Empirical Research

# The Effects of Depression on Number Perception and its Implications for Theories of Numerical Cognition

Dale J. Cohen*[a], Katherine A. Barker[a], Madeline R. White[a]

[a] University of North Carolina Wilmington, Wilmington, NC, USA.

## Abstract

Most theories of numerical cognition assume that the perception of a quantity is independent of that which the quantity describes (termed an abstract quantity representation). Beck's cognitive theory of depression, in contrast, assumes that depressed individuals maintain negative perceptual biases and that depressed individuals' perception of quantity will be dependent on that which the quantity describes. Here, we explore the nature of quantity representations by assessing whether level of depression and valence of events influences individuals' perceptions of numerical quantities. In a number bisection task, we presented participants with three quantities: one associated with the time until a positive event, one associated with the time until a negative event, and a target number. The participant was asked to judge whether the quantity denoted by the target number was closer to the time until the positive or negative event. Results indicated that event valence influenced the perception of quantity and this perceptual bias interacted with the level of depression. Thus, these findings indicate that quantity representations are malleable and are represented non-abstractly in the brain.

*Keywords:* depression, numerical cognition, numerical bias, number bisection, quantity representation, abstract quantity representation

There is an ongoing debate in the field of numerical cognition concerning whether there exists a single, abstract psychological representation of quantity that links to all numerical symbols (e.g., Dehaene, 1992; McCloskey, 1992; McCloskey, Caramazza, & Basili, 1985; McCloskey & Macaruso, 1995; McCloskey, Sokol, & Goodman, 1986), or whether the psychological representation of quantity is non-abstract (Cohen, 2010; Cohen, Ferrell, & Johnson, 2002; Cohen Kadosh & Walsh, 2009; McCloskey & Macaruso, 1995). Independence between the perception of a quantity (e.g., 5) and that which the quantity describes (e.g., five oranges, five bananas, etc.) is a fundamental property of an abstract quantity representation. However, Beck's theory of depression suggests that depressed individuals will interpret quantities differently depending on the affect associated with the item the quantity describes (e.g., a positive vs a negative event). Here, we tested these predictions by examining how varying levels of depression influence participants' perceptions of quantities when quantities are paired with positive and negative events in a number bisection task.

## Numerical Cognition and Depression

Numbers are symbols that denote quantity. A number's quantity representation refers to the constellation of features that are encoded, stored, or derived by the brain with respect to the magnitude denoted by a numerical symbol. Accepting the law of perceptual variability (Ashby & Lee, 1993), researchers generally assume that the quantity representation of a specific numeral (e.g., 5) is best described as a distribution situated on a "mental number-line" with a specific central tendency and variance. Here, "mental number-line" is a figurative shorthand used to describe a set of features in common with a physical number-line, such as a continuum of quantities that are linearly arranged.

There is a continuing debate concerning whether there exists a single, abstract quantity representation that links to all expressions of quantity (e.g., Dehaene, 1992; McCloskey et al., 1985; McCloskey & Macaruso, 1995; McCloskey, Sokol, & Goodman, 1986), or whether there are multiple, non-abstract quantity representations that are more flexible and each linked to specific classes of expressions of quantity (e.g., Cohen, 2010; Cohen et al., 2002; Cohen Kadosh & Walsh, 2009; González & Kolers, 1982). Abstract representation models posit that the psychological representation of quantity is independent of the symbol or item it represents (e.g., Dehaene, 1992; McCloskey et al., 1985). McCloskey's single representation model is one example of such a theory (McCloskey et al., 1985; McCloskey & Macaruso, 1995; McCloskey, Sokol, & Goodman, 1986).

McCloskey's single representation theory states that the cognitive number system is comprised of three separate modules – number comprehension, production, and calculation – that all communicate through a single abstract quantity representation (McCloskey et al., 1985; McCloskey & Macaruso, 1995; McCloskey et al., 1986). The number comprehension system is responsible for converting different numerical symbols through format-specific modules into a common abstract representation. The common abstract representation is where additional processing in the calculation or production systems takes place. Dehaene's Triple Code model is an extension of McCloskey's model that accounts for the completion of mathematical tasks that do not access any quantity representation (e.g., memory recall of multiplication facts; Dehaene & Akhavein, 1995). Thus, McCloskey's and Dehaene's models imply that abstract quantity representations are independent of the objects or symbols that they denote.

Support has emerged for the various mechanisms involved in McCloskey's number processing system, primarily through the study of subjects with brain damage (McCloskey et al., 1986; McCloskey et al., 1985). For example, McCloskey and colleagues (1986) found that a man who suffered from a left-hemisphere cerebro-vascular accident made number production and processing errors that support the assumption of a dissociation between processing Arabic numbers and verbal numbers in McCloskey's model. In addition, McCloskey and colleagues' (1985) study of MW, who also suffered brain trauma, displayed a dissociation between arithmetic fact retrieval deficits and in-tact calculation abilities.

Recently, the view that numbers are represented by an abstract quantity representation has been challenged by theories proposing that quantity is not independent of the symbolic system or the items it represents (Cohen, 2010; Cohen et al., 2002; Cohen Kadosh & Walsh, 2009). Such *non-abstract quantity representation* theories hypothesize that quantity is tied to the symbolic system and may even be malleable based on situational factors (e.g., Campbell, 1994; Cohen, 2010; Cohen et al., 2002; Cohen Kadosh & Walsh, 2009; González & Kolers, 1982). Thus, non-abstract quantity representations may be susceptible to the influence of selective perceptual bias on numerical cognition because the psychological representation of quantity is bound to the numerical for-

mat and, perhaps, the item that the quantity is describing. Cohen's Multiple Quantity Representation model is one such model that is founded on the non-abstract representation of quantity (Cohen et al., 2002; Cohen Kadosh & Walsh, 2009; González & Kolers, 1982).

Cohen's Multiple Quantity Representation model suggests that each different numerical format activates a separate, non-abstract quantity representation (Cohen, 2010; Cohen et al., 2002; Cohen Kadosh & Walsh, 2009; González & Kolers, 1982). For example, the presentation of the written word "five" and the Arabic number "5" would activate two separate format dependent quantity representations. The Multiple Quantity Representation model asserts that all formats are directly linked to one another, allowing formats to be converted without activating the quantity representation. To compare numerical quantities of two different formats, the system converts one symbol into the format of the other symbol. Following the conversion, the two numbers would then activate the same quantity representation and their quantities could then be compared (Cohen, Warren, & Blanc-Goldhammer, 2013). Cohen's Multiple Representations model has been supported for relative frequencies (Warren & Cohen, 2013), decimals (Cohen, 2010), Arabic digits, written and spoken number words (Cohen et al., 2013), and roman numerals (González & Kolers, 1982).

Whether quantities are represented abstractly or non-abstractly has implications beyond the field of numerical cognition. For example, there is abundant evidence suggesting that depressed and non-depressed individuals perceive the world differently (Andersen, Spielman, & Bargh, 1992; Beck, 1970; MacLeod & Byrne, 1996; MacLeod & Cropley, 1995). These perceptual biases, however, can only extend to the biased perception of quantities if numbers are represented non-abstractly. If numbers are represented abstractly, then perceived quantity should be independent of the item it describes.

Beck's cognitive theory of depression posits that depressed individuals have specific negative cognitions that revolve around pessimistic views concerning the self, the world, and the future (known as the *cognitive triad*; Beck, 1970). These pessimistic views prompt depressed individuals to exhibit systematic biases that are supported by negative schematic content. In turn, these biases subsequently cause depressed individuals to make decisions that complement and reinforce pre-existing dysfunctional beliefs and perceptions.

Numerous studies have demonstrated support for Beck's cognitive theory of depression (e.g., Dunning & Story, 1991; MacLeod & Byrne, 1996). In particular, research consistent with Beck's cognitive theory indicates that depressed individuals selectively attend to negative stimuli in the external environment (Beck, 1970; Gotlib & Joormann, 2010; Wang, Brennen, & Holte, 2006) as well as negative feedback pertaining to themselves (McKendree-Smith & Scogin, 2000). Consistent with these findings, the negativity biases of depressed individuals have also been found to influence information processing through difficulties inhibiting mood congruent information (Gotlib & Joormann, 2010), attributing more negative and less positive adjectives as self-descriptive (Dozois & Dobson, 2001), and interpreting ambiguous situations as negative (Wisco & Nolen-Hoeksema, 2010).

Negativity biases have also been demonstrated to influence a depressed individual's interpretation and expectation of what the future holds (Beck, 1970; Dunning & Story, 1991; MacLeod & Byrne, 1996; MacLeod & Cropley, 1995; Moore & Fresco, 2007; Pyszczynski, Holt, & Greenberg, 1987). Depressed individuals are more concerned about the future than non-depressed individuals and worry about it often. This results in overly pessimistic expectations and a preoccupation with ideas related to future events (Beck, 1970). Pyszczynski and colleagues (1987) showed that depressed individuals are typically more pessimistic when making probabilistic

judgments concerning future life events in comparison to their non-depressed counterparts. Additionally, Dunning and Story (1991) demonstrated that depressed individuals' pessimistic outlook concerning future life events was a perceptual bias, rather than an accurate indicator of how future events would unfold.

Beck's cognitive theory of depression, therefore, predicts that level of depression should influence how individuals process and understand numerical quantities when the numerical quantities are associated with affective content. For example, Beck's theory of depression predicts that depressed individuals should perceive the magnitude associated with a particular number (e.g., 5) as shorter if it describes the time (5 months) until a negative event (lose your job) relative to when it describes a time until a positive event (win the lottery). This prediction, however, can only manifest if quantities are represented non-abstractly. Otherwise, perceived quantity will be unaffected by that which the quantity describes.

## The Current Study

Here, we assess whether quantity representations are abstract or non-abstract by testing the relation between participant's scores on a depression scale (the BDI-II[i]) and their perceptions of quantity. We assessed participants' perception of quantity with a modified number bisection task[ii]. Past research has found the numerical bisection task to be an adequate assessment of underlying quantity representations (e.g., Göbel et al., 2006; Loftus, Nicholls, Mattingley, Chapman, & Bradshaw, 2009; Longo & Lourenco, 2010; Lourenco & Longo, 2009; Zorzi, Priftis, & Umiltà, 2002). Traditionally, models of quantity representation assume that large quantities are perceptually more similar than small quantities (i.e., that the distributional overlap between consecutive quantities increases with magnitude). Such quantity representations would manifest as a leftward bias among healthy individuals in the numerical bisection task (pseudoneglect) (e.g., Göbel et al., 2006; Loftus et al., 2009; Longo & Lourenco, 2007, 2010; Lourenco & Longo, 2009; Zorzi et al., 2002). Göbel and colleagues (2006) showed that neurologically normal individuals produced this predicted a leftward bias while performing number bisection tasks. Longo and Lourenco (2007) replicated and extended these results, concluding that the constant leftward bias on numerical bisections manifests because larger numbers are subjectively perceived as closer together. Loftus and colleagues (2009) found similar results when they presented a pre-bisected numerical interval to participants and asked them to judge whether the interval was correctly bisected at the true center. Loftus and colleagues (2009) explain these findings by suggesting that the bias typically observed during number bisections is dependent on the mental representation of numbers consistent with a logarithmic or scalar variance representation.

Our number bisection task consisted of two numbers – one on the right, and one on the left – each associated with a valenced event statement. One of the statements (e.g., the left) was negative (e.g., "You will lose your job in 3 months"), and one of the statements (e.g., the right) was positive (e.g., "You will win the lottery in 48 months"). A third number was positioned between the two event statements (termed the *probe* number). The participant's task was to indicate whether the probe number was quantitatively closest to the number contained in the right or left event statement.

Consistent with non-abstract quantity representation theories, we predict as BDI scores increase, participants will perceive quantities describing the time until the negative event as smaller than those same quantities describing the time until a positive event. This perception will push their perceived midpoint towards the positive event. As BDI scores decrease, this midpoint bias towards the positive event will decrease. These predicted

results, where midpoint biases are influenced by the affect of the event as depression scores increase, would support non-abstract quantity representation theories.

# Method

## Participants

Two hundred and thirty-three undergraduate students were recruited to participate in exchange for class credit. Sample size was determined by (a) setting a minimum number of participants, (b) estimating the time necessary to collect that number of participants, (c) posting all available experimental slots for the time estimated in "b," and (d) running all participants who signed up. We set the minimum number of participants at 200 to ensure enough power to accurately estimate the relation between the numerical bias functions and depression. This procedure resulted in the collection of more than the minimum number of participants because of a higher than expected sign-up rate.

## Apparatus and Materials

All stimuli (with the exception of the BDI) were presented on a 24-in. LED color screen controlled by a Mac mini. Participants completed a paper version of the Beck's Depression Inventory II (BDI-II; Beck, Steer, & Brown, 1996), which determined each participant's level of depression.

### Life Events List

The life events used in the current study were compiled during an earlier study that created a comprehensive list of validated and standardized affect-related life events (Cohen, Barker, & White, 2018). The compiled list includes three event valence categories (positive, negative, and neutral), each of which contains 57 life events, creating an overall list of 171 life events. Participants who rated life events in the earlier study also completed the BDI-II to assess levels of depression. Importantly, depression levels did not influence how life events were rated.

### BDI-II

We used Beck's Depression Inventory II (BDI-II) to assess participants' depressive symptoms. Beck and colleagues (1996) demonstrate the validity of the BDI-II, reporting a high positive correlation with the revised Hamilton Psychiatric Rating Scale for Depression (a validated measure of depression) (Beck et al., 1996; Riskind, Beck, Brown, & Steer, 1987; $r$ = .71). Beck and colleagues (1996) also reported that outpatients who completed the BDI-II two weeks apart produced highly similar scores ($r$ = .93, $p$ < .001), thus demonstrating the reliability of the inventory. The BDI-II consists of 21 statement groupings, each of which assesses a specific depression-related symptom (sadness, pessimism, agitation, etc.). Participants are asked to indicate the extent to which they experience each of these symptoms using a four-point scale. Responses to each item are then added together to create a total BDI-II score, with lower scores indicating lower levels of depressive symptoms and higher scores indicating higher levels of depressive symptoms. We slightly modified the inventory by removing the item that assessed suicidal thoughts. We did this for IRB purposes.

## Number Bisection Task

Each trial of the number bisection task consisted of two affective event statements presented on the right and left side of the screen. One event was always positive and one was always negative. The side of the negative event was randomized. The affective event statements each contained a number that indicated the time (in months) until that event would occur. In between the two event statements (in the center of the computer screen) was a probe number. The participant's task was to judge whether the probe number was quantitatively closer to the number on the right or the number on the left (see Figure 1). Below, we describe each feature of a trial.
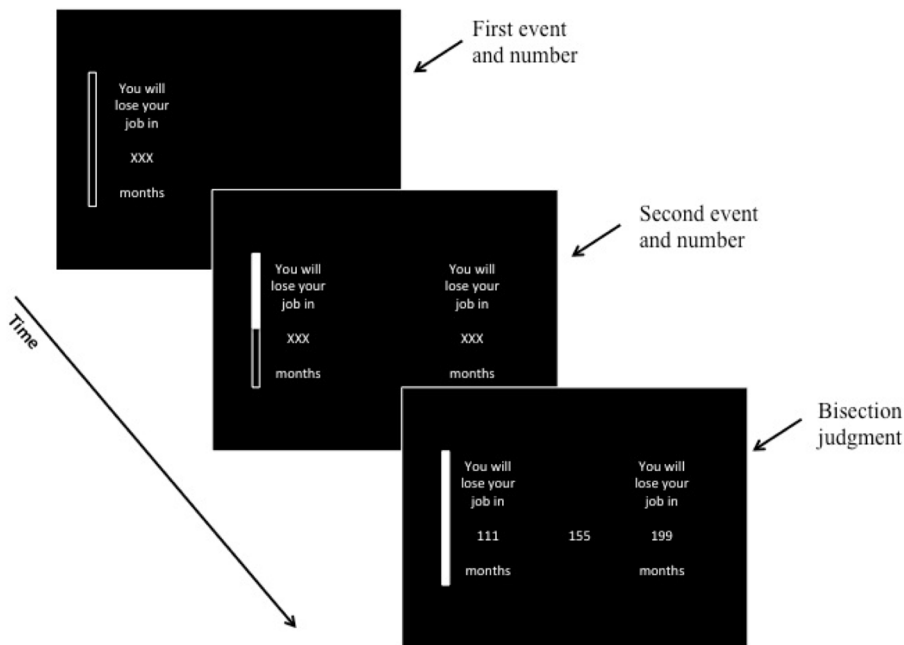


*Figure 1.* Number bisection trial.

*Note.* The top, left figure is an example of what will first be presented to participants in the number bisection task, where the numbers representing the interval will be masked. Once the time frame for participants to read the event statements has elapsed, the numbers will be revealed, which is shown in the bottom, right figure. Once the numbers have been unmasked, participants will have 3 seconds to submit a response.

At the beginning of each trial, participants were presented the events with the numbers masked. This was done so that the participants could read and understand the events without being able to gather any information about the numerical symbols. The structure of this part of the trial went as follows. First, the event statement with a mask covering its associated number on the left side of the screen was presented for 300 ms per word. The numbers were masked with three pound signs (i.e., "###"). A timer bar was also presented to the left of the event. The timer bar was gradually filled in with white from top to bottom as the time ran out to read the event. The 300 milliseconds per word time limit gave participants enough time to read the event without making them wait too long for the timer to complete. Once the allotted time to read the left event elapsed, the second event was presented on the right side of the screen with its associated number also masked for 300 ms per word. At this point, both events were visible. Once the allotted time to read the right event elapsed, the timer bar completely filled and turned blue.

At this point, participants were asked to judge the valence of the events. This was done to ensure that participants read and paid attention to the events presented. Half of the participants were instructed to identify the event that was more positive, whereas the other half of participants were instructed to identify the event that was more negative. Half of the participants were assigned to use the mouse to make responses and half of the participants used buttons on the keyboard. We implemented both input methods to ensure that response input method did not influence the results (the data confirmed they did not).

Once participants made a valence response, the two numbers of the interval within the event statements were unmasked and a probe number appeared centered between the events. All three numbers were presented on the same horizontal line on the computer screen so that participants could quickly see the numbers once they were unmasked. As quickly as possible, participants were to identify the event statements that contained the number that was numerically closest to the probe number.

The numbers paired with the affective events represented the to-be-bisected interval. Similar to Lourenco and Longo (2009), the numbers for the interval varied between 111 and 199, with each number being randomly selected. We added 100 to Lourenco and Longo's (2009) original range of 11-99 to (1) prevent the left most digit from providing key quantitative information, and (2) reduce the influence of the compressed quantity perception at the low numbers. The interval was presented in ascending order, with the smaller number always presented to the left and the larger number to the right. To prevent the intervals from being too small, the intervals ranged from a numerical distance of 21 to 87. The smaller numbers in the interval ranged from 111 to 177. The larger numbers ranged from 133 to 199. A total of 112 events (56 positive events and 56 negative events) were used from Cohen et al.'s (2018) study. For each interval, one number always described a positive event and one number always described a negative event. Thus, if a positive event was linked to the smaller number in an interval, then the larger number was linked to a negative event (and vice-versa).

Each participant completed a total of 56 trials during the number bisection task. For 28 of the trials, a positive event was linked to the smaller number and a negative event to the larger number. For the remaining 28 trials, a positive event was linked to the larger number and a negative event to the smaller number. The order of the trials was randomized.

To make a bisection response, participants determined which number (within either the positive or negative event statement) was quantitatively closest to the probe number. The probe number ranged from -4 to 4 units from the true midpoint of the presented interval. This range included 0 so that the true midpoint was presented. For every trial, the probe number was chosen at random from within the -4 to 4 unit range. Between subjects, this resulted in varying numbers of trials encountered for each of the nine possible distances from the true midpoint.

Participants made their responses in one of two ways, either by using the mouse or by pressing designated keys on the keyboard. Half of the participants made their responses by using the mouse and clicking on either the left or right event. For these participants, the cursor was not visible on the computer screen. Instead, a yellow outlined box appeared to indicate which side of the interval the cursor was hovering over. The yellow box automatically adjusted in size depending on the length of the event statement. The other half of the participants made their responses by using the keyboard, where the "d" key selected the event on the left and the "k" key selected the event on the right.

To ensure that participants did not have enough time to perform any calculations, a reaction time pressure was implemented. This was done by having a beep sound that informed participants if their bisection responses were too slow. For the first trial, the RT deadline was set at 3 seconds (Cattaneo, Fantino, Silvanto, Tinti, & Vecchi, 2011). If the participant made a bisection response after the 3 second deadline, they heard a beep at the end of the trial. Throughout the trials, the RT deadline decreased as a function of the speed of the participant's previous four responses. Specifically, the deadline was replaced when the second fastest RT of the previous four trials was lower than the set deadline. For example, if a participant responded after 3 sec. for their first three trials but on their fourth trial they responded in 2.8 sec., their new RT deadline would change to 2.8 sec. This would be their deadline until their second fastest RT in their last four trials was faster than 2.8 sec. This process continued until all trials were completed to pressure the participants to respond as quickly as possible. All participants wore headphones throughout the experiment.

## Procedure

Participants were run individually in a small, dark room on a Mac Mini running OSX with a 24-inch LED screen. The ceiling light in each participant's testing room was turned off to eliminate distraction, make it easier for participants to view the experiment on the computer screen, and to ensure that all participants completed the experiment under the same environmental conditions. At the start of the experiment, the computer presented instructions that explained the number bisection task and instructed participants to put on a pair of headphones for use during the task. The instructions provided information about the task format, how to make event ratings (e.g., "you are to choose which event you feel is more negative"), and how to make quantitative judgments (e.g., "identify which of the life event numbers is quantitatively closest to the center number." Here, the probe number is more simply referred to as the center number in the instructions). In addition, the instructions included examples that illustrated how to complete the task and provided information about the reaction time pressure (e.g., "you will hear a beep if your response was too slow"). Participants were required to wear headphones in order to hear the beeping sound presented throughout the experiment (the time pressure manipulation used is described in detail above). Each participant completed four practice trials that were identical to the experimental trials. Participants completed 56 experimental trials as described above. Participant's accuracy levels and reaction times were recorded for all trials.

Upon finishing the number bisection task, participants completed Beck's Depression Inventory (BDI-II), which was used to measure the presence of depression symptoms for each participant. Once they completed the BDI-II, participants were thanked for their participation and were given course credit, marking the end of the experiment.

# Results

Six participants did not complete the experiment due to technical issues and were removed from data analysis.

Participants' depression levels were estimated by their scores on the BDI-II, where higher scores indicate higher levels of depression. Scores on the BDI-II ranged from 0-42, with an average depression score of 10.34 ($SD$ = 7.50). Figure 2 shows a histogram of BDI-II scores.
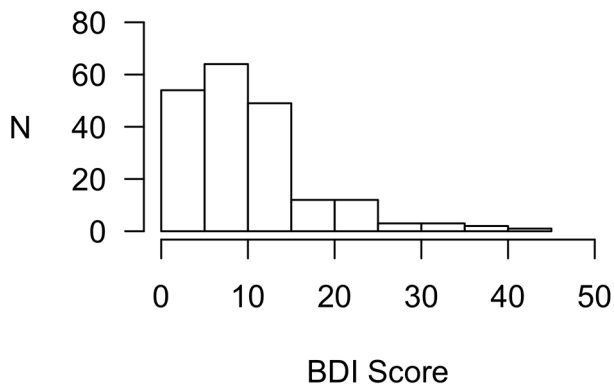
*Figure 2.* Histogram of BDI-II scores.

*Note.* Scores on the BDI-II ranged from 0-42, with an average depression score of 10.34 (*SD* = 7.50).

## Number Bisection

To ensure that our analyses reflected participants who relied on estimates rather than calculations, we removed any participants who performed 40% or more of their bisection judgments in longer than 3 seconds[iii]. This removed a total of 27 participants. Nonetheless, the patterns of observed results are virtually identical regardless of whether all participants are included in the analysis. In addition, we removed all trials where the bisection judgment exceeded 5 seconds. This constraint eliminated 1.2% of the data.

To determine whether the valence of presented events influenced the perceived midpoint, we separated the data into two conditions: negative event on the left side of the interval (termed *Negative Left*) vs. negative event on the right side of the interval (termed *Negative Right*). The probe number ranged from a distance of -4 to 4 units from the true midpoint. For each distance from the midpoint, we calculated the proportion of judgments that each participant identified the probe number as "above." A participant who accurately identifies the true midpoint will never respond "above" when the probe is below the true midpoint and will always respond "above" when the probe is above the true midpoint. We expect an accurate participant to respond "above" 50% of the time when the probe is equal to the true midpoint. To estimate midpoint bias, we performed a linear regression with distance of the probe number from the midpoint as the predictor variable and the proportion of "above" responses as the criterion variable. The midpoint bias will be the position whereby the best fit line crosses the 50% mark.

For the Negative Right condition, there was a significant positive relationship found between distance of the probe number from the midpoint and proportion of "above" responses (intercept = 0.47, slope = 0.03), with distance from the midpoint accounting for a significant proportion of the variation in "above" responses, $F(1,7) = 94.19$, $p < .001$, $r^2 = .92$, (Bayes Factor = 474). For the Negative Left condition, distance of the probe number from the midpoint was positively related to "above" responses (intercept = 0.51, slope = 0.03), with distance from the midpoint accounting for a significant proportion of the variation in "above" responses, $F(1,7) = 114.7$, $p < .001$, $r^2 = .93$, (Bayes Factor = 810). For both of these regressions, the effect size and Bayes Factors are extremely large, indicating that the model fits are excellent. These findings demonstrate that as distance between the probe number and the true midpoint decreased, bisection judgments became more error-prone. A t-test on the slope parameters of the regressions indicated that the slopes between the Negative Left and Negative Right conditions were not significantly different, $t(14) = 1.13$, $p = .28$, $\eta^2 = .08$; Bayes Factor = 1.57). Both

the effect size and Bayes Factor confirm that there is little evidence of a slope difference. A *t*-test on the intercept parameters of the regressions indicated intercepts were significantly different, $t(14) = 3.25$, $p < .01$, $\eta^2 = .43$ (Bayes Factor = 8.65). The Bayes factor confirms that there is moderate to strong evidence for a large effect size for the difference in intercepts. As seen in Figure 3b, these results demonstrate that participants show a leftward bias in the Negative Left condition, based on the point at which 50% of participants' bisection judgments indicated an "above" response. In addition, participants exhibited a rightward bias in the Negative Right condition. Specifically, in the Negative Left condition, participants demonstrated a midpoint bias of -0.42 units from the true midpoint, whereas in the Negative Right condition participants demonstrated a midpoint bias of 0.74 units from the true midpoint. These results indicate that participants' perceptions of the midpoint of numerical intervals are biased towards the corresponding side of negative presented events. These findings indicate that participants shrink the distance between the probe number and the positive event, demonstrating a positivity bias. This is what the depressive realism theory predicts for non-depressed participants. Because most of our participants had low BDI-II scores, this result is expected.
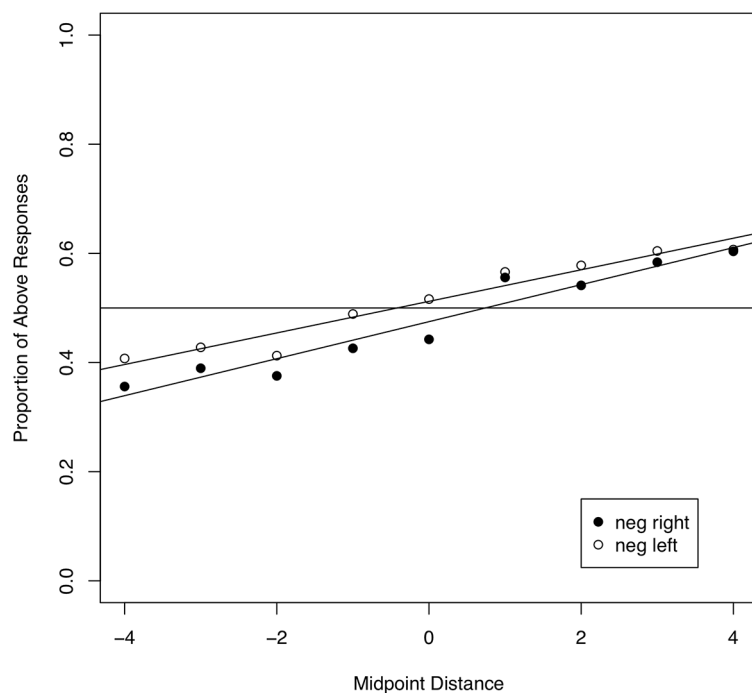


*Figure 3.* Midpoint bias.

*Note.* The graph shows that when the negative event is presented on the left, participants have a slight left bias in their perception of the interval midpoint. On the other hand, when the negative event is presented on the right, participants exhibited a right bias in their bisections of the presented interval.

To test the hypothesis that participants' BDI-II scores would be related to their midpoint bias, we first calculated each participant's proportion of "above" responses in the Negative Right and Negative Left conditions. When the participant's midpoint bias is closer to positively valenced events in the Negative Right condition, the proportion above will be relatively large. In contrast, when the participant's midpoint bias is closer to positively valenced events in the Negative Left condition, the proportion above will be relatively small. To detect a consistent bias, we subtracted each participant's proportion of "above" responses in the Negative Right condition from their proportion of "above" responses in the Negative Left condition. From these calculations, a negative num-

ber indicates a stronger midpoint bias towards the positive event (i.e., negativity bias - compressed quantities associated with a negative event), whereas a positive number indicates a stronger midpoint bias towards the negative event (i.e., positivity bias - compressed quantities associated with a positive event). To assess the influence of depression scores on midpoint bias, we (i) averaged the bias scores for each BDI II score, and (ii) calculated a linear regression with depression scores squared as the predictor variable and the difference in "above" responses as the criterion variable. The results indicated that depression scores accounted for a significant proportion of the variation in the difference of "above" responses, $F(1,33) = 10.66$, $p < .003$, $r^2 = .24$, (Bayes Factor = 14.6; slope = -0.01). The Bayes Factor confirms that there is strong evidence for the large effect size of depression on participants' numerical bias. Importantly, the intercept (intercept = 0.12) was not significantly different from 0 $t(33) = 1.6$, $p = .12$, $\eta^2 = .04$; Bayes Factor = 1.75). Both the effect size and Bayes Factor confirm that there is little evidence of a slope difference. These findings demonstrate that as depression scores increase, (1) participants' midpoint bias moved increasingly towards the positive event, and thus, (2) participants' perceptions of quantities associated with negative events decreased (see Figure 4).
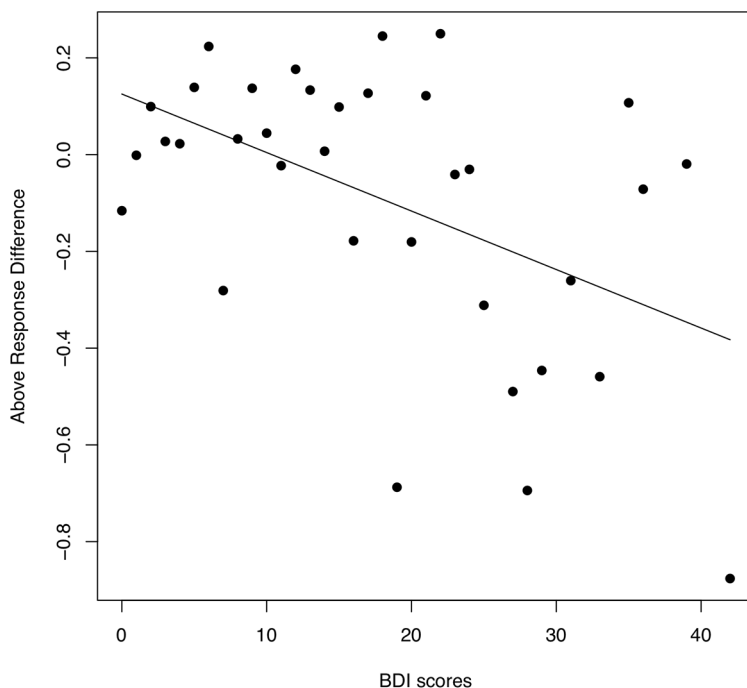


*Figure 4.* Effects of depression on midpoint bias.

*Note.* The graph shows that as depression scores increase, participants' midpoint bias becomes more drastic towards the negative event presented on the right side of the interval.

# Discussion

We assessed whether state of mind and the information associated with a quantity influenced the perception of the quantity. The predominant theories of numerical cognition assume that the psychological representation of quantity is abstract. That is, there exists a single quantity representation that is separate and independent from the information associated with it (e.g., Dehaene, 1992; McCloskey, 1992). As such, one's psychological under-

standing of a quantity (e.g., 5) should be unaffected by ancillary attributes such as the format of the numeral (e.g., "5," "five," "V," etc.), the object it describes (e.g., five oranges, five bananas, etc.), etc.

Independence between the perception of a quantity and that which the quantity describes is a fundamental property of an abstract quantity representation. Therefore, if quantity representation is abstract, people's perception of quantity should not be influenced by the valence associated with an event or an object – regardless of the participant's state of mind. Beck's cognitive theory of depression, in contrast, is founded on the assertion that depressed individuals maintain negative perceptual biases (Beck, 1970). When applied to numerical cognition, Beck's cognitive theory of depression predicts that depressed individuals will overestimate quantities associated with the time until positive events occur and underestimate quantities associated with the time until negative events occur (i.e., depressed individuals see negative events as more temporally proximal and positive events as more temporally distal). Thus, abstract quantity representation theories and Beck's cognitive theory of depression make conflicting predictions with regards to perceptions of quantities associated with an affective event.

In the current study, we tested these predictions by examining how varying levels of depression influence participants' perceptions of quantities when quantities are paired with positive and negative events in a number bisection task. The number bisection task revealed a significant effect of event valence on perceived midpoint. Specifically, when a quantity is associated with a time until a positive event, participants in general (collapsed across BDI-II scores) perceive that quantity as smaller than when that same quantity is associated with a time until a negative event. We also found that as depression scores increased, participants had stronger biases to perceive quantities associated with a time until a negative event as smaller than quantities associated with a time until a positive event. These findings (a) contradict the predictions stemming from an assumption of abstract quantity representations and (b) are predicted by Beck's cognitive theory of depression.

Because the present data contradict predictions stemming from an assumption of an abstract representation of quantity, theories that rest on this assumption must be viewed more critically. Cohen and colleagues (e.g., Cohen et al., 2002; Cohen et al., 2013; Warren & Cohen, 2013) have recently proposed an architecture of numerical cognition that does not assume an abstract representation of quantity. This architecture assumes that quantity representation is inherently linked to the format of the number symbol. Findings from the current study suggest that the quantity associated with a particular numeral is flexible– at least when presented as an Arabic digit. For example, a participant interprets the quantity associated with a "5" differently depending on whether it is paired with a negative or positively valenced event. The results presented here contradict the predictions of Cohen's and colleagues' non-abstract architectures as well. Specifically, it is unclear how the valence bias can manifest. Cohen Kadosh and Walsh (2009) propose a dual code model of number processing in which a non-abstract quantity representation is followed by a more precise, controlled abstract processing of quantity. The authors propose that this latter stage is influenced by intentional states, task demands, etc. However, Cohen Kadosh and Walsh (2009) propose that the second stage is controlled and effortful. Because the number bisection task forces our participants to respond quickly, the task likely inhibits controlled processing. This suggests that a second, intentional, processing stage does not account for the pattern of data. Our data suggests that the initial, preattentive mechanism is subject to bias and the second, intentional mechanism may be used to correct the initial bias. Bias is often conceptualized as a preattentive mechanism (e.g., Bargh, 1989; Eckhardt & Cohen, 1997; Lecci & Cohen, 2002; Lecci & Cohen, 2007; Luecken, Tartaro, & Appelhans, 2004), and the systems that process quantity appear vulnerable to this mechanism. From the present experiment, we cannot describe the

exact process by which the preattentive bias influences quantity representations. Future research should further examine how characteristics of the individual and those associated with a given quantity affect numerical bias across a variety of numerical estimation tasks. If numerical bias consistently fluctuates in response to changing mood states and/or quantity characteristics, findings would demonstrate robust support for non-abstract quantity representation theories.

Our data not only support the predictions of Beck's cognitive theory of depression, but also the theory of depressive realism. According to the depressive realism theory, non-depressed individuals systematically demonstrate unrealistic cognitions that are influenced and sustained by optimistic biases (e.g., Alloy & Abramson, 1979; Alloy & Abramson, 1982; Dykman, Abramson, Alloy, & Hartlage, 1989). When applied to numerical cognition, the theory of depressive realism predicts that non-depressed individuals would underestimate quantities associated with the time until positive events occur and overestimate quantities associated with the time until negative events occur. Our data (collapsed across all participants) supports this prediction. Specifically, we demonstrate that, as a group, our participants were biased to perceive quantities associated with a positive event as smaller than those associated with a negative event. This trend, however, reversed for depressed individuals. This reversal supports Beck's cognitive theory of depression, which asserts that the differences between depressed and non-depressed individuals are primarily the result of the pessimistic perceptual biases maintained by depressed individuals. Thus, both depressed and non-depressed individuals exhibit differential perceptual biases of quantities depending on the valence of the event that they modify.

In addition, the influence of depression score on quantity perception sheds light on a largely unexplored aspect of the literature regarding the negativity biases of depressed individuals. Particularly, current literature does not explain whether negativity biases become stronger as depression levels increase. The current study begins to explore whether negativity biases are more robust in severely depressed individuals (those with a BDI score of 29 or higher) in comparison to mildly depressed individuals (those with a BDI score of 14-19). By assessing perceptions of quantity across the continuum of BDI scores, our results indicate that individuals' estimation biases do become more drastic as depression levels increase. Thus, our data suggest that the negativity biases of depressed individuals become stronger as depression levels increase. Given the non-clinical sample used in the current study and the limited amount of information that can be drawn from BDI-II scores, future research examining clinically depressed populations is recommended to provide more insight into this perceptual bias.

## Conclusion

In sum, the results of the current study indicate that the valence of an event, as well as an individual's level of depression (as measured by the BDI-II), influence an individual's perception of quantity. Specifically, low BDI scorers overestimate the quantities associated with the time until a future negative event and underestimate the quantities associated with the time until a future positive event. As BDI scores increase, this trend reverses. These results (1) challenge models of numerical cognition based on abstract quantity representations, and (2) support both Beck's Cognitive Theory of Depression and the theory of depressive realism.

### Notes

i) Here, we will refer to high BDI scorers to represent individuals who experience depressive symptoms and low BDI scorers to represent individuals who experience mild or no depressive symptoms. Due to the nonclinical sample recruited for the current study, we apply these terms in order to outline the current hypotheses. It is important to note that all analyses

assessed the relation between scores on the BDI-II and number perception. We did not dichotomize the scale into high and low scorers. We simply use these terms here to simplify predictions.

ii) Although stimulus valence has not been shown to influence number perception, there is some evidence that stimulus valence can influence line bisection tasks. Unfortunately, this evidence is a bit contradictory. When the to-be-bisected line is composed of affect words, the emotional content magnified the typical leftward bias (Hatin & Sykes Tottenham, 2016). However, when the line is composed of emotional faces, the emotional content reduced the typical leftward bias (Hatin & Sykes Tottenham, 2016). Furthermore, when emotional faces flanked a line, some have shown that the emotional content consistently magnified the leftward bias (Armaghani, Crucian, & Heilman, 2014), whereas others have shown that only the negative and neutral emotional content magnified the leftward bias relative to positive content (Cattaneo et al., 2014). Such findings suggest that a non-numerical, affect related, perceptual bias may exist in the non-depressed population and this bias may manifest in the line-bisection task. However, the exact nature of that bias is currently unclear.

iii) There was a trend towards a negative between RT and BDI scores, $F(1,198) = 3.82$, $p = .052$, $r^2 = .02$, but Bayes Factor = 1.09 indicated that the evidence is very weak in favor of this effect.

## Funding

## Competing Interests

## Acknowledgments

## Data Availability

For this study, the data and *r* code are freely available (see the Supplementary Materials section).

# Supplementary Materials

The data and the *r* code for the current experiment can be downloaded from
https://github.com/ccpluncw/ccpl_data_JNC2018.git

### Index of Supplementary Materials

Cohen, D. J., Barker, K. A., & White, M. R. (2019). *GitHub – ccpluncw/ccpl_data_JNC2018* [Supplementary materials].
https://github.com/ccpluncw/ccpl_data_JNC2018.git

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