0.009
Condition ✻ Rumination	54462	1	54462	1.36	.251	0.031
Residual	1.69E+06	42	40166			

** $p < .01$, * $p < .05$

Note. Type 3 Sums of Squares

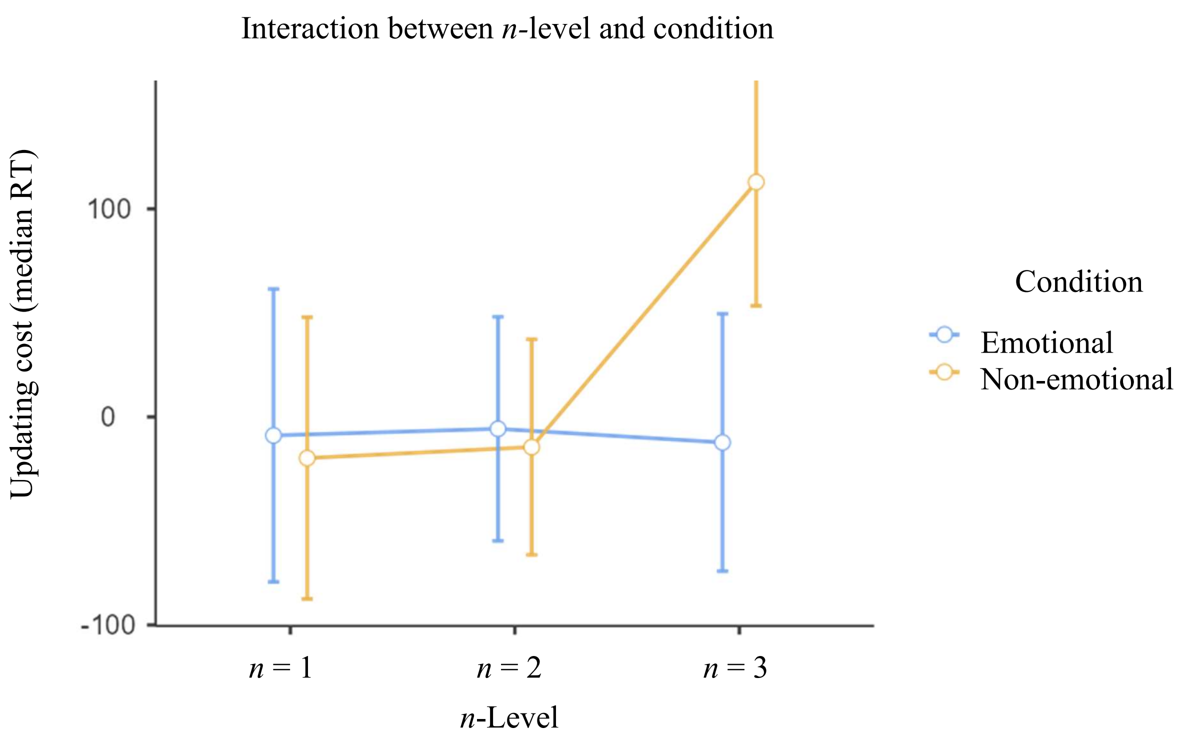


Figure 4. Interaction effect between *n*-level and condition on set 2 median RT updating costs.

Set 2 ANOVA Switch Costs: Median RT Difference Scores. None of the switch cost difference score within-subject nor between-subject effects were significant (all p-values > .05). These effects are shown in Table 11.

Table 11. Set 2 ANOVA median RT switch cost effects.

Within Subjects Effects

	Sphericity Correction	Sum of Squares	df	Mean Square	F	p	η^2p
N-Level	None	9802.4	1	9802.4	1.36	.250	0.029
	GG	9802.4	1	9802.4	1.36	.250	0.029
	HF	9802.4	1	9802.4	1.36	.250	0.029
N-Level ✻ CESD-R Threshold	None	20.8	1	20.8	0.00	.957	0.000
	GG	20.8	1	20.8	0.00	.957	0.000
	HF	20.8	1	20.8	0.00	.957	0.000
N-Level ✻ Negative Mood	None	3992	1	3992	0.55	.461	0.012
	GG	3992	1	3992	0.55	.461	0.012
	HF	3992	1	3992	0.55	.461	0.012
N-Level ✻ Positive Mood	None	4809.5	1	4809.5	0.67	.419	0.015
	GG	4809.5	1	4809.5	0.67	.419	0.015
	HF	4809.5	1	4809.5	0.67	.419	0.015
N-Level ✻ Rumination	None	2849.2	1	2849.2	0.39	.533	0.009
	GG	2849.2	1	2849.2	0.39	.533	0.009
	HF	2849.2	1	2849.2	0.39	.533	0.009
N-Level ✻ Condition	None	10147.6	1	10147.6	1.40	.242	0.030
	GG	10147.6	1	10147.6	1.40	.242	0.030
	HF	10147.6	1	10147.6	1.40	.242	0.030
N-Level ✻ CESD-R Threshold ✻ Condition	None	1826.1	1	1826.1	0.25	.618	0.006
	GG	1826.1	1	1826.1	0.25	.618	0.006
	HF	1826.1	1	1826.1	0.25	.618	0.006
Residual	None	325087.1	45	7224.2			
	GG	325087.1	45	7224.2			
	HF	325087.1	45	7224.2			

GG = Greenhouse-Geisser, HF = Huynh-Feldt

Between Subjects Effects

	Sphericity Correction	Sum of Squares	df	Mean Square	F	p	η^2p
CESD-R Threshold	NA	1592	1	1592	0.12	.732	0.003
Condition	NA	18468	1	18468	1.38	.247	0.030
CESD-R Threshold ✻ Condition	NA	616	1	616	0.05	.831	0.001
Negative Mood	NA	3372	1	3372	0.25	.619	0.006
Positive Mood	NA	830	1	830	0.06	.805	0.001
Rumination	NA	2710	1	2710	0.20	.655	0.004
Residual	NA	604147	45	13425			

Note. Type 3 Sums of Squares

Set 2 ANOVA Updating Costs: Mean Accuracy Difference Scores. There was a significant effect of *n*-level, $F(2, 90) = 21.83$, $p < .001$, $\eta^2_p = .327$. Specifically, the $n = 1$ updating accuracy cost was greater than both the updating accuracy costs for $n = 2$ (mean difference = 0.057), $t(45) = 4.68$, $p_{\text{Tukey}} < .001$, and for $n = 3$ (mean difference = 0.076), $t(45) = 5.98$, $p_{\text{Tukey}} < .001$.

There was also a significant interaction between *n*-level and CESD-R threshold, $F(2, 90) = 3.42$, $p = .037$, $\eta^2_p = .071$ (see Figure 5). Within this interaction, the mean accuracy updating cost at $n = 1$ below CESD-R threshold was greater than at $n = 2$ below threshold (mean difference = 0.02), $t(45) = 4.72$, $p < .001$; the mean accuracy updating cost at $n = 1$ below threshold was also greater than at $n = 3$ below threshold (mean difference = 0.11), $t(45) = 5.20$, $p < .001$. None of the other effects were significant (all $p > .05$). These within- and between-subject effects are shown in Table 12.

Table 12. Set 2 ANOVA mean accuracy updating cost effects.

Within Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*p*	*η²p*
***N*-Level**	**0.17008**	**2**	**0.09**	**21.83**	**< .001****	**0.327**
N-Level ✻ Negative Mood	0.02248	2	0.01	2.89	.061	0.060
N-Level ✻ Positive Mood	0.00449	2	0.00	0.58	.564	0.013
N-Level ✻ Rumination	0.00182	2	0.00	0.23	.792	0.005
***N*-Level ✻ CESD-R Threshold**	**0.02665**	**2**	**0.01**	**3.42**	**.037**	**0.071**
N-Level ✻ Condition	0.02501	2	0.01	3.21	.045	0.067
N-Level ✻ CESD-R Threshold ✻ Condition	0.00633	2	0.00	0.81	.447	0.018
Residual	0.35065	90	0.00			
Between Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*p*	*η²p*

CESD-R Threshold	0.02093	1	0.02	0.56	.459	0.012
Condition	0.11502	1	0.12	3.06	.087	0.064
CESD-R Threshold ✻ Condition	0.00625	1	0.01	0.17	.685	0.004
Negative Mood	0.02994	1	0.03	0.80	.377	0.017
Positive Mood	2.77E-06	1	0.00	0.00	.993	0.000
Rumination	0.01037	1	0.01	0.28	.602	0.006
Residual	1.69105	45	0.04			

** $p < .01$, * $p < .05$

Note. Type 3 Sums of Squares

Interaction between *n*-level and CESD-R Threshold

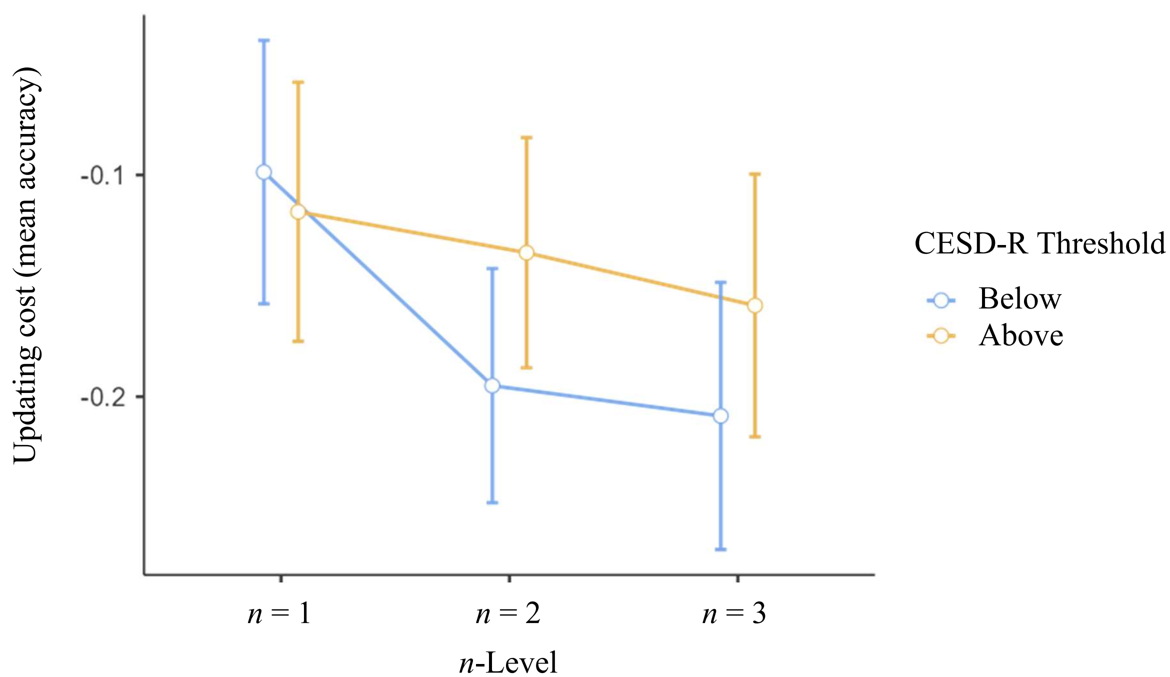


Figure 5. Interaction between *n*-level and CESD-R threshold on the mean accuracy updating cost in set 2.

Set 2 ANOVA Switch Costs: Mean Accuracy Difference Scores. There was a significant main effect of condition, $F(1, 45) = 4.42$, $p = .041$, $\eta^2_p = .089$. Specifically, the switch cost in accuracy for the emotional condition was slightly higher than for the non-emotional condition (mean difference = 0.02), $t(45) = 2.10$, $p_{tukey} = .041$. No other effects were significant ($p >= .05$). These within- and between-subject results are show in Table 13.

Table 13. Set 2 ANOVA mean accuracy switch cost effects.

Within Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
N-Level	0.00	1	0.00	1.42	.240	0.030
N-Level ✻ Negative Mood	0.00	1	0.00	0.27	.607	0.006
N-Level ✻ Positive Mood	0.00	1	0.00	0.10	.754	0.002
N-Level ✻ Rumination	0.00	1	0.00	0.23	.635	0.005
N-Level ✻ CESD-R Threshold	0.01	1	0.01	2.51	.120	0.053
N-Level ✻ Condition	0.00	1	0.00	1.07	.307	0.023
N-Level ✻ CESD-R Threshold ✻ Condition	0.00	1	0.00	0.24	.624	0.005
Residual	0.12	45	0.00			
Between Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
CESD-R Threshold	0.01	1	0.01	4.05	.050	0.083
Condition	**0.01**	**1**	**0.01**	**4.42**	**.041***	**0.089**
CESD-R Threshold ✻ Condition	0.00	1	0.00	0.91	.345	0.020
Negative Mood	0.00	1	0.00	2.02	.162	0.043
Positive Mood	0.00	1	0.00	0.22	.645	0.005
Rumination	0.00	1	0.00	1.89	.176	0.040
Residual	0.10	45	0.00			

** $p < .01$, * $p < .05$

Note. Type 3 Sums of Squares

Affective Transfer: Set 2 Regression Analyses

I used linear regression to predict the updating costs and switch costs from experimental condition, the mood and rumination survey measures, and the interactions between condition and these survey measures in three model blocks. In the first block, the predictors were negative mood, positive mood, rumination, condition, and CESD-R threshold status. In the second block, two-way interactions between condition and each of the mood and rumination variables were included (i.e., condition*negative mood, condition*positive mood, condition*rumination, and condition*CESD-R threshold), as were two-way interactions between negative mood and rumination and between CESD-R threshold and rumination. Finally, in the third block, three-way interactions were added to investigate whether affective transfer occurs as a result of negative mood and depressive rumination (i.e., condition*negative mood*rumination and condition*CESD-R threshold*rumination). These two-way and three-way interactions are key for investigating whether affective transfer occurs. If affective transfer occurs for individuals with depressive symptoms, I should see a significant interaction between condition and the negative mood principal component. If affective transfer occurs for individuals with depressive symptoms who also tend to engage in depressive rumination, I should see a significant three-way interaction between condition, negative mood or CESD-R threshold status, and rumination

Set 2 Regression Updating Costs: Bin Scores. Condition, negative mood, positive mood, rumination, CESD-R threshold status, as well as the interactions between condition and each of these variables, were not predictive of $n = 1$, $n = 2$, or $n = 3$ updating costs in the set 2 bin score data (see Table 14, Table 15, and Table 16 for the R^2, R^2 change, and beta coefficients with *p*-values for these models). This is not surprising, since none of the main effects nor interaction models were significantly better than simply using the mean for any level of n. Furthermore, including the aforementioned interactions with condition failed to improve any of the model fits (see Table 17 and Table 18).

Table 14. Standardized regression coefficients for set 2, *n* = 1 bin score updating costs.

	Bin Score Updating Costs, *n* = 1					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.51	.073	0.10	.872	0.12	.856
Negative Mood	0.09	.624	-0.13	.627	-0.14	.621
Positive Mood	0.00	.981	0.26	.417	0.28	.398
Rumination	0.08	.648	0.30	.429	0.23	.605
CESD-R Threshold (above – below)	0.22	.539	0.90	.150	0.93	.154
Negative Mood ✻ Condition			0.51	.208	0.52	.258
Positive Mood ✻ Condition			-0.30	.448	-0.30	.466
Rumination ✻ Condition			-0.28	.498	-0.08	.936
Condition ✻ CESD-R Threshold			-1.22	.130	-1.26	.139
Negative Mood ✻ Rumination			0.01	.967	-0.04	.892
CESD-R Threshold ✻ Rumination			-0.12	.844	0.07	.931
Condition ✻ Negative Mood ✻ Rumination					0.16	.769
Condition ✻ CESD-R Threshold ✻ Rumination					-0.50	.703
R^2	0.13	.266	0.19	.601	0.20	.760
R^2 Change			0.06	.802	0.00	.929

Table 15. Standardized regression coefficients for set 2, *n* = 2 bin score updating costs.

	Bin Score Updating Costs, *n* = 2					
	Model 1		Model 2		Model 3	
Predictor	***beta***	***p***	***beta***	***p***	***beta***	***p***
Condition (non-emotional – emotional)	-0.40	.163	0.42	.396	0.56	.318
Negative Mood	0.00	.988	-0.28	.299	-0.32	.254
Positive Mood	-0.14	.376	0.08	.809	0.15	.642
Rumination	0.14	.427	-0.06	.826	-0.27	.474
CESD-R Threshold (above – below)	-0.28	.448	0.58	.341	0.70	.263
Negative Mood ✻ Condition			0.59	.145	0.66	.141
Positive Mood ✻ Condition			-0.23	.550	-0.27	.507
Rumination ✻ Condition			-0.08	.850	0.43	.513
Condition ✻ CESD-R Threshold			-1.49	.067	-1.65	.050
Negative Mood ✻ Rumination			-0.18	.446	-0.29	.291
CESD-R Threshold ✻ Rumination			0.65	.276	1.21	.126
Condition ✻ Negative Mood ✻ Rumination					0.35	.522
Condition ✻ CESD-R Threshold ✻ Rumination					-1.36	.292
R^2	0.09	.517	0.19	.601	0.22	.657

R^2 Change			0.10	.544	0.03	.529

Table 16. Standardized regression coefficients for set 2, $n = 3$ bin score updating costs.

	Bin Score Updating Costs, $n = 3$					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.53	.068	-0.02	.991	0.07	.855
Negative Mood	0.19	.307	0.07	.788	0.05	.877
Positive Mood	0.07	.660	0.13	.680	0.21	.530
Rumination	0.10	.536	0.14	.721	-0.08	.826
CESD-R Threshold (above – below)	-0.19	.610	0.34	.592	0.45	.482
Negative Mood ✻ Condition			0.34	.403	0.38	.401
Positive Mood ✻ Condition			-0.06	.882	-0.08	.849
Rumination ✻ Condition			0.01	.982	0.60	.373
Condition ✻ CESD-R Threshold			-1.02	.212	-1.16	.168
Negative Mood ✻ Rumination			0.01	.972	-0.13	.639
CESD-R Threshold ✻ Rumination			-0.15	.810	0.44	.580
Condition ✻ Negative Mood ✻ Rumination					0.46	.407
Condition ✻ CESD-R Threshold ✻ Rumination					-1.52	.249
R^2	0.11	.342	0.16	.764	0.19	.786
R^2 Change			0.04	.916	0.03	.500

Table 17. Regression model fits for set 2 bin score updating costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (2-way Interactions)		Model 3 (3-way Interactions)	
Updating, $n = 1$	$F(5, 45) = 1.38$	$p = .266$	$F(11, 39) = 0.84$	$p = .601$	$F(13, 37) = 0.69$	$p = .760$
Updating, $n = 2$	$F(5, 45) = 0.86$	$p = .517$	$F(11, 39) = 0.84$	$p = .601$	$F(13, 37) = 0.80$	$p = .657$
Updating, $n = 3$	$F(5, 45) = 1.16$	$p = .342$	$F(11, 39) = 0.66$	$p = .764$	$F(13, 37) = 0.66$	$p = .786$

Table 18. Regression model comparisons for set 2 bin score updating costs at all levels of *n*.

	Model 1 (Main Effects) v. Model 2 (2-way Interactions)		Model 2 (2-way Interactions) v. Model 3 (3-way Interactions)	
Updating cost, $n = 1$	$F(6, 39) = 0.50$	$p = .802$	$F(2, 37) = 0.07$	$p = .929$
Updating Cost, $n = 2$	$F(6, 39) = 0.84$	$p = .544$	$F(2, 37) = 0.65$	$p = .529$

Updating Cost, $n = 3$	$F(6, 39) = 0.33$	$p = .916$	$F(2, 37) = 0.71$	$p = .500$

Set 2 Regression Switch Costs: Bin Scores. Condition and negative mood were somewhat predictive of $n = 2$ switch costs in the set 2 bin score data, but their interaction was not. In fact, condition was only a significant predictor when no interactions were included in the model.

For $n = 2$ switch costs, model 1 (main effects), model 2 (2-way interactions), and model 3 (3-way interactions) were significantly better fits than simply using the mean ($p < .001$, $p = .004$, and $p = .013$, respectively; see Table 19). However, adding the interactions did not improve model fit ($p = .909$ and $p = .892$, respectively for model 2 and model 3; see Table 20).

Table 19. Regression model fits for set 2 bin score switch costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (2-way Interactions)		Model 3 (3-way Interactions)	
Switch, $n = 2$	$F(5, 45) = 5.48$	$p < .001$**	$F(11, 39) = 3.12$	$p = .004$	$F(13, 37) = 2.54$	$p = .013$
Switch, $n = 3$	$F(5, 45) = 0.97$	$p = .450$	$F(11, 39) = 1.11$	$p = .378$	$F(13, 37) = 0.92$	$p = .545$

Table 20. Regression model comparisons for set 2 bin score switch costs at all levels of *n*.

	Model 1 (Main Effects) v. Model 2 (2-way Interactions)		Model 2 (2-way Interactions) v. Model 3 (3-way Interactions)	
Switch, $n = 2$	$F(6, 39) = 1.10$	$p = .380$	$F(2, 37) = 0.10$	$p = .909$
Switch, $n = 3$	$F(6, 39) = 1.21$	$p = .320$	$F(2, 37) = 0.12$	$p = .892$

In model 1, condition was the only significant predictor of $n = 2$ bin score switch costs, $p < .001$. In model 2, condition ceased to be significant, $p = .084$, but negative mood became significant, $p = .032$. In model 3, negative mood was also the only significant effect, $p = .035$.

None of the other predictors, including all interaction effects, were significant (all $p > .05$). Table 21 and Table 22 contain these standardized regression coefficients, their significance, and measures of model fit (R^2, R^2 change, and the p-values from the model fit ANOVA tests), for n = 2 and n =3 bin score switch costs, respectively.

Table 21. Standardized regression coefficients for set 2, n = 2 bin score switch costs.

	Bin Score Switch Costs, n = 2					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	**-1.05**	**< .001****	-0.81	.084	-0.76	.157
Negative Mood	-0.28	.079	**-0.48**	**.032***	**-0.50**	**.035***
Positive Mood	-0.19	.172	-0.15	.547	-0.13	.627
Rumination	0.15	.277	0.27	.438	0.20	.639
CESD-R Threshold (above – below)	-0.07	.826	0.03	.044	0.07	.877
Negative Mood ✻ Condition			0.01	.973	0.70	.062
Positive Mood ✻ Condition			-0.51	.131	-0.01	.991
Rumination ✻ Condition			-0.49	.444	-0.36	.560
Condition ✻ CESD-R Threshold			-0.24	.197	-0.55	.417
Negative Mood ✻ Rumination			0.32	.510	-0.27	.221
CESD-R Threshold ✻ Rumination					0.49	.442
Condition ✻ Negative Mood ✻ Rumination					0.09	.837
Condition ✻ CESD-R Threshold ✻ Rumination					-0.41	.697
R^2	0.38	< .001	0.47	.004	0.47	.013
R^2 Change			0.09	.380	0.00	.909
** $p < .01$, * $p < .05$						

Table 22. Standardized regression coefficients for set 2, n = 3 bin score switch costs.

	Bin Score Switch Costs, n = 3					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.32	.259	0.41	.287	0.49	0.285
Negative Mood	-0.23	.230	-0.53	.051	-0.5404	0.055
Positive Mood	-0.12	.443	-0.10	.741	-0.1064	0.74
Rumination	-0.01	.992	-0.21	.525	-0.1904	0.625
CESD-R Threshold (above – below)	0.42	.253	1.09	.072	1.11	.082
Negative Mood ✻ Condition			0.70	.078	0.77	.087
Positive Mood ✻ Condition			0.13	.729	0.10	.803
Rumination ✻ Condition			-0.21	.602	-0.40	.544

Condition ✻ CESD-R Threshold			-1.32	.091	-1.37	.101
Negative Mood ✻ Rumination			-0.18	.423	-0.12	.647
CESD-R Threshold ✻ Rumination			0.71	.225	0.62	.419
Condition ✻ Negative Mood ✻ Rumination					-0.24	.646
Condition ✻ CESD-R Threshold ✻ Rumination					0.39	.760
R^2	0.10	.450	0.24	.378	0.24	.545
R^2 Change			0.14	.320	0.01	.892

** $p < .01$, * $p < .05$

For $n = 3$ switch costs, neither model 1, model 2, nor model 3 were any better than simply using the mean (all $p > .05$; see Table 19). Furthermore, fit did not improve with the addition of the interactions in these models ($p = .320$ and $p = .892$, for models 2 and 3, respectively; see Table 20).

Set 2 Regression Updating Costs: Median RT Difference Scores. Experimental condition, negative mood, positive mood, rumination, CESD-R threshold status, as well as the relevant two- and three-way interactions between these variables were not predictive of updating costs in the median RT data at any level of *n*, with the exception of condition at $n = 3$. Condition was a significant predictor of $n = 3$ median RT updating costs ($p = .005$), but only when interactions between condition and the mood and rumination variables were not included in the regression model. Table 23, Table 24, and Table 25 contain these standardized regression coefficients, their significance, and measures of model fit (R^2, R^2 change, and the *p*-values from the model fit ANOVA tests).

Table 23. Standardized regression coefficients for set 2, $n = 1$ median RT updating costs.

	Median RT Updating Costs, $n = 1$					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.08	.793	0.01	.800	0.04	.818
Negative Mood	-0.05	.782	-0.08	.820	-0.08	.847

Positive Mood	-0.14	.392	-0.40	.213	-0.46	.168
Rumination	-0.17	.347	-0.17	.741	-0.01	.878
CESD-R Threshold (above – below)	0.10	.789	0.23	.771	0.18	.863
Negative Mood ✻ Condition			0.09	.818	0.16	.772
Positive Mood ✻ Condition			0.32	.423	0.30	.466
Rumination ✻ Condition			0.60	.148	-0.01	.900
Condition ✻ CESD-R Threshold			-0.33	.688	-0.31	.768
Negative Mood ✻ Rumination			0.33	.167	0.49	.085
CESD-R Threshold ✻ Rumination			-0.97	.121	-1.48	.071
Condition ✻ Negative Mood ✻ Rumination					-0.57	.308
Condition ✻ CESD-R Threshold ✻ Rumination					1.48	.271
R^2	0.04	.869	0.15	.778	0.18	.808
R^2 Change			0.11	.516	0.03	.530
** $p < .01$, * $p < .05$						

Table 24. Standardized regression coefficients for set 2, $n = 2$ median RT updating costs.

	Median RT Updating Costs, $n = 2$					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.08	.789	-0.31	.650	-0.59	.387
Negative Mood	-0.06	.778	0.14	.620	0.19	.508
Positive Mood	0.06	.726	-0.25	.457	-0.29	.406
Rumination	-0.18	.315	-0.24	.571	-0.16	.720
CESD-R Threshold (above – below)	0.24	.518	-0.04	.914	-0.16	.776
Negative Mood ✻ Condition			-0.24	.564	-0.47	.336
Positive Mood ✻ Condition			0.35	.385	0.46	.280
Rumination ✻ Condition			0.37	.384	0.54	.434
Condition ✻ CESD-R Threshold			0.33	.694	0.54	.536
Negative Mood ✻ Rumination			0.09	.708	0.03	.930
CESD-R Threshold ✻ Rumination			-0.58	.367	-0.70	.396
Condition ✻ Negative Mood ✻ Rumination					0.39	.504
Condition ✻ CESD-R Threshold ✻ Rumination					-0.10	.944
R^2	0.05	.819	0.10	.942	0.13	.948
R^2 Change			0.06	.864	0.03	.561
** $p < .01$, * $p < .05$						

Table 25. Standardized regression coefficients for set 2, n = 3 median RT updating costs.

	Median RT Updating Costs, n = 3					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	**0.76**	**.005**	0.31	.589	0.20	.807
Negative Mood	-0.09	.614	0.15	.531	0.18	.478
Positive Mood	-0.20	.169	-0.31	.287	-0.36	.244
Rumination	-0.15	.342	-0.16	.658	-0.05	.934
CESD-R Threshold (above – below)	-0.36	.282	-0.80	.162	-0.87	.139
Negative Mood ✻ Condition			-0.62	.098	-0.69	.099
Positive Mood ✻ Condition			0.14	.695	0.18	.634
Rumination ✻ Condition			0.10	.793	-0.11	.847
Condition ✻ CESD-R Threshold			0.91	.218	1.01	.184
Negative Mood ✻ Rumination			0.08	.707	0.13	.619
CESD-R Threshold ✻ Rumination			-0.09	.868	-0.39	.594
Condition ✻ Negative Mood ✻ Rumination					-0.10	.840
Condition ✻ CESD-R Threshold ✻ Rumination					0.66	.586
R^2	0.25	.019	0.31	.125	0.32	.218
R^2 Change			0.06	.720	0.01	.784
** $p < .01$, * $p < .05$						

For n = 3 updating costs, model 1 (main effects only) was better for prediction than simply using the mean (p = .019, see Table 26). None of the other main effects and interaction models were significantly better at predicting updating costs in the median RT data than simply using the mean (all $p > .05$, see Table 26). For all levels of n, including the aforementioned interactions with condition failed to improve any of the model fits (see Table 27).

Table 26. Regression model fits for set 2 median RT updating costs at all levels of n.

	Model 1 (Main Effects)		Model 2 (2-way Interactions)		Model 3 (3-way Interactions)	
Updating, n = 1	$F(5, 46) = 0.37$	p = .869	$F(11, 40) = 0.65$	p = .780	$F(13, 38) = 0.64$	p = .808
Updating, n = 2	$F(5, 46) = 0.44$	p = .819	$F(11, 40) = 0.41$	p = .942	$F(13, 38) = 0.43$	p = .948

Updating, $n = 3$	$F(5, 46) = 3.02$	$p = .019$*	$F(11, 40) = 1.64$	$p = .125$	$F(13, 38) = 1.37$	$p = .218$

Table 27. Regression model comparisons for set 2 median RT updating costs at all levels of *n*.

	Model 1 (Main Effects) v. Model 2 (2-way Interactions)		Model 2 (2-way Interactions) v. Model 3 (3-way Interactions)	
Updating cost, $n = 1$	$F(6, 40) = 0.88$	$p = .516$	$F(2, 38) = 0.65$	$p = .530$
Updating Cost, $n = 2$	$F(6, 40) = 0.42$	$p = .864$	$F(2, 38) = 0.59$	$p = .561$
Updating Cost, $n = 3$	$F(6, 40) = 0.61$	$p = .720$	$F(2, 38) = 0.24$	$p = .784$

Set 2 Regression Switch Costs: Median RT Difference Scores. Condition, negative mood, positive mood, rumination, CESD-R threshold status, as well as the interactions between condition and each of these variables, were not predictive of switch costs at $n = 2$ and $n = 3$ in the set 2 median RT difference score data (all $p > .05$). These standardized regression coefficients, their significance, and measures of model fit (R^2, R^2 change, and the *p*-values from the model fit ANOVA tests) are in Table 28 and Table 29. None of the models used to predict median RT switch costs were any better than simply using the mean, for any level of *n* (see Table 30 and Table 31).

Table 28. Standardized regression coefficients for set 2, $n = 2$ median RT switch costs.

	Median RT Switch Costs, n = 2					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.42	.143	-0.16	.738	-0.25	.677
Negative Mood	0.14	.460	0.08	.812	0.09	.792
Positive Mood	0.09	.590	0.22	.496	0.24	.487
Rumination	-0.11	.539	-0.13	.652	-0.18	.588
CESD-R Threshold (above – below)	-0.12	.744	0.07	.882	0.06	.888
Negative Mood ✻ Condition			0.30	.472	0.22	.624
Positive Mood ✻ Condition			-0.16	.681	-0.13	.757

Rumination ✻ Condition			-0.38	.357	-0.08	.973
Condition ✻ CESD-R Threshold			-0.48	.556	-0.43	.597
Negative Mood ✻ Rumination			-0.30	.210	-0.39	.178
CESD-R Threshold ✻ Rumination			0.58	.361	0.76	.359
Condition ✻ Negative Mood ✻ Rumination					0.35	.546
Condition ✻ CESD-R Threshold ✻ Rumination					-0.66	.629
R^2	0.07	.644	0.12	.888	0.13	.944
R^2 Change			0.05	.870	0.01	.831
** $p < .01$, * $p < .05$						

Table 29. Standardized regression coefficients for set 2, $n = 3$ median RT switch costs.

	Median RT Switch Costs, n = 3					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.08	.778	-0.08	.747	-0.26	.561
Negative Mood	-0.01	.972	-0.09	.722	-0.06	.815
Positive Mood	-0.05	.761	0.27	.413	0.25	.455
Rumination	0.00	.995	0.53	.201	0.54	.262
CESD-R Threshold (above – below)	-0.10	.787	-0.11	.862	-0.17	.795
Negative Mood ✻ Condition			0.37	.377	0.21	.624
Positive Mood ✻ Condition			-0.45	.265	-0.38	.368
Rumination ✻ Condition			-0.86	.043	-0.63	.449
Condition ✻ CESD-R Threshold			-0.15	.856	-0.01	.974
Negative Mood ✻ Rumination			-0.19	.434	-0.26	.361
CESD-R Threshold ✻ Rumination			-0.08	.895	-0.06	.938
Condition ✻ Negative Mood ✻ Rumination					0.36	.534
Condition ✻ CESD-R Threshold ✻ Rumination					-0.35	.797
R^2	0.01	.999	0.13	.870	0.14	.922
R^2 Change			0.12	.480	0.01	.744
** $p < .01$, * $p < .05$						

Table 30. Regression model fits for set 2 median RT switch costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (2-way Interactions)		Model 3 (3-way Interactions)	
Switch, $n = 2$	$F(5, 46) = 0.68$	$p = .644$	$F(11, 40) = 0.51$	$p = .888$	$F(13, 38) = 0.44$	$p = .944$
Switch, $n = 3$	$F(5, 46) = 0.05$	$p = .999$	$F(11, 40) = 0.53$	$p = .870$	$F(13, 38) = 0.48$	$p = .922$

Table 31. Regression model comparisons for set 2 median RT switch costs at all levels of *n*.

	Model 1 (Main Effects) v. Model 2 (2-way Interactions)		Model 2 (2-way Interactions) v. Model 3 (3-way Interactions)	
Switch, $n = 2$	$F(6, 40) = 0.41$	$p = .870$	$F(2, 38) = 0.19$	$p = .831$
Switch, $n = 3$	$F(6, 40) = 0.94$	$p = .480$	$F(2, 38) = 0.30$	$p = .744$

Set 2 Regression Updating Costs: Mean Accuracy Difference Scores. Experimental condition, negative mood, positive mood, rumination, CESD-R threshold status, as well as the two-way interactions between condition and each of these mood variables, were not useful, for the most part, at predicting mean accuracy updating costs at any level of *n*. Condition was a significant predictor of $n = 1$ updating costs ($p = .017$), but only when interactions were not included in the model. No other predictor variables were significant in any other model. These standardized regression coefficients, their significance, and measures of model fit (R^2, R^2 change, and the *p*-values from the model fit ANOVA tests) are in Table 32, Table 33, and Table 34. None of the models (main effects nor interactions) were any better than simply using the mean for prediction, for any level of *n* in the mean accuracy set 2 data (see Table 35 and Table 36).

Table 32. Standardized regression coefficients for set 2 mean accuracy updating costs, n = 1.

	Mean Accuracy Updating Costs, n = 1					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	**0.67**	**.017***	0.85	.094	0.71	.225
Negative Mood	-0.06	.732	-0.10	.671	-0.06	.801
Positive Mood	0.01	.951	0.09	.768	-0.02	.960
Rumination	-0.07	.665	-0.11	.691	0.18	.688
CESD-R Threshold (above – below)	-0.16	.652	-0.06	.964	-0.20	.740
Negative Mood ✻ Condition			0.18	.657	0.12	.825
Positive Mood ✻ Condition			-0.03	.931	0.01	.982
Rumination ✻ Condition			-0.42	.290	-1.16	.082
Condition ✻ CESD-R Threshold			-0.29	.709	-0.14	.950
Negative Mood ✻ Rumination			-0.25	.268	-0.08	.772
CESD-R Threshold ✻ Rumination			0.64	.283	-0.15	.842
Condition ✻ Negative Mood ✻ Rumination					-0.56	.291
Condition ✻ CESD-R Threshold ✻ Rumination					2.02	.115
R^2	0.16	.156	0.21	.481	0.27	.420
R^2 Change			0.06	.818	0.05	.259
** $p < .01$, * $p < .05$						

Table 33. Standardized regression coefficients for set 2 mean accuracy updating costs, n = 2.

	Mean Accuracy Updating Costs, n = 2					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	0.23	.430	0.16	.760	0.003	.964
Negative Mood	-0.07	.717	0.14	.630	0.18	.528
Positive Mood	0.03	.874	-0.10	.769	-0.19	.569
Rumination	-0.12	.491	-0.18	.603	0.07	.878
CESD-R Threshold (above – below)	0.52	.173	0.38	.553	0.24	.744
Negative Mood ✻ Condition			-0.26	.545	-0.34	.447
Positive Mood ✻ Condition			0.16	.692	0.21	.613
Rumination ✻ Condition			-0.06	.883	-0.66	.342
Condition ✻ CESD-R Threshold			0.07	.932	0.23	.723
Negative Mood ✻ Rumination			-0.16	.510	-0.02	.944
CESD-R Threshold ✻ Rumination			0.06	.921	-0.63	.445

Condition ✻ Negative Mood ✻ Rumination					-0.42	.467
Condition ✻ CESD-R Threshold ✻ Rumination					1.69	.218
R^2	0.06	.724	0.11	.933	0.15	.909
R^2 Change			0.05	.903	0.92	.409
** $p < .01$, * $p < .05$						

Table 34. Standardized regression coefficients for set 2 mean accuracy updating costs, $n = 3$.

	Mean Accuracy Updating Costs, $n = 3$					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	0.40	.153	0.55	.316	0.57	.378
Negative Mood	-0.33	.088	-0.46	.099	-0.46	.114
Positive Mood	-0.06	.693	0.11	.743	0.02	.940
Rumination	-0.04	.820	-0.09	.767	0.14	.731
CESD-R Threshold (above – below)	0.39	.281	0.53	.380	0.46	.482
Negative Mood ✻ Condition			0.22	.594	0.29	.568
Positive Mood ✻ Condition			-0.19	.631	-0.21	.608
Rumination ✻ Condition			-0.26	.526	-1.06	.117
Condition ✻ CESD-R Threshold			-0.17	.829	-0.15	.940
Negative Mood ✻ Rumination			-0.15	.519	0.05	.850
CESD-R Threshold ✻ Rumination			0.61	.325	-0.07	.928
Condition ✻ Negative Mood ✻ Rumination					-0.74	.183
Condition ✻ CESD-R Threshold ✻ Rumination					1.97	.141
R^2	0.11	.341	0.15	.791	0.20	.737
R^2 Change			0.04	.944	0.05	.327
** $p < .01$, * $p < .05$						

Table 35. Regression model fits for set 2 mean accuracy updating costs at all levels of n.

	Model 1 (Main Effects)		Model 2 (2-way Interactions)		Model 3 (3-way Interactions)	
Updating, $n = 1$	$F(5, 46) = 1.69$	$p = .156$	$F(11, 40) = 0.98$	$p = .481$	$F(13, 38) = 1.06$	$p = .420$
Updating, $n = 2$	$F(5, 46) = 0.57$	$p = .724$	$F(11, 40) = 0.43$	$p = .933$	$F(13, 38) = 0.50$	$p = .909$
Updating, $n = 3$	$F(5, 46) = 1.17$	$p = .341$	$F(11, 40) = 0.63$	$p = .791$	$F(13, 38) = 0.72$	$p = .737$

Table 36. Regression model comparisons for set 2 mean accuracy updating costs at all *n*-levels.

	Model 1 (Main Effects) – Model 2 (2-way Interactions)		Model 2 (2-way Interactions) – Model 3 (3-way Interactions)	
Updating cost, *n* = 1	$F(6, 40) = 0.48$	$p = .818$	$F(2, 38) = 1.40$	$p = .259$
Updating Cost, *n* = 2	$F(6, 40) = 0.36$	$p = .903$	$F(2, 38) = 0.92$	$p = .409$
Updating Cost, *n* = 3	$F(6, 40) = 0.28$	$p = .944$	$F(2, 38) = 1.15$	$p = .327$

Set 2 Regression Switch Costs: Mean Accuracy Difference Scores. Experimental condition, negative mood, positive mood, rumination, CESD-R threshold status, as well as the relevant interactions between these variables, were mostly not predictive of switch costs in the set 2 mean accuracy difference score data at any level of *n*. However, rumination was predictive of *n* = 2 mean accuracy switch costs (*beta* = -0.80, *p* = .027) in model 2 and in model 3 (*beta* = -1.04, *p* = .01), but not in model 1. Additionally, in model 3 for *n* = 2 (but not for *n* = 3), the interaction between rumination and CESD-R threshold status was significant (*beta* = 1.66, *p* = .030). These standardized regression coefficients, their significance, and measures of model fit (R^2, R^2 change, and the *p*-values from the model fit ANOVA tests) are in Table 37 and Table 38, respectively, for *n* = 2 and *n* = 3.

Table 37. Standardized regression coefficients for set 2 mean accuracy switch costs, *n* = 2.

	Mean Accuracy Switch Costs, *n* = 2					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.24	.413	-0.55	.240	-0.10	.824
Negative Mood	0.15	.429	0.23	.402	0.14	.626
Positive Mood	0.16	.325	0.09	.761	0.20	.515
Rumination	-0.15	.377	**-0.80**	**.027**	**-1.04**	**.010***
CESD-R Threshold (above – below)	-0.03	.938	-0.38	.578	-0.15	.892

Negative Mood ✻ Condition			-0.42	.287	-0.09	.817
Positive Mood ✻ Condition			0.02	.963	-0.14	.704
Rumination ✻ Condition			0.56	.156	0.71	.326
Condition ✻ CESD-R Threshold			0.93	.231	0.56	.504
Negative Mood ✻ Rumination			-0.16	.488	-0.16	.530
CESD-R Threshold ✻ Rumination			1.08	.072	**1.66**	**.030***
Condition ✻ Negative Mood ✻ Rumination					-0.22	.664
Condition ✻ CESD-R Threshold ✻ Rumination					-0.91	.458
R^2	0.07	.647	0.23	.381	0.31	.262
R^2 Change			0.17	.225	0.07	.152
** $p < .01$, * $p < .05$						

Table 38. Standardized regression coefficients for set 2 mean accuracy switch costs, $n = 3$.

	Mean Accuracy Switch Costs, $n = 3$					
	Model 1		Model 2		Model 3	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*
Condition (non-emotional – emotional)	-0.49	.072	-0.29	.528	-0.30	.553
Negative Mood	0.21	.259	0.11	.681	0.11	.666
Positive Mood	0.02	.911	0.13	.680	0.09	.788
Rumination	-0.18	.271	-0.36	.336	-0.25	.591
CESD-R Threshold (above – below)	**-0.74**	**.039**	-0.44	.473	-0.48	.439
Negative Mood ✻ Condition			0.04	.926	0.06	.923
Positive Mood ✻ Condition			-0.19	.615	-0.19	.627
Rumination ✻ Condition			0.34	.384	-0.03	.912
Condition ✻ CESD-R Threshold			-0.30	.695	-0.28	.771
Negative Mood ✻ Rumination			0.07	.762	0.16	.545
CESD-R Threshold ✻ Rumination			0.15	.801	-0.19	.811
Condition ✻ Negative Mood ✻ Rumination					-0.33	.539
Condition ✻ CESD-R Threshold ✻ Rumination					0.94	.470
R^2	0.18	.095	0.22	.443	0.23	.582
R^2 Change			0.04	.906	0.01	.767
** $p < .01$, * $p < .05$						

In the $n = 3$ switch cost data, but only in model 1, CESD-R threshold status was a significant predictor (beta = -0.74, $p = .039$), although this effect's significance was eliminated upon the inclusion of the interactions of interest in models two and three. None of the models (main effects nor interactions) fit any better than simply using the mean for prediction, for any level of *n* in the mean accuracy set 2 data (see Table 39 and Table 40).

Table 39. Regression model fits for set 2 mean accuracy switch costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (2-way Interactions)		Model 3 (3-way Interactions)	
Switch, $n = 2$	$F(5, 46) = 0.67$	$p = .647$	$F(11, 40) = 1.12$	$p = .381$	$F(13, 38) = 1.29$	$p = .262$
Switch, $n = 3$	$F(5, 46) = 2.01$	$p = .095$	$F(11, 40) = 1.03$	$p = .443$	$F(13, 38) = 0.88$	$p = .582$

Table 40. Regression model comparisons for set 2 mean accuracy switch costs at all levels of *n*.

	Model 1 (Main Effects) – Model 2 (2-way Interactions)		Model 2 (2-way Interactions) – Model 3 (3-way Interactions)	
Switch, $n = 2$	$F(6, 40) = 1.44$	$p = .225$	$F(2, 38) = 1.98$	$p = .152$
Switch, $n = 3$	$F(6, 40) = 0.35$	$p = .906$	$F(2, 38) = 0.27$	$p = .767$

Cognitive Deficits: Set 1 ANOVA

I addressed the secondary question of whether there are mood-congruent or general deficits in the WM processes of updating and focus switching, by examining these effects in the set 1 emotional condition data at the trial valence level (i.e., comparing performance on negatively-valenced items with performance on neutrally-valenced items), as well as whether any such observed differences depend on depression and/or rumination. If participants with depression symptoms have general WM deficits, I expect them to have worse performance than those without depressive symptoms, regardless of trial valence. If participants with depressive symptoms have WM deficits only for mood congruent stimuli, then I expect them to have worse performance than their non-depressed counterparts only on negatively-valenced trials.

The within-subjects variables were *n*-level and trial valence. Trial valence was whether the stimulus on that trial was negatively-valenced or neutrally-valenced. Negative mood, positive mood, and rumination were entered as covariates. CESD-R threshold was a simple categorical factor with two levels: above threshold, which indicated the presence of depressive symptoms, and below threshold, which indicated the absence of any clinically significant depressive symptoms).

Set 1 ANOVA Updating Costs: Bin Scores. There was a significant effect of *n*-level, $F(2, 40) = 4.16$, $p = .023$, , $\eta^2_p = .172$. Specifically, the $n = 1$ updating cost was greater than the $n = 2$ updating cost (mean difference = 0.628), $t(20) = 4.76$, $p_{\text{Tukey}} < .001$. No other effects were significant (all *p*-values > .05, see Table 41).

Table 41. Set 1 ANOVA bin score updating cost effects.

Within Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	$\eta^2 p$
***N*-Level**	**6.42**	**2**	**3.21**	**4.16**	**.023***	**0.172**
N-Level ✻ Negative Mood	0.02	2	0.01	0.01	.990	0.001
N-Level ✻ Positive Mood	1.55	2	0.77	1.00	.376	0.048
N-Level ✻ Rumination	1.26	2	0.63	0.81	.451	0.039
N-Level ✻ CESD-R Threshold	0.67	2	0.34	0.43	.651	0.021
Residual	30.88	40	0.77			
Trial Valence	0.11	1	0.11	0.10	.752	0.005
Trial Valence ✻ Negative Mood	0.66	1	0.66	0.63	.436	0.031
Trial Valence ✻ Positive Mood	0.10	1	0.10	0.09	.765	0.005
Trial Valence ✻ Rumination	0.94	1	0.94	0.90	.354	0.043
Trial Valence ✻ CESD-R Threshold	0.02	1	0.02	0.02	.883	0.001
Residual	20.96	20	1.05			
N-Level ✻ Trial Valence	3.37	2	1.68	3.26	.049	0.140

N-Level ✻ Trial Valence ✻ Negative Mood	1.09	2	0.55	1.05	.358	0.050
N-Level ✻ Trial Valence ✻ Positive Mood	1.52	2	0.76	1.47	.243	0.068
N-Level ✻ Trial Valence ✻ Rumination	0.36	2	0.18	0.35	.705	0.017
N-Level ✻ Trial Valence ✻ CESD-R Threshold	0.13	2	0.07	0.13	.879	0.006
Residual	20.69	40	0.52			

Between Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	*η²p*
CESD-R Threshold	0.0288	1	0.0288	0.00403	.950	0
Negative Mood	0.0877	1	0.0877	0.01227	.913	0.001
Positive Mood	2.3612	1	2.3612	0.33032	.572	0.016
Rumination	2.6432	1	2.6432	0.36976	.550	0.018
Residual	142.9666	20	7.1483			

Note. Type 3 Sums of Squares
** $p < .01$, * $p < .05$

Set 1 ANOVA Switch Costs: Bin Scores. The main effect of *n*-level was significant, $F(1, 20) = 13.73$, $p = .001$, $\eta^2_p = .407$. Specifically, $n = 2$ had greater switch costs than $n = 3$ (mean difference = 1.21), $t(20) = 3.21$, $p_{tukey} = .004$. There was also a significant main effect of trial valence, $F(1, 20) = 33.52$, $p < .001$, $\eta^2_p = .626$; the switch cost for neutral trials was slightly higher than for negative trials (mean difference = 1.86), $t(20) = -6.35$, $p < .001$. No other effects were significant (all $p > .05$, see Table 42).

Table 42. Set 1 ANOVA bin score switch cost effects.

Within Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*P*	*η²p*
***N*-Level**	**47.13**	**1**	**47.13**	**13.73**	**.001****	**0.407**
N-Level ✻ Negative Mood	0.00	1	0.00	0.00	.981	0.000
N-Level ✻ Positive Mood	9.31	1	9.31	2.71	.115	0.119
N-Level ✻ Rumination	2.20	1	2.20	0.64	.433	0.031
N-Level ✻ CESD-R Threshold	0.00	1	0.00	0.00	.973	0.000
Residual	68.67	20	3.43			
Trial Valence	**69.85**	**1**	**69.85**	**33.52**	**< .001****	**0.626**

Trial Valence ✻ Negative Mood	0.54	1	0.54	0.26	.617	0.013
Trial Valence ✻ Positive Mood	0.00	1	0.00	0.00	.962	0.000
Trial Valence ✻ Rumination	3.49	1	3.49	1.68	.210	0.077
Trial Valence ✻ CESD-R Threshold	1.20	1	1.20	0.58	.457	0.028
Residual	41.67	20	2.08			
N-Level ✻ Trial Valence	0.45	1	0.45	0.41	.530	0.020
N-Level ✻ Trial Valence ✻ Negative Mood	0.02	1	0.02	0.02	.884	0.001
N-Level ✻ Trial Valence ✻ Positive Mood	0.56	1	0.56	0.51	.485	0.025
N-Level ✻ Trial Valence ✻ Rumination	0.26	1	0.26	0.24	.630	0.012
N-Level ✻ Trial Valence ✻ CESD-R Threshold	0.18	1	0.18	0.16	.693	0.008
Residual	22.03	20	1.10			

Between Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
CESD-R Threshold	1.56	1	1.56	0.25	.626	0.012
Negative Mood	0.29	1	0.29	0.04	.835	0.002
Positive Mood	7.32	1	7.32	1.15	.297	0.054
Rumination	0.23	1	0.23	0.04	.850	0.002
Residual	127.40	20	6.37			

Note. Type 3 Sums of Squares
** $p < .01$, * $p < .05$

Set 1 ANOVA Updating Costs: Median RT Difference Scores. No within-subject effects were significant (all *p*-values > .05). No between-subject effects were significant either (all *p*-values > .05). These effects are shown in Table 43.

Table 43. Set 1 ANOVA median RT updating cost effects.

Within Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
N-Level	158278	2	79139	1.7347	.189	0.08
N-Level ✻ CESD-R Threshold	1173	2	586	0.0129	.987	0.001
N-Level ✻ Negative Mood	62035	2	31018	0.6799	.512	0.033
N-Level ✻ Positive Mood	39613	2	19807	0.4341	.651	0.021
N-Level ✻ Rumination	94124	2	47062	1.0316	.366	0.049
Residual	1.82E+06	40	45622			
Trial Valence	35643	1	35643	3.4685	.077	0.148

Trial Valence ✻ CESD-R Threshold	726	1	726	0.0706	.793	0.004
Trial Valence ✻ Negative Mood	2014	1	2014	0.196	.663	0.01
Trial Valence ✻ Positive Mood	3022	1	3022	0.294	.594	0.014
Trial Valence ✻ Rumination	11601	1	11601	1.129	.301	0.053
Residual	205521	20	10276			
N-Level ✻ Trial Valence	26839	2	13420	1.1398	.330	0.054
N-Level ✻ Trial Valence ✻ CESD-R Threshold	46411	2	23206	1.971	.153	0.09
N-Level ✻ Trial Valence ✻ Negative Mood	20437	2	10219	0.8679	.428	0.042
N-Level ✻ Trial Valence ✻ Positive Mood	5252	2	2626	0.2231	.801	0.011
N-Level ✻ Trial Valence ✻ Rumination	38121	2	19060	1.6189	.211	0.075
Residual	470938	40	11773			

Between Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*P*	*η²p*
CESD-R Threshold	75331	1	75331	0.413	.528	0.02
Negative Mood	42735	1	42735	0.234	.634	0.012
Positive Mood	94030	1	94030	0.516	.481	0.025
Rumination	134108	1	134108	0.736	.401	0.035
Residual	3.65E+06	20	182308			

Note. Type 3 Sums of Squares
** $p < .01$, * $p < .05$

Set 1 ANOVA Switch Costs: Median RT Difference Scores. No within-subject effects were significant (all p-values > .05), nor were any between-subject effects significant (all *p*-values > .30). These effects are displayed in Table 44.

Table 44. Set 1 ANOVA median RT switch cost effects.

Within Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	*η²p*
Trial Valence	10807	1	10807	0.49	.490	0.024
Trial Valence ✻ Negative Mood	42892	1	42892	1.96	.177	0.089
Trial Valence ✻ Positive Mood	816	1	816	0.04	.849	0.002
Trial Valence ✻ Rumination	1444	1	1444	0.07	.800	0.003
Trial Valence ✻ CESD-R Threshold	1119	1	1119	0.05	.823	0.003

Residual	437593	20	21880			
N-Level	3602	1	3602	0.06	.811	0.003
N-Level ✻ Negative Mood	50606	1	50606	0.83	.374	0.040
N-Level ✻ Positive Mood	53915	1	53915	0.88	.359	0.042
N-Level ✻ Rumination	37469	1	37469	0.61	.443	0.030
N-Level ✻ CESD-R Threshold	71621	1	71621	1.17	.292	0.055
Residual	1.22E+06	20	61130			
Trial Valence ✻ *N*-Level	37153	1	37153	4.06	.058	0.169
Trial Valence ✻ *N*-Level ✻ Negative Mood	18986	1	18986	2.07	.165	0.094
Trial Valence ✻ *N*-Level ✻ Positive Mood	13336	1	13336	1.46	.242	0.068
Trial Valence ✻ *N*-Level ✻ Rumination	26766	1	26766	2.92	.103	0.127
Trial Valence ✻ *N*-Level ✻ CESD-R Threshold	32359	1	32359	3.53	.075	0.150
Residual	183205	20	9160			
Between Subjects Effects						
	Sum of Squares	df	Mean Square	*F*	*p*	$\eta^2 p$
CESD-R Threshold	179873	1	179873	1.21	.285	0.057
Negative Mood	11343	1	11343	0.08	.786	0.004
Positive Mood	81124	1	81124	0.54	.470	0.026
Rumination	48535	1	48535	0.33	.575	0.016
Residual	2.99E+06	20	149264			

Note. Type 3 Sums of Squares
** $p < .01$, * $p < .05$

Set 1 ANOVA Updating Costs: Mean Accuracy Difference Scores. There was a significant effect of trial valence, $F(1, 20) = 5.40$, $p = .031$, $\eta^2_p = .213$. Specifically, there was a slightly greater accuracy updating cost for neutral trials than for negative trials (mean difference = 0.04, $t(20) = 2.12$, $p_{\text{Tukey}} = .047$. This is not what I would expect if there were mood congruent WM deficits. No other effects were significant (all *p*-values > .05). These effects are shown in Table 45.

Table 45. Set 1 ANOVA mean accuracy updating cost effects.

Within Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	*η²p*
N-Level	0.00	2	0.00	0.16	.853	0.008
N-Level ✻ CESD-R Threshold	0.01	2	0.00	0.33	.722	0.016
N-Level ✻ Rumination	0.01	2	0.01	0.53	.595	0.026
N-Level ✻ Positive Mood	0.01	2	0.00	0.25	.778	0.012
N-Level ✻ Negative Mood	0.01	2	0.00	0.41	.670	0.020
Residual	0.43	40	0.01			
Trial Valence	**0.07**	**1**	**0.07**	**5.40**	**.031***	**0.213**
Trial Valence ✻ CESD-R Threshold	0.01	1	0.01	0.47	.501	0.023
Trial Valence ✻ Rumination	0.00	1	0.00	0.30	.593	0.015
Trial Valence ✻ Positive Mood	0.01	1	0.01	0.49	.494	0.024
Trial Valence ✻ Negative Mood	0.00	1	0.00	0.08	.774	0.004
Residual	0.25	20	0.01			
N-Level ✻ Trial Valence	0.00	2	0.00	0.14	.870	0.007
N-Level ✻ Trial Valence ✻ CESD-R Threshold	0.00	2	0.00	0.06	.940	0.003
N-Level ✻ Trial Valence ✻ Rumination	0.00	2	0.00	0.24	.788	0.012
N-Level ✻ Trial Valence ✻ Positive Mood	0.01	2	0.00	0.54	.586	0.026
N-Level ✻ Trial Valence ✻ Negative Mood	0.01	2	0.00	0.32	.729	0.016
Residual	0.33	40	0.01			

Between Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	*η²p*
CESD-R Threshold	0.00	1	0.00	0.02	.904	0.001
Rumination	0.00	1	0.00	0.06	.813	0.003
Positive Mood	0.00	1	0.00	0.07	.793	0.004
Negative Mood	0.00	1	0.00	0.00	.956	0.000
Residual	1.09	20	0.05			

Note. Type 3 Sums of Squares
** $p < .01$, * $p < .05$

Set 1 ANOVA Switch Costs: Mean Accuracy Difference Scores. There was a significant interaction between *n*-level and trial valence, $F(1, 20) = 5.17$, $p = .034$, $\eta^2_p = .205$. None of the post hoc pairwise comparisons for this interaction were significant (all Tukey corrected *p*-values > .10). However, there is a cross-over interaction based on the estimated marginal means plot (see Figure 6), where the marginal difference between negative and neutral trial valence switch costs reverses from $n = 2$ to $n = 3$. Since these pairwise differences were non-significant, this probably is not interesting. No other effects were significant (all *p*-values > .05); these are shown in Table 46.

Table 46. Set 1 ANOVA mean accuracy switch cost effects.

Within Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
N-Level	0.00	1	0.00	0.50	.488	0.024
N-Level ✻ Negative Mood	0.00	1	0.00	1.07	.312	0.051
N-Level ✻ Positive Mood	0.00	1	0.00	0.13	.726	0.006
N-Level ✻ Rumination	0.01	1	0.01	3.15	.091	0.136
N-Level ✻ CESD-R Threshold	0.00	1	0.00	0.00	.977	0
Residual	0.05	20	0.00			
Trial Valence	0.00	1	0.00	0.01	.914	0.001
Trial Valence ✻ Negative Mood	0.00	1	0.00	0.28	.603	0.014
Trial Valence ✻ Positive Mood	0.00	1	0.00	0.46	.506	0.022
Trial Valence ✻ Rumination	0.00	1	0.00	0.00	.974	0
Trial Valence ✻ CESD-R Threshold	0.00	1	0.00	0.30	.591	0.015
Residual	0.17	20	0.01			
***N*-Level ✻ Trial Valence**	**0.03**	**1**	**0.03**	**5.17**	**.034***	**0.205**
N-Level ✻ Trial Valence ✻ Negative Mood	0.00	1	0.00	0.06	.805	0.003
N-Level ✻ Trial Valence ✻ Positive Mood	0.00	1	0.00	0.07	.793	0.004
N-Level ✻ Trial Valence ✻ Rumination	0.00	1	0.00	0.12	.737	0.006
N-Level ✻ Trial Valence ✻ CESD-R Threshold	0.00	1	0.00	0.86	.364	0.041
Residual	0.10	20	0.01			

Between Subjects Effects

	Sum of Squares	df	Mean Square	*F*	*p*	η^2p
CESD-R Threshold	0.00	1	0.00	0.23	.635	0.011
Negative Mood	0.00	1	0.00	0.49	.494	0.024
Positive Mood	0.00	1	0.00	0.46	.504	0.023
Rumination	0.01	1	0.01	1.14	.298	0.054
Residual	0.19	20	0.01			

Note. Type 3 Sums of Squares
** $p < .01$, * $p < .05$

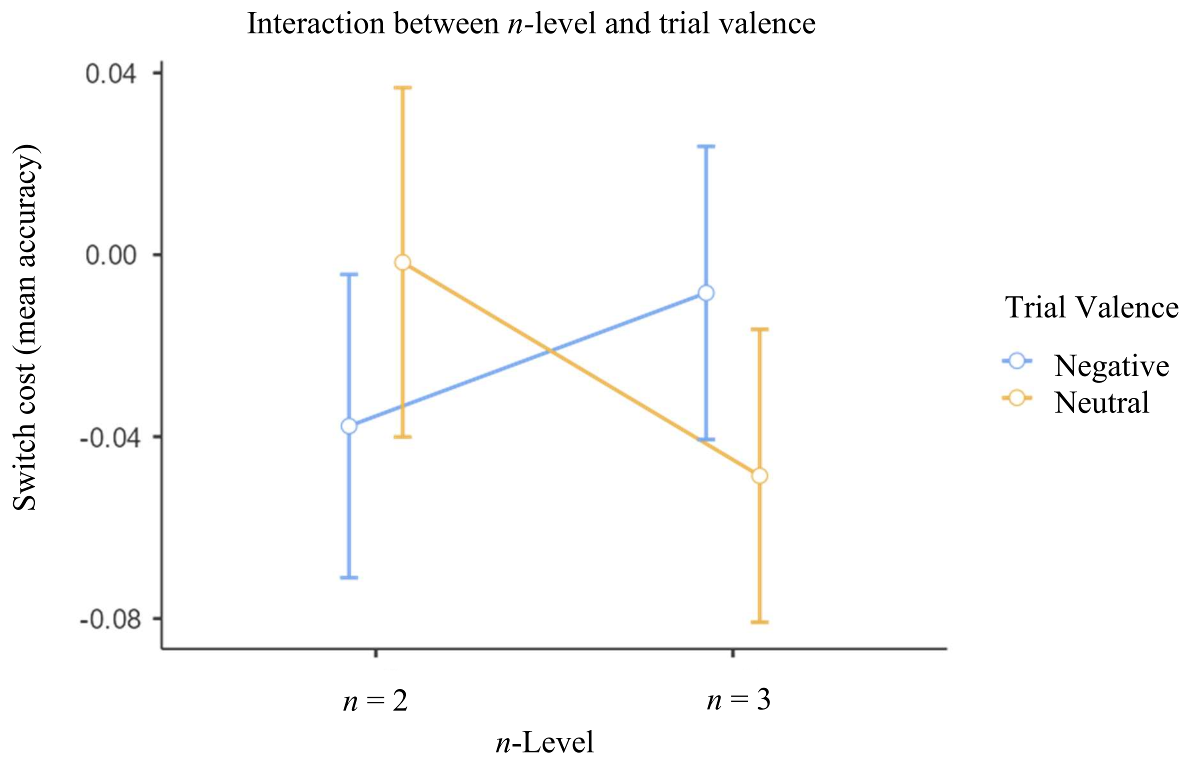


Figure 6. Interaction between *n*-level and trial valence on mean accuracy switch costs in set 1.

Cognitive Deficits: Set 1 Regression Analyses

For the set 1 data, I used linear regression to predict the updating costs and switch costs from the mood and rumination survey measures for both negatively and neutrally valence trials. I did this in two steps. In model 1, I included only the main effects of negative mood, positive mood, rumination, and CESD-R threshold status. In model 2, I added two two-way interactions: negative mood*rumination and CESD-R threshold*rumination.

If there are general WM deficits related to depression, I expect to see them in both the neutrally-valenced and negatively-valenced trials. If there are only mood congruent WM deficits, I expect to see them in only the negatively-valenced trials.

Set 1 Regression Updating Costs: Bin Scores. Condition, negative mood, positive mood, rumination, and CESD-R threshold status were not predictive of updating costs on negatively-valenced nor on neutrally-valenced trials in the set 1 bin score data at any level of *n*, nor were the interactions between negative mood and rumination and between CESD-R status and rumination. These standardized regression coefficients, their significance, and measures of model fit (R^2 and the *p*-values from the model fit ANOVA tests) are displayed in Table 47, Table 48 and Table 49, for each level of *n*, respectively. None of the set 1 bin score updating cost regression models were any better than simply using the mean for prediction (see Table 50).

Table 47. Standardized regression coefficients and model fit for bin score updating costs on negative and neutral trials at $n = 1$.

	Bin Score Updating Costs, $n = 1$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	-0.02	.946	0.06	.854	0.12	.686	0.24	.452
Positive Mood	-0.29	.365	-0.31	.376	-0.32	.323	-0.40	.257
Rumination	0.09	.765	0.09	.891	-0.14	.668	0.00	.961
CESD-R Threshold (above – below)	0.16	.785	0.03	.959	0.18	.764	-0.05	.930
Negative Mood ✻ Rumination			-0.22	.497			-0.17	.588
CESD-R Threshold ✻ Rumination			0.14	.873			-0.22	.795
R^2	0.16	.444	0.20	.612	0.13	.572	0.20	.615
R^2 Change			0.04	.653			0.07	.466
** $p < .01$, * $p < .05$								

Table 48. Standardized regression coefficients and model fit for bin score updating costs on negative and neutral trials at $n = 2$.

	Bin Score Updating Costs, $n = 2$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	

Predictor	beta	p	beta	p	beta	p	beta	p
Negative Mood	0.15	.616	0.17	.607	-0.12	.686	0.05	.872
Positive Mood	-0.15	.639	-0.04	.899	0.13	.708	-0.02	.951
Rumination	0.17	.610	-0.19	.607	0.20	.558	0.51	.290
CESD-R Threshold (above – below)	-0.19	.761	-0.13	.878	0.01	.988	-0.36	.560
Negative Mood ✻ Rumination			-0.43	.191			-0.13	.681
CESD-R Threshold ✻ Rumination			1.09	.215			-0.68	.435
R^2	0.11	.663	0.20	.631	0.02	.979	0.18	.678
R^2 Change			0.09	.393			0.16	.199
** $p < .01$, * $p < .05$								

Table 49. Standardized regression coefficients and model fit for bin score updating costs on negative and neutral trials at $n = 3$.

	Bin Score Updating Costs, $n = 3$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	beta	p	beta	p	beta	p	beta	p
Negative Mood	0.15	.577	0.06	.828	-0.15	.604	-0.14	.676
Positive Mood	0.04	.882	0.17	.595	-0.30	.365	-0.40	.270
Rumination	0.47	.128	0.15	.755	0.15	.630	0.45	.318
CESD-R Threshold (above – below)	-0.18	.743	0.04	.917	-0.20	.738	-0.30	.626
Negative Mood ✻ Rumination			-0.11	.714			0.27	.413
CESD-R Threshold ✻ Rumination			0.82	.308			-0.85	.340
R^2	0.24	.218	0.30	.303	0.12	.627	0.16	.742
R^2 Change			0.06	.455			0.05	.623
** $p < .01$, * $p < .05$								

Table 50. Model fits for set 1 bin score updating costs at all levels of n.

	Model 1 (Main Effects)		Model 2 (Interactions)		Model 1 v. Model 2	
Bin Score Updating cost, $n = 1$, negative	$F(4, 20) = 0.97$	$p = .444$	$F(6, 18) = 0.76$	$p = .612$	$F(2, 18) = 0.44$	$p = .653$
Bin Score Updating Cost, $n = 2$, negative	$F(4, 20) = 0.61$	$p = .663$	$F(6, 18) = 0.73$	$p = .631$	$F(2, 18) = 0.98$	$p = .393$
Bin Score Updating Cost, $n = 3$, negative	$F(4, 20) = 1.58$	$p = .218$	$F(6, 18) = 1.31$	$p = .303$	$F(2, 18) = 0.82$	$p = .455$

Bin Score Updating cost, n = 1, neutral	$F(4, 20) = 0.75$	$p = .572$	$F(6, 18) = 0.753$	$p = .615$	$F(2, 18) = 0.80$	$p = .466$
Bin Score Updating Cost, n = 2, neutral	$F(4, 20) = 0.11$	$p = .979$	$F(6, 18) = 0.67$	$p = .678$	$F(2, 18) = 1.77$	$p = .199$
Bin Score Updating Cost, n = 3, neutral	$F(4, 20) = 0.67$	$p = .627$	$F(6, 18) = 0.58$	$p = .742$	$F(2, 18) = 0.49$	$p = .623$

Set 1 Regression Switch Costs: Bin Scores. Condition, negative mood, positive mood, rumination, and CESD-R threshold status were not predictive switch costs on negative trials nor on neutral trials at any level of *n* in the set 1 bin score data, nor were the interactions between negative mood and rumination and between CESD-R status and rumination. The standardized regression coefficients, their significance, and measures of model fit (R^2 and the *p*-values from the model fit ANOVA tests), for each level of *n,* can be found in Table 51 and Table 52. None of the set 1 bin score switch cost regression models were any better than simply using the mean for prediction (see Table 53).

Table 51. Standardized regression coefficients and model fit for bin score switch costs on negative and neutral trials at $n = 2$.

	Bin Score Switch Costs, n = 2							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	0.12	.656	0.06	.833	-0.0252	.931	-0.0305	.933
Positive Mood	0.63	.048	0.68	.053	0.3595	.281	0.3265	.376
Rumination	0.42	.170	0.31	.477	-0.0291	.928	0.0766	.853
CESD-R Threshold (above – below)	-0.06	.915	0.06	.910	0.3559	.562	0.3369	.632
Negative Mood ✻ Rumination			0.04	.887			0.1215	.718
CESD-R Threshold ✻ Rumination			0.23	.782			-0.3194	.724
R^2	0.24	.212	0.26	.422	0.10	.713	0.10	.347
R^2 Change			0.02	.808			0.01	.929
** $p < .01$, * $p < .05$								

Table 52. Standardized regression coefficients and model fit for bin score switch costs on negative and neutral trials at $n = 3$.

	Bin Score Switch Costs, $n = 3$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	0.10	.738	-0.01	.984	-1.19e−4	1.00	0.04	.905
Positive Mood	-0.11	.736	-0.03	.928	0.05	.884	0.02	.959
Rumination	0.03	.918	-0.12	.820	-0.24	.466	-0.18	.705
CESD-R Threshold (above – below)	0.12	.853	0.34	.611	0.39	.537	0.31	.666
Negative Mood ✻ Rumination			0.12	.714			-0.04	.896
CESD-R Threshold ✻ Rumination			0.31	.732			-0.12	.900
R^2	0.06	.861	0.12	.863	0.06	.869	0.07	.968
R^2 Change			0.06	.553			0.01	.924
** $p < .01$, * $p < .05$								

Table 53. Regression model fits for set 1 bin score switch costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (Interactions)		Model 1 v. Model 2	
Bin Score Switch Cost, $n = 2$, negative	$F(4, 20) = 1.61$	$p = .212$	$F(6, 18) = 1.06$	$p = .422$	$F(2, 18) = 0.22$	$p = .808$
Bin Score Swich Cost, $n = 3$, negative	$F(4, 20) = 0.32$	$p = .861$	$F(6, 18) = 0.41$	$p = .863$	$F(2, 18) = 0.61$	$p = .553$
Bin Score Switch Cost, $n = 2$, neutral	$F(4, 20) = 0.53$	$p = .713$	$F(6, 18) = 0.35$	$p = .902$	$F(2, 18) = 0.07$	$p = .929$
Bin Score Switch Cost, $n = 3$, neutral	$F(4, 20) = 0.31$	$p = .869$	$F(6, 18) = 0.21$	$p = .968$	$F(2, 18) = 0.08$	$p = .924$

Set 1 Regression Updating Costs: Median RT Difference Scores. Condition, negative mood, positive mood, rumination, and CESD-R threshold status were not predictive of updating costs on negative nor on neutral trials in the set 1 median RT data at any level of *n,* nor were the interactions between negative mood and rumination and between CESD-R status and rumination. Table 54, Table 55, and Table 56 contain these standardized regression coefficients, their significance, and measures of model fit (R^2 and the *p*-values from the model fit ANOVA tests)

for each level of n. None of the set 1 median RT updating cost regression models were any better than simply using the mean for prediction (see Table 57).

Table 54. Standardized regression coefficients and model fit for median RT updating costs on negative and neutral trials at $n = 1$.

	Median RT Updating Costs, $n = 1$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	-0.05	.867	-0.05	.899	0.20	.497	0.14	.640
Positive Mood	0.13	.708	0.06	.871	0.00	.996	0.00	.992
Rumination	0.10	.770	0.30	.522	-0.16	.630	-0.10	.862
CESD-R Threshold (above – below)	-0.01	.987	-0.07	.903	-0.65	.290	-0.57	.392
Negative Mood ✻ Rumination			0.20	.566			0.19	.559
CESD-R Threshold ✻ Rumination			-0.60	.526			-0.23	.797
R^2	0.01	.993	0.03	.994	0.11	.645	0.14	.823
R^2 Change			0.02	.808			0.02	.793
** $p < .01$, * $p < .05$								

Table 55. Standardized regression coefficients and model fit for median RT updating costs on negative and neutral trials at $n = 2$.

	Median RT Updating Costs, $n = 2$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	-0.16	.556	-0.09	.763	-0.23	.440	-0.16	.638
Positive Mood	0.25	.413	0.12	.704	0.07	.833	-0.08	.830
Rumination	0.52	.095	0.85	.056	0.11	.735	0.50	.279
CESD-R Threshold (above – below)	-0.66	.248	-0.86	.155	-0.06	.927	-0.29	.639
Negative Mood ✻ Rumination			0.17	.578			0.20	.543
CESD-R Threshold ✻ Rumination			-0.89	.276			-1.05	.249
R^2	0.48	.245	0.29	.341	0.05	.891	0.13	.827
R^2 Change			0.06	0.480			0.08	0.446

** $p < .01$, * $p < .05$

Table 56. Standardized regression coefficients and model fit for median RT updating costs on negative and neutral trials at $n = 3$.

	Median RT Updating Costs, $n = 3$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	-0.20	.481	-0.17	.596	-0.16	.592	-0.09	.782
Positive Mood	0.30	.360	0.15	.656	0.32	.326	0.23	.523
Rumination	0.27	.399	0.69	.120	0.42	.201	0.66	.170
CESD-R Threshold (above – below)	-0.20	.736	-0.37	.531	-0.26	.673	-0.42	.505
Negative Mood ✻ Rumination			0.35	.277			0.08	.817
CESD-R Threshold ✻ Rumination			-1.20	.167			-0.61	.487
R^2	0.12	.599	0.21	.571	0.12	.595	0.16	.746
R^2 Change			0.09	.375			0.04	.682
** $p < .01$, * $p < .05$								

Table 57. Regression model fits for set 1 median RT updating costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (Interactions)		Model 1 v. Model 2	
Median RT Updating cost, $n = 1$, negative	$F(4, 20) = 0.06$	$p = .993$	$F(6, 18) = 0.11$	$p = .994$	$F(2, 18) = 0.22$	$p = .808$
Median RT Updating Cost, $n = 2$, negative	$F(4, 20) = 1.48$	$p = .245$	$F(6, 18) = 1.22$	$p = .341$	$F(2, 18) = 0.76$	$p = .480$
Median RT Updating Cost, $n = 3$, negative	$F(4, 20) = 0.70$	$p = .599$	$F(6, 18) = 0.82$	$p = .571$	$F(2, 18) = 1.04$	$p = .375$
Median RT Updating cost, $n = 1$, neutral	$F(4, 20) = 0.63$	$p = .645$	$F(6, 18) = 0.468$	$p = .823$	$F(2, 18) = 0.24$	$p = .793$
Median RT Updating Cost, $n = 2$, neutral	$F(4, 20) = 0.28$	$p = .891$	$F(6, 18) = 0.468$	$p = .827$	$F(2, 18) = 0.846$	$p = .446$
Median RT Updating Cost, $n = 3$, neutral	$F(4, 20) = 0.71$	$p = .595$	$F(6, 18) = 0.574$	$p = .746$	$F(2, 18) = 0.390$	$p = .682$

Set 1 Regression Switch Costs: Median RT Difference Scores. Condition, negative mood, positive mood, rumination, and CESD-R threshold status were not predictive of switch

costs on negative or neutral trials in the set 1 median RT data at any level of *n*. Table 58 and Table 59 contain these standardized regression coefficients, their significance, and measures of model fit (R^2 and the *p*-values from the model fit ANOVA tests), for $n = 2$ and $n = 3$, respectively. None of the set 1 median RT switch cost regression models were any better than simply using the mean for prediction (see Table 60).

Table 58. Standardized regression coefficients and model fit for median RT switch costs on negative and neutral trials at $n = 2$.

	Median RT Switch Costs, $n = 2$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	0.39	.163	0.44	.149	-0.01	.975	0.01	.958
Positive Mood	-0.43	.172	-0.33	.315	-0.28	.395	-0.36	.330
Rumination	-0.40	.203	-0.75	.074	-0.16	.626	0.05	.880
CESD-R Threshold (above – below)	-1.10	.067	-1.08	.095	-0.67	.278	-0.76	.257
Negative Mood ✻ Rumination			-0.47	.122			0.16	.625
CESD-R Threshold ✻ Rumination			1.11	.175			-0.60	.507
R^2	0.20	.315	0.31	.299	0.10	.691	0.12	.853
R^2 Change			0.10	.287			0.02	.796
** $p < .01$, * $p < .05$								

Table 59. Standardized regression coefficients and model fit for median RT switch costs on negative and neutral trials at $n = 3$.

	Median RT Switch Costs, $n = 3$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	-0.03	.929	-0.05	.859	-0.11	.720	-0.14	.661
Positive Mood	0.02	.950	0.17	.633	-0.09	.790	0.00	.995
Rumination	0.06	.858	-0.39	.370	-0.10	.771	-0.34	.471
CESD-R Threshold (above – below)	-0.01	.985	0.14	.798	-0.36	.564	-0.25	.741
Negative Mood ✻ Rumination			-0.42	.220			-0.17	.623
CESD-R Threshold ✻ Rumination			1.32	.156			0.66	.466
R^2	0.00	1.00	0.11	.884	0.07	.805	0.10	.904
R^2 Change			0.11	.351			0.03	.754
** $p < .01$, * $p < .05$								

Table 60. Regression model fits for set 1 median RT switch costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (Interactions)		Model 1 v. Model 2	
Median RT Switch Cost, $n = 2$, negative	$F(4, 20) = 1.27$	$p = .315$	$F(6, 18) = 1.32$	$p = .299$	$F(2, 18) = 1.34$	$p = .287$
Median RT Swich Cost, $n = 3$, negative	$F(4, 20) = 0.01$	$p = 1.00$	$F(6, 18) = 0.38$	$p = .884$	$F(2, 18) = 1.11$	$p = .351$
Median RT Switch Cost, $n = 2$, neutral	$F(4, 20) = 0.57$	$p = .691$	$F(6, 18) = 0.42$	$p = .853$	$F(2, 18) = 0.23$	$p = .796$
Median RT Switch Cost, $n = 3$, neutral	$F(4, 20) = 0.40$	$p = .805$	$F(6, 18) = 0.34$	$p = .904$	$F(2, 18) = 0.29$	$p = .754$

Set 1 Regression Updating Costs: Mean Accuracy Difference Scores. Condition, negative mood, positive mood, rumination, and CESD-R threshold status were not predictive of updating costs on negative nor on neutral trials in the set 1 mean accuracy data at any level of *n*, nor were the interactions between rumination and negative mood and between CESD-R status and negative mood. Table 61, Table 62, and Table 63 contain these standardized regression coefficients, their significance, and measures of model fit (R^2 and the *p*-values from the model fit

ANOVA tests) for each level of *n*. None of the set 1 mean accuracy updating cost regression models were any better than simply using the mean for prediction (see Table 64).

Table 61. Standardized regression coefficients and model fit for mean accuracy updating costs on negative and neutral trials at *n* = 1.

	Mean Accuracy Updating Costs, *n* = 1							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	0.02	.925	-0.08	.787	0.01	.970	-0.04	.910
Positive Mood	0.11	.757	0.26	.477	0.18	.590	0.22	.557
Rumination	-2.44e−4	.999	-0.38	.422	0.16	.640	0.08	.863
CESD-R Threshold (above – below)	-0.18	.782	0.11	.843	-0.05	.942	0.06	.930
Negative Mood ✻ Rumination			-0.10	.767			0.05	.879
CESD-R Threshold ✻ Rumination			0.96	.292			0.15	.870
R^2	0.03	.968	0.12	.855	0.02	.975	0.04	.994
R^2 Change			0.10	.389			0.01	.887
** $p < .01$, * $p < .05$								

Table 62. Standardized regression coefficients and model fit for mean accuracy updating costs on negative and neutral trials at *n* = 2.

	Mean Accuracy Updating Costs, *n* = 2							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	0.09	.767	0.04	.884	0.05	.870	-0.16	.614
Positive Mood	0.02	.957	-0.02	.967	-0.01	.967	0.10	.769
Rumination	-0.07	.836	0.07	.834	-0.14	.682	-0.31	.540
CESD-R Threshold (above – below)	-0.18	.774	-0.14	.827	0.29	.645	0.68	.279
Negative Mood ✻ Rumination			0.28	.428			0.36	.251
CESD-R Threshold ✻ Rumination			-0.50	.594			0.22	.790
R^2	0.01	.989	0.05	.984	0.03	.970	0.25	.471
R^2 Change			0.04	.715			0.22	.100
** $p < .01$, * $p < .05$								

Table 63. Standardized regression coefficients and model fit for mean accuracy updating costs on negative and neutral trials at $n = 3$.

	Mean Accuracy Updating Costs, $n = 3$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	-0.31	.262	-0.26	.390	-0.01	.980	-0.04	.892
Positive Mood	-0.24	.436	-0.38	.256	0.29	.391	0.41	.263
Rumination	-0.35	.258	0.03	.899	-0.05	.877	-0.40	.374
CESD-R Threshold (above – below)	0.16	.780	-0.03	.926	0.48	.442	0.62	.343
Negative Mood ✻ Rumination			0.25	.418			-0.28	.394
CESD-R Threshold ✻ Rumination			-1.04	.212			0.99	.275
R^2	0.21	.306	0.28	.376	0.07	.828	0.13	.837
R^2 Change			0.07	.430			0.06	.542
** $p < .01$, * $p < .05$								

Table 64. Regression model fits for set 1 mean accuracy updating costs at all levels of n.

	Model 1 (Main Effects)		Model 2 (Interactions)		Model 1 v. Model 2	
Mean Accuracy Updating cost, $n = 1$, negative	$F(4, 20) = 0.14$	$p = .968$	$F(6, 18) = 0.42$	$p = .855$	$F(2, 18) = 1.00$	$p = .389$
Mean Accuracy Updating Cost, $n = 2$, negative	$F(4, 20) = 0.07$	$p = .989$	$F(6, 18) = 0.16$	$p = .984$	$F(2, 18) = 0.34$	$p = .715$
Mean Accuracy Updating Cost, $n = 3$, negative	$F(4, 20) = 1.29$	$p = .306$	$F(6, 18) = 1.15$	$p = .376$	$F(2, 18) = 0.89$	$p = .430$
Mean Accuracy Updating cost, $n = 1$, neutral	$F(4, 20) = 0.12$	$p = .975$	$F(6, 18) = 0.11$	$p = .994$	$F(2, 18) = 0.12$	$p = .887$
Mean Accuracy Updating Cost, $n = 2$, neutral	$F(4, 20) = 0.13$	$p = .970$	$F(6, 18) = 0.97$	$p = .471$	$F(2, 18) = 2.62$	$p = .100$
Mean Accuracy Updating Cost, $n = 3$, neutral	$F(4, 20) = 0.37$	$p = .828$	$F(6, 18) = 0.45$	$p = .837$	$F(2, 18) = 0.06$	$p = .542$

Set 1 Regression Switch Costs: Mean Accuracy Difference Scores. Condition, negative mood, positive mood, rumination, and CESD-R threshold status were not predictive of switch costs on negative or neutral trials in the set 1 mean accuracy data at any level of n, nor

were the interactions between rumination and negative mood and between CESD-R status and negative mood. Table 65 and Table 66 contain these standardized regression coefficients, their significance, and measures of model fit (R^2 and the p-values from the model fit ANOVA tests) for each level of *n*, respectively. None of the set 1 mean accuracy switch cost regression models fit any better than simply using the mean for prediction (see Table 67).

Table 65. Standardized regression coefficients and model fit for mean accuracy switch costs on negative and neutral trials at all levels of $n = 2$.

	Mean Accuracy Switch Costs, $n = 2$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	0.345	.245	0.48	.137	0.09	.766	0.19	.557
Positive Mood	-0.265	.423	-0.35	.324	-0.07	.822	-0.05	.881
Rumination	-0.354	.280	-0.21	.623	-0.38	.245	-0.53	.215
CESD-R Threshold (above – below)	-0.126	.836	-0.38	.552	-0.21	.725	-0.34	.611
Negative Mood ✻ Rumination			-0.19	.552			-0.42	.189
CESD-R Threshold ✻ Rumination			-0.24	.777			0.60	.484
R^2	0.10	.695	0.19	.660	0.12	.617	0.22	.566
R^2 Change			0.09	.403			0.10	.352
** $p < .01$, * $p < .05$								

Table 66. Standardized regression coefficients and model fit for mean accuracy switch costs on negative and neutral trials at all levels of $n = 3$.

	Mean Accuracy Switch Costs, $n = 3$							
	Negative Trial Valence				Neutral Trial Valence			
	Model 1		Model 2		Model 1		Model 2	
Predictor	*beta*	*p*	*beta*	*p*	*beta*	*p*	*beta*	*p*
Negative Mood	0.09	.765	0.15	.672	-0.03	.917	-0.06	.844
Positive Mood	-0.28	.402	-0.26	.481	0.07	.829	0.13	.726
Rumination	-0.09	.791	-0.20	.635	0.03	.928	-0.13	.793
CESD-R Threshold (above – below)	-0.66	.297	-0.72	.309	0.30	.644	0.39	.575
Negative Mood ✻ Rumination			-0.26	.440			-0.08	.827

CESD-R Threshold * Rumination			0.42	.643			0.41	.661
R^2	0.06	.847	0.10	.914	0.01	.991	0.03	.997
R^2 Change			0.03	.714			0.01	.887
** $p < .01$, * $p < .05$								

Table 67. Regression model fits for set 1 mean accuracy switch costs at all levels of *n*.

	Model 1 (Main Effects)		Model 2 (Interactions)		Model 1 v. Model 2	
Mean Accuracy Switch Cost, *n* = 2, negative	$F(4, 20) = 0.56$	$p = .695$	$F(6, 18) = 0.69$	$p = .660$	$F(2, 18) = 0.96$	$p = .403$
Mean Accuracy Switch Cost, *n* = 3, negative	$F(4, 20) = 0.34$	$p = .847$	$F(6, 18) = 0.33$	$p = .914$	$F(2, 18) = 0.34$	$p = .714$
Mean Accuracy Switch Cost, *n* = 2, neutral	$F(4, 20) = 0.68$	$p = .617$	$F(6, 18) = 0.82$	$p = .566$	$F(2, 18) = 1.11$	$p = .352$
Mean Accuracy Switch Cost, *n* = 3, neutral	$F(4, 20) = 0.07$	$p = .991$	$F(6, 18) = 0.08$	$p = .997$	$F(2, 18) = 0.12$	$p = .887$

CHAPTER 4

DISCUSSION

The two main questions of the current study were (a) whether affective transfer occurs in a modified *n*-back task paradigm, and (b) whether there were depressed-mood-congruent or general deficits in WM in participants with elevated depression levels. Hubbard et al. (2016) found evidence of affective transfer from a reading span with depressive-congruent stimuli to a normal, non-affective reading span task. The main purpose of the current study was to extend this idea of affective transfer to the *n*-back task, and, in doing so, to assess whether WM updating, focus switching, or both are a driving force behind the affective transfer effect. Additionally, the current study investigated whether a similar effect occurs for depressive rumination, or whether affective transfer is limited to depression. The secondary purpose of the current study was to investigate the presence of mood-congruent and/or general deficits in WM in depression and depressive rumination using the same modified *n*-back paradigm.

In the first set of modified *n*-back tasks, participants were randomly sorted into either an emotional condition or a non-emotional control condition. In the emotional condition, participants identified whether the currently presented word was negatively- or neutrally-valenced, and then compared this to a word they had previously encoded into WM. In the non-emotional control condition, participants judged whether the presented words could refer to living things (e.g., towel does not refer to a living thing, but bear can refer to a living thing).

Depending on the specific task, this comparison was either to the originally encoded words within that trial, or to the last word that appeared in the same row as the currently presented word. The former did not involve updating the contents of WM, while the latter required that the contents of WM be updated when each new retrieval probe word was presented. There were three variants of this modified *n*-back task in the current study: random-order presentation without updating (RN), forward-order presentation without updating (FN), and forward-order presentation with updating (FU). I used subtractive logic, as in Price et al. (2014), to isolate the WM processes of focus switching and updating from these three task variants. For the main analyses, I did this by computing bin scores, combining response latencies and accuracy, as in Draheim et al. (2016), rather than traditional difference scores. For the supplementary analyses, I computed difference scores using (a) median response latencies on correct trials, and (b) mean accuracy. I assessed depressive symptoms with the CESD-R and the DASS-21, depressive rumination with the RRS and PTQ, and general mood throughout the study with three administrations of the PANAS. I used principal components analysis to organize these survey measures into three main components: negative mood, positive mood, and rumination. Negative mood consisted of the negative items from the PANAS, the brooding and reflection subscales from the RRS, all items from the CESD-R, and all items from the DASS-21. Positive mood consisted of the positive items from the PANAS. Rumination consisted of all items from the PTQ and the RRS. In addition to these three mood components, I assessed the effect of whether participants met the depressive symptoms cutoff score of 16 on the CESD-R.

Primary Question: Affective Transfer

In the current study, affective transfer should take the form of deficits in RT and/or accuracy in the second set of modified *n*-back tasks, but only for people who were (a) in the emotional condition in set 1, and (b) who had elevated depressive symptoms. This combination is essential; without it there is either a simple mood induction, in the case of a deficit solely due to the emotional condition in set 1, or a general cognitive deficit in depression (neither of which is affective transfer).

Regarding the main research question, I hypothesized that affective transfer would occur in individuals with elevated depressive symptoms, but that this should be enhanced if the individuals also tended to engage in depressive rumination. For the secondary research question, I hypothesized that individuals with elevated depressive symptoms would show mood-congruent deficits in WM switching and WM updating, and that these deficits should be enhanced by the tendency to engage in depressive rumination. If general deficits in these WM processes were to occur, I expected them to be limited to individuals with both heightened depression and depressive rumination.

For the most part, these hypotheses were not supported by the observed data. There was no evidence of affective transfer in the set 2 updating data, regardless of depression symptoms and depressive rumination. Furthermore, there was no evidence of either mood-congruent or general deficits in WM switching and updating in the set 1 data. I discuss the significant effects from these findings in some detail below.

However, there was a significant interaction between condition and negative mood in the bin score switch costs. This switch cost appears to occur at the $n = 2$ (see Figure 7) but not at the $n = 3$ level (see Figure 8), which could indicate a practice effect since $n = 2$ trials were completed before $n = 3$ trials, for people with lower scores on the negative mood component. Since this interaction effect only occurs at the $n = 2$ level, and appears to be in the opposite direction from what I would expect if it was affective transfer, it is not of any particular interest.

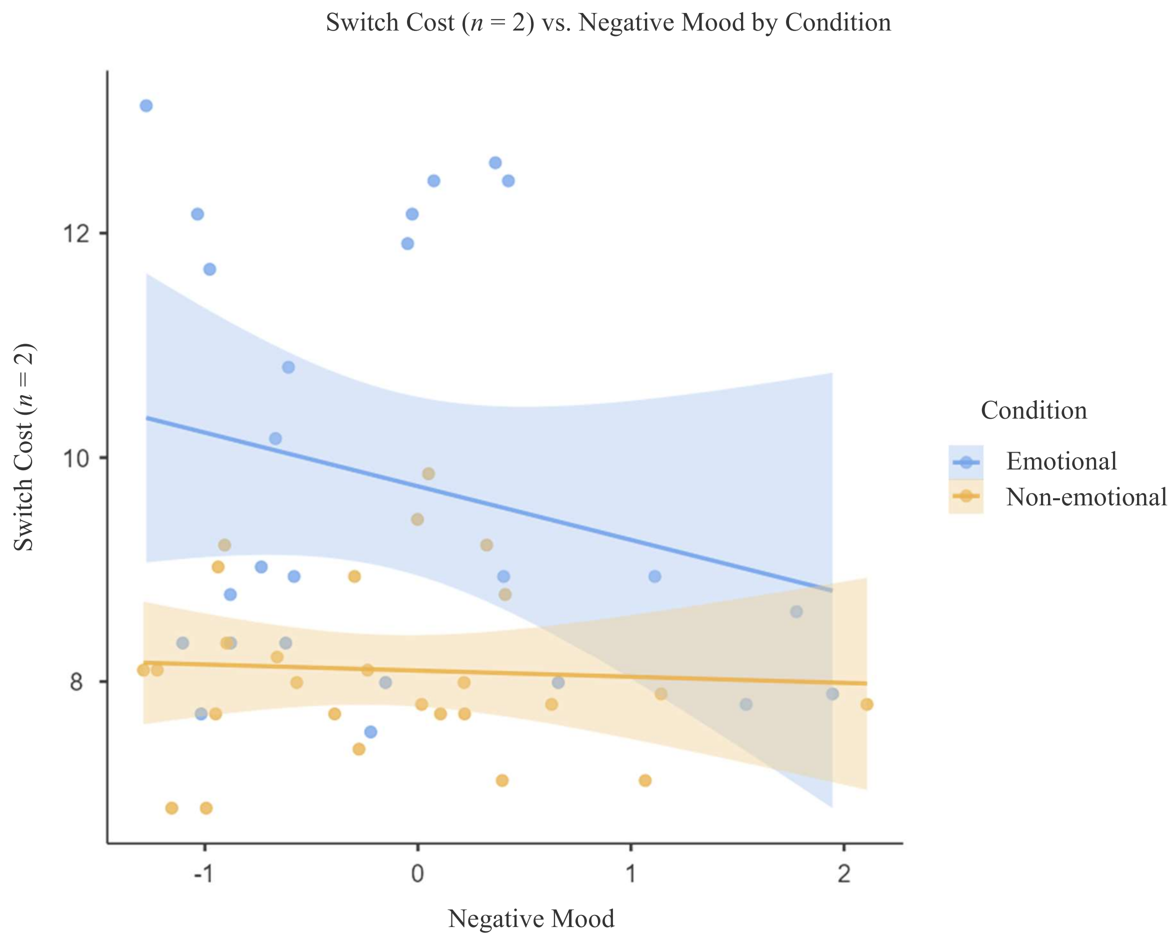


Figure 7. Interaction effect of negative mood and condition on $n = 2$ bin score switch costs.

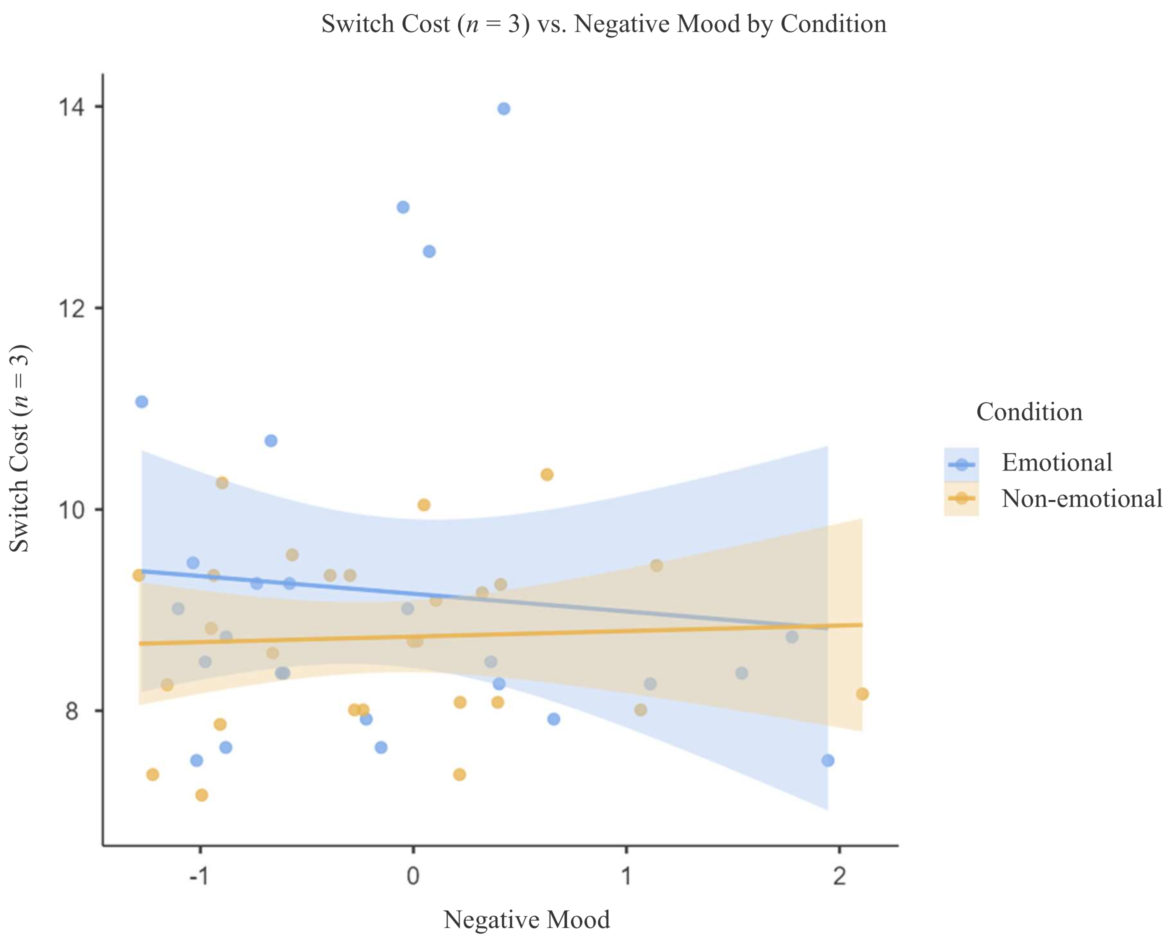


Figure 8. Interaction effect of negative mood and condition on $n = 3$ bin score switch costs.

Set 2 Regression Models: Updating Costs

There was no evidence of affective transfer in any of the set 2 regression models. For example, experimental condition, negative mood, positive mood, rumination, CESD-R threshold status, and the interactions between condition and each of these mood and rumination variables were not predictive of updating costs at $n = 1$, $n = 2$, and $n = 3$ task levels, in either the set 2 bin score or the set 2 mean accuracy data. Condition was a significant predictor of $n = 3$ median RT updating costs in the set 2 median RT data and of $n = 1$ updating costs in the mean accuracy data (but only when no interactions were included in the model) but this is, at most, evidence of a simple mood induction since these effects did not depend on whether participants had depressive symptoms or tended to engage in rumination (e.g., the interactions between condition and negative mood and between condition and rumination were not significant). As such, there was no evidence of affective transfer in terms of updating costs in the set 2 data.

Set 2 Regression Models: Switch Costs

Condition and negative mood both predicted $n = 2$ switch costs in the set 2 bin score data, but their interaction was not significant, and as such, this does not constitute evidence of affective transfer. Furthermore, these were not significant at the $n = 3$ level.

There was no evidence of affective transfer in terms of switch costs in the set 2 bin score data. Although there was some evidence for a mood induction from set 1 to set 2 in terms of worsening $n = 2$ switch costs (i.e., condition was a significant predictor of these switch costs, but only when interactions were not included in the model), since this did not depend on depression or rumination, it is not affective transfer. Similarly, the effect of negative mood in model 2 of the $n = 3$ switch cost bin score data is not affective transfer since it did not depend on whether the initial condition was negatively-valenced or neutrally-valenced.

Condition, negative mood, positive mood, rumination, CESD-R threshold status, as well as the interactions between condition and each of these variables, were not predictive of switch costs at the $n = 2$ or $n = 3$ level in the set 2 median RT data. In the set 2 mean accuracy data, rumination was predictive of mean accuracy switch costs at the $n = 2$ level (but only when interactions were included in the model). Additionally, there was a significant interaction between CESD-R threshold status and rumination in the full interaction model at the $n = 2$ level, but not at the $n = 3$ level. CESD-R threshold status was only predictive as a standalone main effect in the absence of interaction effects. However, since none of the interactions between condition and the survey measures of mood and rumination were significant, there is no evidence of affective transfer here either.

Overall, then, there was no evidence of affective transfer in terms of updating or switch costs in any of the set 2 regression analyses (i.e., on the bin score data, on the median RT data, and on the mean accuracy data). Furthermore, there was no conclusive evidence of even a simple mood induction, as this was only present in a few cases.

Secondary Question: WM Deficits

Recall that if mood-congruent-with-depression WM deficits were present, then the negative mood principal component variable should be a significant predictor for negative but not for neutral trial data. If general depression WM deficits were present, then negative mood should be a significant predictor for both negative and neutral trial data. Similarly, if there are WM deficits due to rumination, they could be mood congruent and only manifest in the negative trial valence data, or they could be general and manifest in both the negative and neutral trial valence data.

There was a significant effect of trial valence in bin score switch costs in the set 1 data. This took the form of a greater cost of focus switching for neutral trials than for negative trials, which could indicate a facilitation of attentional capture by negative stimuli. Note that this effect did not depend on rumination or depressive symptoms. There was no such effect in the median RT difference score data, but there was an equivalent effect in the mean accuracy difference score data, so that appears to be what caused the effect in the combined RT and accuracy bin scores. Finally, there was also a significant interaction between n-level and trial valence in the mean accuracy switch cost data, but none of the post hoc tests exploring this interaction were significant, so it may not be meaningful to interpret.

None of the set 1 regression analyses, then, provided evidence of either mood congruent or general WM deficits (in the form of switch costs or updating costs) in the set 1 bin score, median RT, or mean accuracy data from set 1, for either depression or rumination.

Additional Effects

I now discuss the additional significant effects from the set 2 and set 1 analyses of variance. None of these effects provide evidence of affective transfer or mood-congruent deficits, but may still be of some interest for interpretation.

Set 2 ANOVA Significant Effects

The interaction between n-level and condition had a significant effect on switch costs in the set 2 bin score data, but not in the median RT or mean accuracy data, and on updating costs in the median RT data, but not in the bin score or mean accuracy data. For updating costs in the median RT data, this interaction occurred because the non-emotional condition was unusually high at the $n = 3$ level relative to the other levels of n. This spike in difficulty only at the $n = 3$ updating level in the non-emotional task seems likely to be a spurious effect since there is no obvious theoretical explanation.

For switch costs in the set 2 bin score data, this interaction was driven by a mean difference in the bin scores of the emotional and non-emotional groups at the $n = 2$ level, but not at the $n = 3$ level. Specifically, bin score switch costs were noticeably higher at the n = 2 level in the emotional task than in the non-emotional task. However, after participants progressed to the 3-back task level, the difference between these switch costs leveled off. How to interpret this is unclear. It could simply reflect task difficulties between judging whether a word is negative or neutral and judging whether a word can refer to a living thing. Perhaps the former task improves with practice and the latter does not. Also, recall that this interaction was absent from the median RT and mean accuracy data.

The interaction between n-level and negative mood had a significant effect on updating costs, but only in the set 2 mean accuracy data. This was explored in more detail in the regression analyses, which showed that negative mood was not predictive of updating costs at any level of n in the mean accuracy data. However, this interaction did not yield any interpretable results: there was a non-significant negative trend for $n = 1$ and $n = 3$ and a non-significant positive trend for $n = 2$.

The interaction between n-level and CESD-R threshold had a significant effect on updating costs, but only in the set 2 mean accuracy data. Participants with little or no depressive symptoms improved their accuracy on 2-back and 3-back updating tasks, which came after the initial $n = 1$ updating trials, relative to participants who did have elevated depressive symptoms.

Whether the task was a 1-back, 2-back, or 3-back (i.e., n-level) had a significant effect on updating costs in the bin score, median RT, and mean accuracy data from set 2. In the bin score data, updating costs at $n = 3$ were greater than for the other levels of n; in the median RT data, updating costs at $n = 3$ were slightly higher than at $n = 2$; in the mean accuracy data, this pattern reversed, with the highest accuracy cost of updating at $n = 1$, relative to $n = 2$ and $n = 3$. In the bin score and median RT data, this is evidence that updating was most difficult at higher levels of n, which is what I expected to see (e.g, Price et al., 2014); the greater difficulty with accurate updating at $n = 1$ may be due to unfamiliarity with this initial stage of the updating task, relative to the higher n levels at later stages. Essentially, people slowed down and maintained or improved accuracy as the task difficulty increased.

Condition had a significant effect on switch costs in the set 2 bin score and mean accuracy data, but not in the median RT data. In both the bin score and mean accuracy data, the emotional condition had slightly higher switch costs than the non-emotional condition. As such, focus switching was slightly more difficult in the non-emotional task after the emotional condition than after the non-emotional condition. However, this effect did not interact with any of the measures of depression, rumination, or positive mood. This can be best interpreted as a general mood induction effect on focus switch costs in set 2, following the emotional condition in set 1, but unrelated to the pre-existing positive or negative mood, depression level, and tendency to ruminate of the participants.

Set 1 ANOVA Significant Effects

The interaction between *n*-level and trial valence had a significant effect on switch costs in the mean accuracy data, but not in the bin score data or median RT data. In terms of the mean accuracy data, this interaction took the form of a decreased accuracy switch cost from 2-back to 3-back for neutral-valence trials. Conversely, there was a slight increase in accuracy switch cost from 2-back to 3-back negative-valence trials. I reiterate that, in spite of the significance of this interaction, the individual post hoc tests were not significant. The reason for this discrepancy is unclear, but the effect size of this interaction ($\eta^2_p = .205$) may have been insufficient to overcome the family-wise error rate Tukey correction.

Trial valence had a significant effect on switch costs in the set 1 emotional condition bin score data and on updating costs in the mean accuracy data. Specifically, in the bin score data, the switch cost for neutral trials was slightly higher than for negative trials. In the mean accuracy data, the effect of trial valence on updating costs took the form of a slightly greater accuracy updating cost for neutral trials relative to negative trials. This could indicate facilitated processing of mood-congruent content in depression.

In the set 1 bin score data, but not in the median RT nor in the mean accuracy data, *n*-level had a significant effect on updating costs and switch costs in the bin score data. The $n = 1$ updating cost was greater than the $n = 2$ updating cost; as such, updating got easier after $n = 1$, but there was no additional improvement between $n = 2$ and $n = 3$. Perhaps the difficulty jump from 2-back to 3-back balanced out the additional practice for a net gain of zero. Meanwhile, switch costs in the bin score data were greater at $n = 2$ than $n = 3$, which can be interpreted as improvement in the task outweighing the difficulty jump from the 2-back to the 3-back.

While these ANOVA effects from the set 2 and set 1 data did not provide evidence of affective transfer or clear deficits for emotional or non-emotional stimuli, respectively, I did observe basic task difficulty effects of *n*-level, and a few examples of mood induction from the emotional stimuli.

Possible Limitations

One major limitation was that the data was collected online, from fall semester 2020 through spring semester 2021 during the COVID-19 pandemic, which certainly may have affected the results. Online data collection removed the controlled experimental environment of an in-person laboratory and may have been a major contributing factor to the prevalence of button-mashing responses that had to be filtered out, which greatly reduced the final sample size for analysis. Furthermore, the extent to which this floor effect was entirely button-mashing is unclear, as lack of motivation, especially during the COVID-19 pandemic, and task difficulty are likely to have contributed. Somewhat in contrast to this obvious interpretation, I found that attrition was predicted by higher scores on the positive mood principal component (which was constructed out of the positive items from the three administrations of the PANAS). That is, participants who experienced a more positive mood state were less likely to achieve adequate levels of performance.

I think that relegating emotionally-valenced stimuli to a distractor role in future studies should alleviate this somewhat, although doing so limits the ability to directly measure response latencies to emotional stimuli. Another option would be to interleave emotional stimuli between *n*-back trials, in a hybrid design of *n*-back and complex span, but this seems likely to be an incredibly difficult task, as *n*-backs alone are challenging at higher levels of *n*.

I had originally intended to use structural equation modeling to create depression and rumination variables from the survey, but due to the small effective sample size, I opted to use a simpler principal components analysis followed by regression. The reduced sample size also reduced the power level to detect significant effects (recall that there were a number of effects with marginal significance at the alpha = .05 level).

Due to the sheer number of stimulus words required to avoid repetitions in the modified *n*-back tasks, there was some possible blur at the cutoff between negative and neutral words; as negative words approach a valence rating of 4, they become more neutral, and as neutral words approach a rating of 6, they become more positive. A design that did not require as many unique words would be able to limit the word pool to more extreme negative and neutral words and thereby avoid this valence blurring.

This also prevented a more fine-grained analysis of the negatively-valenced words. Negatively-valenced stimuli do not have a universal effect in depression; for example, in an eye tracking study that displayed faces with happy, angry, and sad expressions, individuals with MDD took longer to disengage attention from sad emotional faces, relative to controls without

MDD, but did not differ in speed of disengagement from angry or happy faces, and showed no differences in attentional engagement with sad, happy, or angry faces, relative to controls (Sanchez, Vazquez, Marker, LeMoult, & Joormann, 2013).

In addition to such differences in observed deficits to different negative emotions, trait and state depressive rumination differ regarding cognitive processing (Whitmer & Gotlib, 2013). Trait rumination, which remains mostly constant despite changes in current mood (Nolen-Hoeksema, Wisco, and Lyubomirsky, 2008), corresponds to impairments in updating the contents of working memory (e.g., directed forgetting), but also with an enhanced resistance to distractors. People who tend to ruminate tend to be good at staying on task, perhaps because they have difficulty changing the focus of their attention. Conversely, state rumination is associated with broader cognitive control deficits. Whitmer and Gotlib (2013) posited that this cognitive dissociation between tending to ruminate and currently ruminating occurs due to constricted attentional scope; narrowed attentional scope is particularly likely during negative mood states (Easterbrook, 1959; Fredrickson, 2001, 2005; Tucker & Williamson, 1984; as cited in Whitmer & Gotlib, 2013).

Whitmer and Gotlib (2012) found that depressed individuals showed task-switching deficits only while they were currently engaged in depressive rumination. In contrast, trait rumination was related to deficits in inhibiting previous tasks, but not to general, non-inhibitory deficits in task switching. While focus-switching within WM is not the same thing as broader task switching, it might still be applicable. The present study assessed depressive rumination with the RRS and the PTQ, which both assess the general tendency to engage in depressive rumination, rather than whether the participant is currently, actively ruminating. Given that the study was conducted during the height of the COVID-19 pandemic, it is likely that at least some participants were engaged in rumination, but this was not directly assessed.

Furthermore, emotional experiences are personal, and even seemingly simple tasks, such as rating the emotional valence of a word or even just deciding whether that word is emotionally negative, can vary a great deal from person to person. For example, depending on the person and the context in which the word is used, the word “chicken” can refer to a tasty food, an insult to animal welfare, or to a cowardly person. Accordingly, attempting to assign values of incorrect or correct to these ratings may have been misguided, and likely inflated task difficulty beyond that of the depression span from Hubbard et al. (2016).

Future Directions

For the reasons detailed above, in future studies with this modified *n*-back paradigm, I would restrict emotional stimuli to distractors, rather than using them as target stimuli requiring a response based on their emotional content. In this manner, set 1 might have participants rate the valence and self-applicability of a set of emotional words, and then perform non-emotional *n*-back tasks, as in Price et al. (2014), in set 2. This self-referential rating would hopefully act as a mechanism to induce depressive rumination, in addition to assessing trait depressive rumination with measures such as the PTQ and RRS. While this would reduce fidelity to the original affective transfer paradigm from Hubbard et al. (2016), which utilized emotional and non-emotional variants of the reading span task, it would allow clearer analysis of accuracy, as it would remove the subjective component of judging the valence of a presented word outside of the context of a sentence.

Conclusion

The present study did not find evidence of affective transfer in the presence of depressive symptoms nor in the presence of depressive rumination. Furthermore, no clear WM deficits were observed for either mood-congruent or general stimuli. Whether this was due to some idiosyncrasy of the present study, such as its online administration of modified *n*-back tasks vs. in-person administration of modified complex span tasks as in Hubbard et al. (2016), or due to some idiosyncrasy of the effect of affective transfer itself, or to an effect of the pandemic, remains unclear.

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