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Assessing the effect of negative mood states on valence-dependent belief updating

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ASSESSING THE EFFECT OF NEGATIVE MOOD STATES ON VALENCE-DEPENDENT BELIEF UPDATING

by

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ABSTRACT

Individuals consistently tend to underestimate the likelihood of negative events happening to them and fail to update these beliefs adequately when provided with statistical evidence. However, depressed populations are better able to accurately update beliefs. It is not clear if the ability to update beliefs effectively is due to overall dysphoria or are partially due to momentary fluctuations of acute affective states. Undergraduates (N=83) completed a belief updating task where they estimated the likelihood of a negative event happening to them, were presented with the actual likelihood of the event, and then re-estimated the likelihood of the event happening to them. Prior to completing the belief updating task participants were randomized to undergo a neutral or a negative (i.e., sadness) mood induction. After completing the task participants completed the other mood induction and the belief updating task a second time with a second list of events. Whether information was desirable or undesirable (i.e., whether the initial estimate was higher or lower than the actual base rate) had a significant effect on belief updates ($F(1, 72) = 22.126$, $p < .001$, $\eta_G^2 = .042$). No significant effect was found between acute hopelessness and belief updates. Linear mixed modelling revealed a significant interaction effect of information type and induction on belief updates ($\beta = -4.15$, $SE = 1.09$, $p < .001$, 95% CI = -6.29, -2.00). Analyses that accounted for intra-individual and trial-by-trial variation indicated that experiencing a sadness mood induction interacted with the type of information received to reduce optimism bias.

ACKNOWLEDGMENTS

I want to express my deep appreciation for the efforts of my research mentor, Dr. Daniel Capron, to not only help me to develop and execute this project, but also for providing me with foundational knowledge and understanding of the field. Additionally, I wish to recognize the contributions of my thesis committee, Dr. Kelsey Bonfils and Dr. Donald Sacco, whose feedback has been invaluable to me.

DEDICATION

To my family and my wife – thank you for putting up with me during this, it's not easy. To the most beautiful girl in the world – I love you.

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CHAPTER I - INTRODUCTION

1.1 Background

The purpose of the current study is to evaluate the effects of mood and affect dysfunction on human decision-making processes. Human decision-making processes are dependent on an individual's beliefs about the outcomes of future events. These decisions could directly affect the expected outcome (e.g., flipping a light switch or turning a key in a lock), or they could depend on expected future outcomes (e.g., investing in retirement or buying insurance). In both cases, in order to make a rational decision an individual must make predictions about how a current decision will result in a future outcome or be affected by future events to lead to an outcome. According to Rational Decision Theory (RDT), a model describing optimal economic decisions, choices should maximize Subjective Expected Utility (SEU), which is the probability weighted sum of utilities for the possible outcomes of the choices (Koechlin, 2020; Lee, 2006). However, it has frequently been observed that actual human decisions diverge from purely rational choices in multiple domains.

In recent years a large number of cognitive biases have been identified in behavioral economics and experimental psychology research that demonstrate scenarios in which actual human decisions diverge from SEUs. These cognitive biases are instances where human cognition produces systematic distortions in representations of objective reality (Haselton, Nettle, & Murray, 2015). It has been argued that there are three main reasons that these cognitive biases can arise from an evolutionary perspective: 1.) natural selection favors a cognitive shortcut that is not applicable in all situations (i.e., heuristics); 2.) a situation arises for which human cognitive ability is not optimized (artifacts); and 3.) biased cognitive response patterns result in lower "error costs" than unbiased responses (error management biases) (Haselton et al., 2015). Examples of cognitive biases include the base rate fallacy (i.e., the tendency for individuals to ignore relevant information about base rates when judging the likelihood of an event occurring) (Allen, Preiss, & Gayle, 2006), the continued influence effect (i.e., the continued influence of incorrect prior beliefs in the face of new disconfirming evidence) (Johnson & Seifert, 1994), and the backfire effect (i.e., when prior beliefs become more entrenched when presented with contradictory evidence) (Nyhan & Reifler, 2010). This cluster of cognitive biases is related to systematic errors in the process by which individuals incorporate new information to past beliefs (i.e., priors) to form new beliefs about the future (i.e., posteriors).

The process through which individuals incorporate new information into prior beliefs to adjust their predictions about the outcomes of future events can be modeled using Bayes Theorem (Fennell & Baddeley, 2012). Briefly, Bayes theorem suggests that a posterior probability distribution of a hypothesized causal relationship given a new piece of information is defined by the product of the probability of the new information given the hypothesized relationship and the prior probability of the hypothesized relationship divided by the prior probability of the new piece of information (Ajzen & Fishbein, 1975). A reformulation of this relationship shows that the amount that beliefs about a hypothesized causal relationship should change is a function of the likelihood ratio (i.e., the value of the new information for accurately predicting the outcomes of the relationship) (Ajzen & Fishbein, 1975).

Another important theoretical formulation defining the method by which individuals make decisions relates to that person's beliefs about future prospects (i.e., gains and losses). Kahneman and Tversky argued that individuals will make decisions based on their beliefs about prospects as a function of their current "reference point" as a marker for the value of a potential gain or loss (i.e., Prospect Theory) (Kahneman & Tversky, 1979). This can lead to decisions that are biased away from those that would strictly maximize SEU. Kahneman further theorized that decisions biased away from optimal choices according to RDT are due to cognitive heuristics. Specifically, a "fast" cognitive process that recruits fewer mental resources and provides more immediate appraisals than an alternative, more deliberate, "slow" process leads to the biased cognitive appraisals (Kahneman, 2013). These fast cognitive appraisals may be the cause of consistent diversions from SEU resulting in predictable effects of bias in the synthesis of priors with reference frames.

One of these cognitive biases that has been consistently observed – optimism bias – is related to an individual's beliefs about their likelihood of experiencing negative versus positive events (Weinstein, 1980, 1982). When individuals estimate their own attributes and abilities, most report more positives and fewer negatives than average – a statistical impossibility (Alicke, 1985; Brown, 1986; Hoorens, 1993). Additionally, individuals demonstrate optimism about their susceptibility to health problems (Weinstein, 1982) and future life events (Weinstein, 1980), overestimate their own driving (Svenson, 1981) and cognitive abilities (Dunning, 2011; Schlösser, Dunning, Johnson, & Kruger, 2013), and overestimate the quality of their own relationships relative to others' (Schriber, Larwood, & Peterson, 1985). In the context of decision-making as outlined above, the tendency for individuals to overestimate the likelihood of positive life events and underestimate the likelihood of negative ones should therefore be incorporated into Bayesian priors when predicting how individuals will make choices under uncertainty.

Prior research has found reduced optimism bias in belief updating for depressed (Garrett et al., 2014; Korn, Sharot, Walter, Heekeren, & Dolan, 2014) and high-functioning autistic populations (Kuzmanovic, Rigoux, & Vogeley, 2019). Other research has indicated that high trait optimism moderates the presence of self-specific optimism bias, but that individuals with lower trait optimism demonstrate reduced optimistic updating for both themselves and a “similar other” (Kuzmanovic, Jefferson, & Vogeley, 2015). However, while this information is useful for better understanding how optimism bias differs across certain clinical populations, relatively little information regarding acute emotionality and belief updating has been researched.

One recent study has investigated the effect of acute state changes on belief updating (Garrett, González-Garzón, Foulkes, Levita, & Sharot, 2018). Garrett et. al. (2018) experimentally induced perceived threat in a sample of undergraduates by informing participants that they would be required to give a recorded speech on a surprise topic to be graded by a panel of five faculty. In a second experiment, they recruited a sample of fire fighters who were instructed to complete study procedures between calls while on shift to assess perceived threat in a non-experimentally induced natural setting. Both groups were given a belief updating task to complete along with measures of acute anxiety and threat. In the first group, participants integrated bad news into prior beliefs such that biased belief updating observed in low threat groups vanished under experimental conditions. In the second group, firefighters with more self-reported acute anxiety had greater integration of bad news into beliefs in a “natural setting” (Garrett et al., 2018).

Still, a crucial gap remains in the understanding of affective states and belief updating. While clinical depression (Garrett et al., 2014; Korn et al., 2014) and trait optimism (Kuzmanovic et al., 2015) have been found to be related to a reduction in optimistic belief updating, it is not clear if these effects are due solely to factors theorized to be more static, such as personality or persistent dysphoria, or if they are sensitive to moment-to-moment affective fluctuations. Furthermore, as previously stated Garrett et. al. (2018) demonstrated that stress and threat states unrelated to more stable individual factors can reduce the effect of optimism bias on belief updating when induced in participants experimentally. However, it is not clear if affective states related to dysphoria and depression - specifically sadness - are associated with reduced optimistic belief updating.

Determining whether biased belief updating is suppressed only in trait-level depression or low trait-level optimism, or if these effects are at least partially dependent on momentary fluctuations to affective states carries implications for several domains of psychological functioning. Specifically, improving the understanding of affective factors on belief-bias updating will allow for better modelling of individual decision-making under uncertainty by indicating how affective states can be incorporated to interpret predictions about the future according to RDT, Bayes Theorem, and Prospect Theory.

1.1.1 Measurement of Optimism Bias

The usual method of studying optimism bias has historically been to ask participants to compare their likelihood of experiencing a negative life event with the likelihood of the average person to experience one (i.e., the direct comparison method; Harris & Hahn, 2011). This method has several weaknesses, namely, the presence of attenuated response scales, the under-sampling of population minorities, and regressive population base rate estimates can cause rational individuals to produce response patterns to the direct comparison method that approximate optimism bias (Harris & Hahn, 2011; Shah, Harris, Bird, Catmur, & Hahn, 2016). Harris and Hahn (2011) further argue that optimism bias may simply be a statistical artifact due to selection biases and poor study design and that the inclusion of rare positive events is a critical test for distinguishing genuine optimistic responding.

In response to these types of criticisms, a relatively large body of research on optimism bias has been developed in recent years using the "update method" (Garrett & Sharot, 2014, 2016; Garrett et al., 2014, 2018; Kappes & Sharot, 2019; Korn et al., 2014; Kuzmanovic et al., 2015; Kuzmanovic & Rigoux, 2017; Moutsiana et al., 2013; Sharot & Garrett, 2016; Sharot, Guitart-Masip, Korn, Chowdhury, & Dolan, 2012; Sharot, Korn, & Dolan, 2011). Instead of having participants compare their odds of experiencing a negative event to their beliefs about an average person, the update method requires participants to estimate their likelihood of experiencing a positive or negative event. They are then presented with the actual population base rate data for the event, and then they are asked to re-estimate their likelihood of experiencing the event. In this way, the update method assesses optimism bias by measuring people's updated estimates in response to desirable or undesirable information. These studies have consistently found large effect sizes for an optimism bias for belief updating, where individuals with less desirable information (i.e., are informed that the actual base rate of experiencing a negative event is greater than they estimated for themselves) update their beliefs less than when they receive more desirable information (i.e., are informed that the actual base rate of experiencing a negative event is less than they estimated for themselves).

1.2 Present Study

The present study used the belief update method in conjunction with a mood induction to assess the relationship between acute affective states and optimism bias. To accomplish this, participants completed a belief update paradigm using PsychoPy3 simulation software through the Pavlovia.org online portal (Peirce et al., 2019). Participants were divided into two groups. Group A viewed a negative (i.e., sadness) mood induction video and completed half of the belief updating task. They then viewed a neutral mood induction video and completed the remainder of the belief updating task. Procedures were similar for Group B, though they completed the neutral mood induction first and the negative mood induction second. Following each induction video, participants completed an attention check, a brief measure of hopelessness, and a brief measure of the effectiveness of the induction.

There were two major hypotheses tested in this study. First, it was hypothesized that optimistically biased belief updating would be observed in participants following the neutral mood induction, but that this effect would be reduced or absent following the negative mood induction. Second, we hypothesized that acute hopelessness measures would be negatively associated with optimistically biased belief updating.

CHAPTER II – METHODS

2.1 Participants

Participants comprised undergraduate students at the University of Southern Mississippi recruited through the psychology department participant pool (SONA). GPower software was used to calculate the required number of participants to detect a moderate-to-large effect size (f=0.35, α=0.05, Power=0.80) using Analysis of Variance (ANOVA) (Erdfelder, Faul, & Buchner, 1996). GPower indicated that a total sample size of 82 would be sufficient to detect the hypothesized effect. Participants were granted SONA credits as compensation for participation, which can be used for course credit. Only participants over 18 years of age and eligible to receive SONA credits for course credit were included in the study. Participants were also required to confirm stable internet access and the ability to access a web browser compatible with the web distribution of PsychoPy3 via the Pavlovia.org web link. Participants unable to access the online study were excluded.

2.2 Materials

PsychoPy3 (PsychoPy3; Peirce et. al., 2019): PsychoPy3 is a versatile stimulus presentation software package built on the Python programming language with built-in online integration functions through Java scripting which allow for browser based delivery of stimuli (Peirce et al., 2019). PsychoPy3 and the associated online browser delivery service (Pavlovia.org) have been validated for the delivery and measurement of online stimulus and response data with reaction time precision under 4 milliseconds online (Bridges, Pitiot, MacAskill, & Peirce, 2020). The belief updating task was coded using PsychoPy3 and delivered to participants as a web link hosted on Pavlovia.org.

Beck Hopelessness Scale (BHS; Beck, Weissman, Lester, & Trexler, 1974; Aish et al., 2001). A shortened four-item version of the BHS was used to measure acute hopelessness following each mood induction. The full form of the BHS is a 20-item self-report measure of hopelessness and pessimism with well-established psychometric properties (Beck, Weissman, Lester, & Trexler, 1974). Validity of a shortened, four-item version of the BHS has been established for the measurement of acute hopelessness in ecological momentary assessment (Aish, Wasserman, & Renberg, 2001).

Emotional Response Scale (Gilman et al., 2017). An acute emotional response measure was presented to participants following mood induction to assess the effectiveness of video stimuli to induce the intended affective state. Words describing emotional states were presented to participants using a Likert scale indicating the extent to which they experienced the indicated word ranging from 1 (none) to 7 (strong), consistent with procedures established in prior emotion elicitation research (Gilman et al., 2017). A total of four emotion descriptors (sadness, surprise, happiness, disgust) were selected to limit burden on participants.

Memory and Other Controls (Garrett et al., 2018). At the end of the experiment participants were required to report the actual probability that had previously been reported to them during the belief updating procedure to test for memory effects. Additionally, participants were asked to rate stimuli used in the procedure according to 5 factors (i.e., vividness, familiarity, prior experience, emotional arousal, negativity) describing their experience of the stimuli using a 6-point Likert scale (i.e., 1=not at all, 6=very).

2.3 Procedure

Participants were recruited through the SONA system for human subject recruitment at the University of Southern Mississippi and randomly assigned to one of two conditions (i.e., receiving a neutral mood induction first, followed by a negative/sadness mood induction or receiving the negative mood induction first). Randomization was used to mitigate any order effects due to the mood induction and participation.

Participants were directed to a Qualtrics survey link where they completed a consent form and received detailed instructions about how to complete the study and details about its purpose. After completing the informed consent, participants completed baseline assessment measures (see Materials above). Baseline measures included basic demographic information and other baseline psychological information.

2.3.1 Belief Updating Procedure

Participants were directed to an online interface (i.e., Pavlovia.org) developed using PsychoPy3, a social science software package for stimulus presentation via weblink (Peirce et al., 2019). The belief updating task (see Sharot & Garrett, 2016 for a review) was used in this study. Participants viewed instructions for completing the online belief updating task and entered basic demographic information (i.e., sex and race) to generate appropriate likelihood data for their demographic group. They then completed a practice trial of the task with three events.

Event stimuli used in the belief updating task comprised 80 short descriptions of negative life events divided into two lists of 40 items (Garrett et al., 2018; Garrett & Sharot, 2014; Kappes & Sharot, 2019; Kuzmanovic et al., 2015; Moutsiana et al., 2013; Sharot et al., 2011). Participants were randomly assigned one of the lists of 40 items for the belief updating task. The task presented participants with a potential life event (e.g., depression, robbery, car accident, cockroach infestation) and a prompt asking them to estimate the potential likelihood of that event happening to them (3 seconds). Participants were informed at the outset that all likelihoods fall between 3% and 77% for their demographic, but only events with a likelihood between 10% and 70% were actually included in the task to allow for over and underestimation of all possible events. Participants were then presented with a visual analogue scale with reference markers at 3% (i.e., minimum likelihood), 77% (i.e., maximum likelihood), and 40% (i.e., midpoint likelihood). They were then required to select a spot on the scale corresponding to their belief about the likelihood of the event happening to them. After selection, a display generating the percent corresponding to their selection appeared on the screen and a prompt to move to the next slide was generated. At this point participants were free to change their scores or move to the next stimulus.

When they selected a likelihood, a fixation cross was generated (2 to 5 seconds, jittered) and they were then presented with the actual likelihood of the event happening to someone in their corresponding demographic group (3 seconds). Another fixation cross was generated (2 to 5 seconds, jittered), and the next event rating procedure was generated. When the participant completed all the initial event ratings for their trial, they then completed likelihood updates for each of the events presented to them.

During the update segment of each trial, participants were again presented with each event from the initial rating segment (3 seconds). They were then asked to re-rate the likelihood of that event happening to them using the visual analogue scale. After rating the likelihood of each event participants were presented with a fixation cross (2 to

5 seconds, jittered) before moving on to the next event. Following the update procedure, participants were asked to rate the actual likelihood that had been previously presented to them for each of the events listed in the procedure as well as according to the vividness, familiarity, prior experience, emotional arousal, and negativity of the events for them. Figure 2.1 demonstrates the belief update procedure visually.

After participants completed the three-event practice trial they viewed a short (approximately 2.5 minute) mood induction based on their random assignment. For the neutral mood induction, participants viewed a video titled "Wild Denali" that has been shown to elicit little to no emotional reaction in participants (Gilman et al., 2017; Gross & Levenson, 1995; Jenkins & Andrewes, 2012). For the negative/sadness mood induction, participants viewed a clip from the film "The Champ" (1979) that has been demonstrated to induce a single emotional state (i.e., sadness) to the exclusion of other measured emotional states with very high salience (Gilman et al., 2017; Gross & Levenson, 1995; Jenkins & Andrewes, 2012). After viewing the video, participants completed a question asking about the content of the video as an attention check and a brief questionnaire (i.e., emotional response scale, shortened BHS, Brief Acute Suicide Measure). After completing the mood induction, attention check, and brief questionnaire, participants completed the belief updating task on the first 20 events from the randomly selected list of 40 events. When they completed this, they viewed the induction video they did not view in the first trial, completed another attention check, brief questionnaire, and another belief updating task on the second 20 events from the randomly selected list of 40 events.

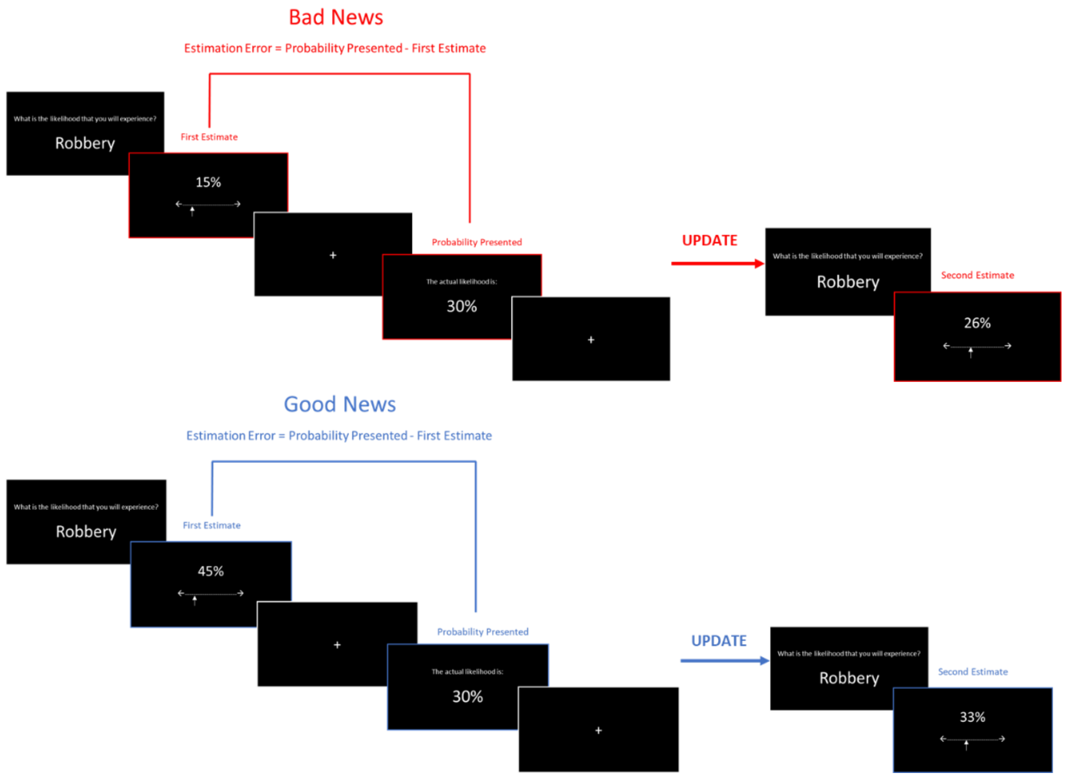

Figure 2.1 *Study procedure*

2.4 Data Analytic Plan

The primary hypothesis of this study (i.e., that optimistically biased belief updating would be observed in participants following the neutral mood induction, but that this effect would be reduced or absent following the negative mood induction) was analyzed using ANOVA and the procedure outlined by Garrett et. al., 2018. Individual event trials were be partitioned according whether they represented “desirable information” (i.e., the likelihood presented was lower than their initial estimate) or “undesirable information” (i.e., the likelihood presented was higher than their initial estimate). Estimation errors (EE) and belief update (BU) scores were then calculated. EEs are the difference between the initial estimate (IE) and the actual base rate (aBR) and BUs are the difference between the IE and the re-estimate (RE) when the EE is positive and the RE from the IE when the EE is negative. All statistical procedures were completed using the R environment for statistical computing (R Core Team, 2019).

2.4.1 Hypothesis 1

Pearson product moment correlation coefficients were calculated to measure the association between EEs and BUs for each participant in the study at each level of information (i.e., desirable and undesirable information) and induction (i.e., negative and neutral induction). This resulted in four sets of Pearson correlations generated for each participant (i.e., desirable information/neutral induction, undesirable information/negative induction, desirable information/neutral induction, undesirable information/negative induction). Data were then screened for outliers, normality, homogeneity of variance, and sphericity. Correlations were submitted to a 3-way ANOVA with information (i.e., desirable/undesirable news) and induction (i.e., negative/neutral induced mood) as within-subjects measures and group (i.e., negative/neutral mood induction first) as a between-subjects factor.

2.4.2 Hypothesis 2

To test the second hypothesis (i.e., acute hopelessness measures will be negatively associated with optimistically biased belief updating), a multiple regression model was generated predicting each Pearson correlation estimate with hopelessness as a covariate. Acute hopelessness following each induction was calculated using the brief 4-item BHS measure (see above) and included in the model. Statistical significance was determined at $\alpha = 0.95$.

2.4.3 Exploratory Modelling

Finally, exploratory statistical methodology was conducted following the protocol developed by Marks and Baines (Marks & Baines, 2017) using linear mixed modelling (LMM). BUs were entered as the dependent variable with information (i.e., desirable/undesirable information) and induction (i.e., negative/neutral induction) as fixed factors with interaction, subject as a random factor, and EEs, emotional arousal, familiarity, negativity, prior experience, and vividness as covariates. Additional models were planned to be generated based on significance identified in the more complex model to achieve the most parsimonious model with the best fit to the data. Likelihood ratio tests and Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores were used to compare model fit for LMMs.

CHAPTER III – Results

3.1 Demographics

A total of 88 participants completed all phases of the study. Five participants failed validity checks (i.e., attention checks following inductions) and were excluded from further analysis yielding a final study sample of 83. Of these 43 (51.8%) were randomized to receive the neutral mood induction first during the belief updating portion of the study, while 40 (48.2%) received the negative mood induction first. The sample comprised 65 (78.3%) female, 18 (21.7%) male participants, 53 (63.9%) White, 23 (27.8%) Black, four (4.8%) Hispanic or Latino/a, two (2.4%) multi-race or multi-ethnic, and one (1.2%) Asian participants. Participants were distributed relatively evenly across year in school with 20 (24.1%) freshmen, 19 (22.9%) sophomores, 15 (18.1%) juniors, and 23 (27.7%) seniors with an additional five (6.0%) students in their 5^{th} year of undergraduate education and one (1.2%) graduate student. The average age of participants was 24.5 (SD=9.1). Following the negative (sadness) mood induction, participants' mean self-rated sadness was 5.9 (SD = 0.8) but was 1.4 (SD = 1.6) following the neutral mood induction. Mean sadness scores following each induction were compared using Welch's two-sample *t*-test and the difference was found to be statistically significant, $t(123) = 23.3$, $p < .001$. See Table 3.1 for a summary of demographic data.

Table 3.1

Demographic information

	Mean	(SD)
Age	24.5	(9.1)
Sadness		
Negative Induction	5.9	(0.81)
Neutral Induction	1.4	(1.56)
	N	**(%)**
Total	83	(100.0)
Sex		
Female	65	(78.3)
Male	18	(21.7)
Race		
White	53	(63.9)
Black	23	(27.8)
Hispanic/Latino(a)	4	(4.8)
Multi-ethnic	2	(2.4)

Asian	1	(1.2)
Year		
First	20	(24.1)
Second	19	(22.9)
Third	15	(18.1)
Fourth	23	(27.7)
Fifth	5	(6.0)
Graduate	1	(1.2)
Induction Group		
Neutral first	43	(51.8)
Negative first	40	(48.2)

3.2 Primary Analyses

3.2.1 Effect of mood induction on belief updates

Data were partitioned for each participant based on whether their EE score was positive (i.e., initial estimate higher than base rate; desirable information) or negative (i.e., initial estimate lower than base rate; undesirable information) and whether the estimates occurred following the negative or neutral mood induction. A Pearson correlation coefficient for each BU/EE relationship was calculated. This procedure yielded a total of 332 Pearson correlations for analysis.

Next, data were screened for outliers using the *identify_outliers* function from the r package *rstatix* (Kassambara, 2020). Extreme outliers (i.e., greater than three times the interquartile range below the first quartile or above the third quartile) and correlations equal to 1 or 0 were removed from further analysis. Normality of the sample distribution was then tested using the Shapiro-Wilk test and density (Figure 3.1) and qq plots (Figure 3.2) were generated to visually inspect normality of data. Data were significantly negatively skewed (-1.18) and violated normality assumptions. To address this, an inverse transformation was performed and tested using the same procedures (see Figures 3.3 and 3.4 for transformed density and QQ plots, respectively). While skew was improved (-0.26), several partitioned groups still failed the Shapiro-Wilk tests of normality and data should be interpreted with this limitation in consideration. See Table 3.2 for a full summary of data included in analysis following exclusion of outliers and data transformation.

Homogeneity of variances was assessed using Levene's test (Levene, 1960). These tests were not significant for any subgroup indicating that the data did not violate the assumption of homogeneity of variances. Finally, tests of sphericity and sphericity corrections were conducted within the package *rstatix* (Kassambara, 2020) during analyses.

These data were used in the three-way ANOVA to assess effects of mood induction on biased belief updating. Results indicated that information (i.e., whether the initial estimate was higher or lower than the actual base rate) had a significant effect on correlations between EEs and BUs ($F(1, 72) = 22.126$, $p < .001$, $\eta_G^2 = .042$). No other main effects or interactions had a significant effect on the outcome of interest. Results of the ANOVA are presented in Table 3.3.

Table 3.2

Summary of correlations and acute hopelessness following removal of outliers and data transformation

				Correlations		Hopelessness	
Information	**Valence**	**Group**	***N***	**Mean**	**SD**	**Mean**	**SD**
Undesirable	Negative	Neutral first	34	.679	.189	1.154	.246
Undesirable	Neutral	Neutral first	37	.707	.169	1.068	.183
Desirable	Negative	Neutral first	37	.766	.164	1.142	.240
Desirable	Neutral	Neutral first	38	.787	.158	1.066	.181
Undesirable	Negative	Negative first	42	.733	.142	1.167	.263
Undesirable	Neutral	Negative first	41	.710	.161	1.146	.237
Desirable	Negative	Negative first	42	.780	.143	1.167	.263
Desirable	Neutral	Negative first	41	.776	.168	1.146	.237

Table 3.3

ANOVA analysis assessing effect of induction (valence) on belief updating

Effect	**DF_n**	**DF_d**	***F***	***p***	η_G^2
Group	1	72	1.774	0.187	.012
Information	*1*	*72*	*22.126*	*<.001*	*.042*
Induction	1	72	.051	.823	<.001
Group:Information	1	72	.458	.501	<.001
Group:Induction	1	72	.651	.422	.002
News:Induction	1	72	.209	.649	<.001
Group:Information:Induction	1	72	.036	.849	<.001

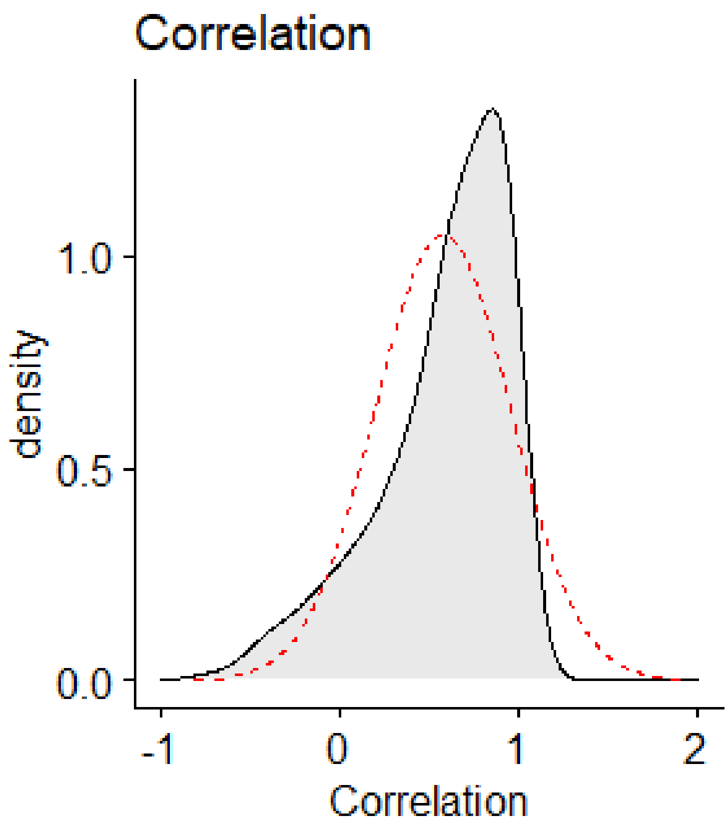

Figure 3.1 *Untransformed density plot*

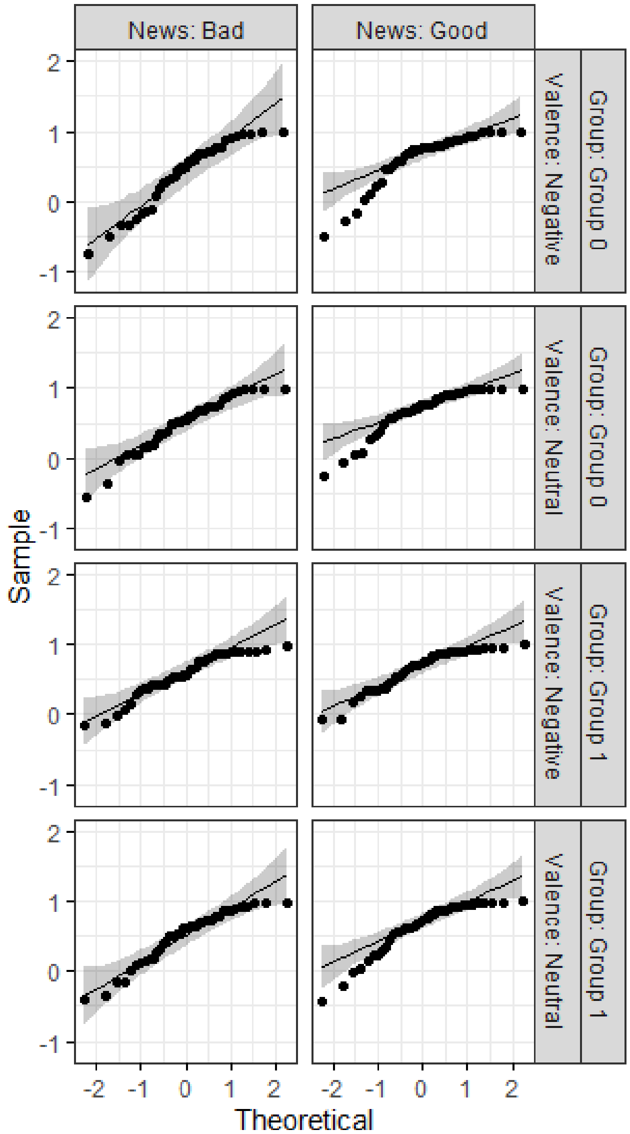

Figure 3.2 *Untransformed QQ plot*

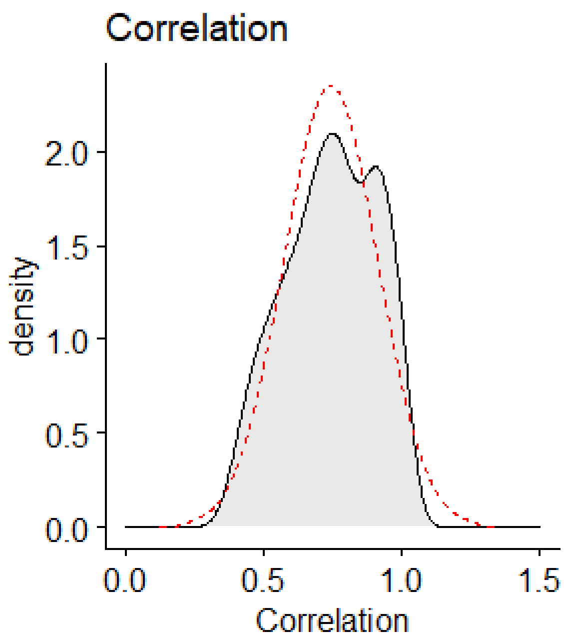

Figure 3.3 *Transformed density plot*

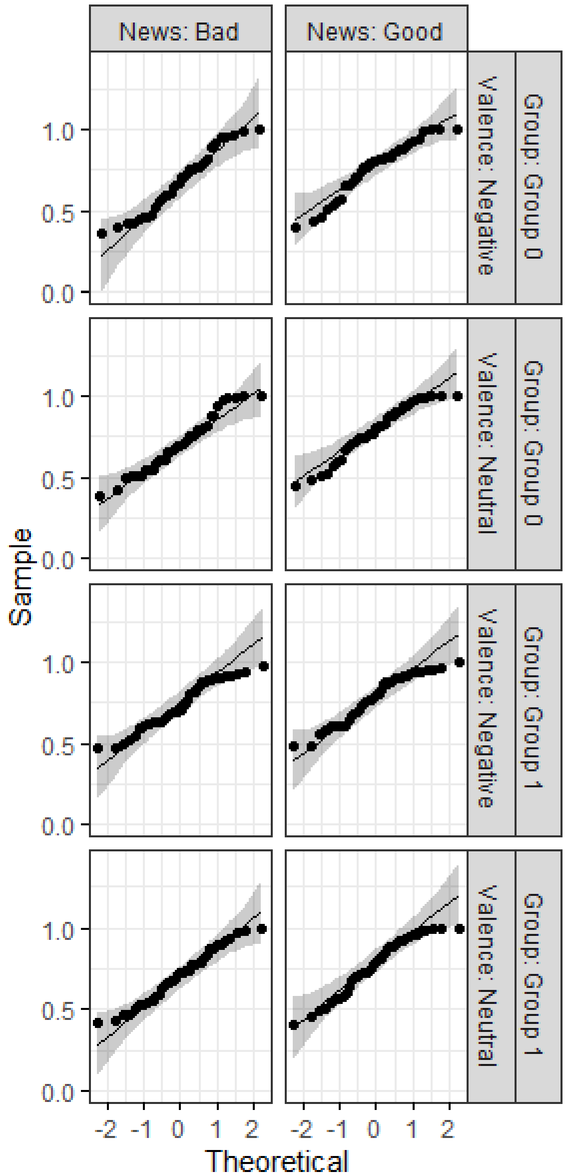

Figure 3.4 *Transformed QQ plot*

3.2.2 Effect of hopelessness on belief updates

To ensure that data did not violate assumptions for multiple regression, processed data from initial analysis assessing the effect of mood induction on belief updates were used to assess the second hypothesis assessing the effect of hopelessness on belief updates. Measures of acute hopelessness following the presentation of neutral and negative mood inductions were averaged at the participant level and matched to each observation. A full summary of hopelessness scores for the sample is included in Table 3.2. A multiple linear regression was performed that included the EE-BU correlations as the dependent variable and information, induction, group, and hopelessness included as independent variables. Results indicated that information type had a statistically significant effect on EE-BU correlation ($\beta = 0.69$, SE = 0.018, $p < .001$, 95% CI = .03, .11). No other variable had a significant effect on outcomes. Regression results are summarized in Table 3.4.

Table 3.4

Multiple regression analysis examining the effect of acute hopelessness on belief updates

	Pearson Correlations			
Predictor	R^2	β	p	F
Desirable Information		*.069*	*<.001*	
Neutral Induction		.003	.888	
Negative First Group		.016	.392	
Hopelessness		-.026	.510	
	.048			3.857

3.3 Exploratory analyses

3.3.1 Effect of mood induction and stimulus ratings on belief updates using linear mixed modelling

An LMM (Model 1) including all variables of interest was first conducted using the r packages *lme4* and *lmerTest* (Bates, 2010; Kuznetsova, Brockhoff, & Christensen, 2017). Results of this model indicated significant main effects for induction (β = 2.2, SE = .76, *p* = .004, 95% CI = .72, 3.68) and EE score (β = .11, SE = .02, *p* < .001, 95% CI = .07, .15). Additionally, a significant interactive effect for induction by information was found (β = -4.04.69, SE = .02, *p* < .001, 95% CI = -6.18, -1.90). No stimuli rating variables had a significant effect on the model. Full regression results are summarized in Table 3.5.

Based on these findings a simplified model (Model 2) including variables that had a significant effect on the more complex model and the information variable were included in a follow-up LMM. This model demonstrated significant main effects for induction (β = 2.25, SE = 0.76, *p* = .003, 95% CI = .77, 3.73) and EE scores (β = 0.12, SE = 0.02, *p* < .001, 95% CI = .08, .16) as well as for the interactive effect of induction by information (β = -4.15, SE = 1.09, *p* < .001, 95% CI = -6.29, -2.00). Full regression results are summarized in Table 3.6.

Models were compared using a log-likelihood ratio test (LRT) as well as AIC and BIC fit statistics. AIC scores for Model 1 (AIC = 26,415.3) were less than Model 2 (AIC = 26,424.0), while BIC scores for Model 1 (BIC = 26,488) were only marginally greater than Model 2 (BIC = 26,466.4). Additionally, the LRT indicated a significant improvement in model fit and parsimony (χ^2 = 18.7, *p* = .002) when comparing the log-likelihood statistics for Model 1 (LL = -13,195.6) to Model 2 (LL = -13,205.0).

Collectively, these findings indicate that Model 2 is a more parsimonious model with superior fit to Model 1 and was retained for further analysis.

The interaction effect between induction and information variables on Model 2 were further probed using estimated marginal (EM) means analysis with the r package *emmeans* (Russell, 2019). EM means were calculated for each induction and information combination (see Table 3.7). Additionally, an interaction plot for EM means was generated (see Figure 3.5). Visual inspection of the EM means interaction plot indicate that the observed induction by information interaction was due to the fact that belief updates following the neutral mood induction were increased for desirable relative to undesirable information, while the inverse relationship (i.e., that belief updates were greater for undesirable information relative to desirable information) was observed following the negative mood induction.

Table 3.5

Linear mixed model analyses assessing the association between induction, information, stimulus scores, error estimates, and belief updates (Model 1)

					95% Confidence Interval	
	β	SE	*T*	*p*	Upper Bound	Lower Bound
Neutral Induction	*2.20*	*.76*	*2.91*	*.004*	*.72*	*3.68*
Undesirable Information	.65	1.07	.61	.541	-1.44	2.74
EE	*.11*	*.02*	*5.29*	*<.001*	*.07*	*.15*
Vividness	.28	.24	1.17	.241	-.19	.75
Prior Experience	.15	.25	.61	.540	-.34	.65
Arousal	.20	.24	.80	.424	-.28	.68
Negativity	-.06	.21	-0.28	.782	-.48	.36
Familiarity	.43	.27	1.59	.111	-.10	.95
Induction:Information	*-4.04*	*1.09*	*-3.71*	*<.001*	*-6.18*	*-1.90*

Table 3.6

Simplified linear mixed model analysis assessing the association between induction, information, error updates, and belief updates (Model 2)

					95% Confidence Interval	
	β	SE	*T*	*p*	Lower Bound	Upper Bound
Neutral Induction	*2.25*	*.76*	*2.97*	*.003*	*.77*	*3.73*
Undesirable Information	.78	1.07	.73	.467	-1.32	2.88
EE	*.12*	*.02*	*5.83*	*< .001*	*.08*	*.16*
Induction:Information	*-4.15*	*1.09*	*-3.79*	*< .001*	*-6.29*	*-2.00*

Table 3.7

Estimated marginal means for induction by information interaction in Model 2

					95% Confidence Interval	
Induction	Information	EM Mean	SE	df	Lower Bound	Upper Bound
Negative	Desirable	10.62	.76	450	9.13	12.11
Neutral	Desirable	12.87	.77	477	11.35	14.38
Negative	Undesirable	11.40	.79	522	9.84	12.95
Neutral	Undesirable	9.50	.79	511	7.95	11.05

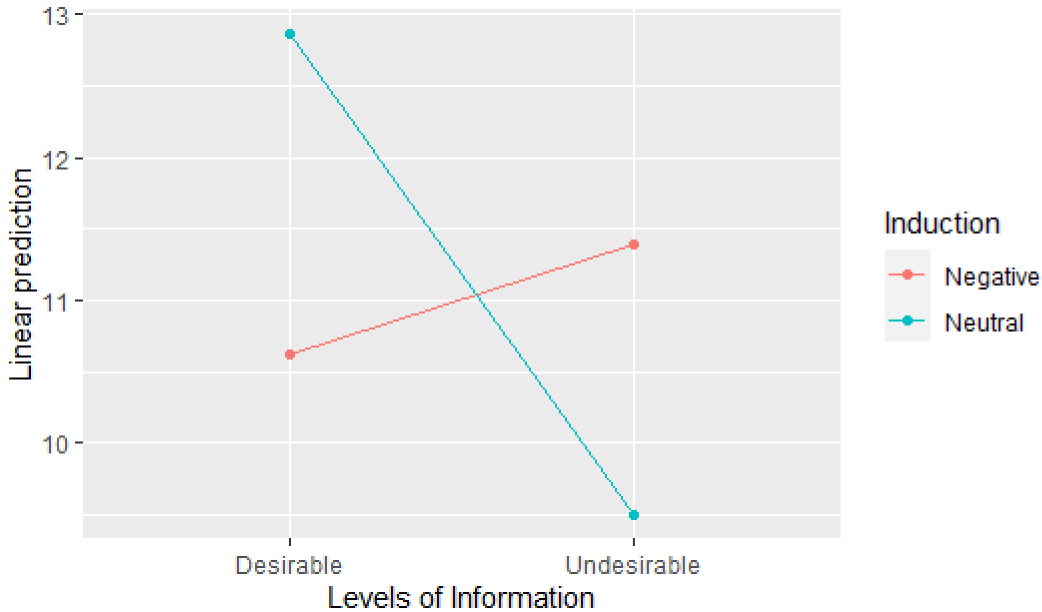

Figure 3.5 *Interaction plot for EM means for induction by information interaction*

CHAPTER IV – DISCUSSION

The purpose of the present study was to examine associations between mood states, specifically sadness, on belief updating. First, we hypothesized that watching a movie selected to induce sadness would be associated with less optimistically biased belief updating in response to undesirable information compared to watching a neutral movie. Second, we hypothesized that acute hopelessness would be associated with reduced optimistically biased belief updating. Based on our primary analyses, we did not find evidence supporting our first hypothesis. We did find evidence of optimistically biased belief updating when receiving undesirable information versus desirable information (i.e., that individuals updated their beliefs less when they were presented with information that indicated that negative future events were more likely to happen to them than when the information indicated that negative events were more likely). This was indicated by a significantly higher correlation with a small to moderate effect size (η_G^2 = .042) between belief updates and estimation errors when individuals received desirable information relative to undesirable information. However, our primary analysis revealed no significant effect of induction group on the correlations between BUs and EEs and no significant interactions between induction, group (i.e., whether they received the negative or neutral induction first), and information type.

These results were somewhat surprising due to prior findings regarding optimistic belief updating. While previous studies identified an association between increased trait optimism and more optimistic belief updates (Kuzmanovic et al., 2015) and between depression and less optimistic belief updates (Garrett et al., 2014; Korn et al., 2014), few studies have used experimental manipulation to assess the relationships between arousal and affective states with belief updating biases. In fact, we were only able to identify one other study that used an experimental manipulation to assess changes in these states by investigating the effect of acute threat response on biased belief updates (Garrett et al., 2018), and none that examined relationships between acute emotional states and belief updating. Based on the previous findings about depression and belief updating, we hypothesized that some of the acute emotionality (specifically sadness) associated with depression might explain differences in belief updating between these groups.

Additionally, we expected the psychological construct of hopelessness to be directly associated with biased belief updating. Hopelessness is related to believing that positive outcomes are unlikely to occur in the future and this construct is a crucial component to theories of depression (Alloy, Abramson, Metalsky, & Hartlage, 1988; Joiner, 2001; Liu, Kleiman, Nestor, & Cheek, 2015). Because hopelessness was related to both depression and individuals' beliefs about the likelihood of future positive and negative events, we hypothesized that this construct would also be related to optimistic belief updating and that the optimistic belief updating bias would be decreased in individuals with higher acute hopelessness scores prior to completing the belief updating task. However, our analysis did not reveal a statistically significant effect of hopelessness on belief updating.

There are a few reasons that we may not have observed the hypothesized effect. First, there was not a large amount of variance observed between the different induction and information groups on the hopelessness variable (see Table 3.2). Despite the successful induction of sad mood and associations between hopelessness and depression, it appears that the induction may not have had a major effect on individual's feelings of hopelessness as measured in this study. That said, the present study utilized a brief version of a more extensive hopelessness measure to assess acute hopelessness. While this measure has been used in prior research to assess acute hopelessness in EMA research (Aish et al., 2001), it has not been extensively validated for the measurement of hopelessness following inductions in experimental research and may be less sensitive to changes in hopelessness than the full form of the BHS.

Second, it is possible that the traditional analytic methods used in this analysis were not sensitive to intra-individual variation in hopelessness and these differences between induction groups. Intra-individual variation has been proposed as a crucial component of better understanding decision-making in the context of individuals as dynamical systems, especially in experimental research (Jensen, 1992; Nesselroade & Ram, 2004). Accordingly, failing to account for these individual differences may have resulted in a failure of our models to detect an effect.

Third, it possible that the hypothesized effect is simply not present. While the connection between hopelessness and beliefs about future negative events appears face valid, research in this area is limited and we know of no studies that have used experimental induction to test relationships between hopelessness and belief updating. One recent study found correlations between hopelessness and less optimistic affective forecasts (i.e., beliefs about how one will feel in the future) (Bauer et al., 2022), but did not include measures of belief updating or experimental inductions of affect to test relationships. Based on these data, further research evaluating relationships between hopelessness and biases associated with future-oriented cognitions are needed to further elucidate how cognitive and affective constructs associated with depression interact.

While we did not observe the hypothesized effect of induction group on belief updates in the main analyses, we did observe a significant main effect of induction and interaction effect of induction by information in our exploratory analyses. Importantly, this model differed from the main analyses by including trial level observations of belief updates with participants included as a random effect. This allowed for modelling the relationships between constructs of interest (i.e., induction, information, EE, and covariates measuring individual event appraisals), while accounting for individual differences in responding and trial-to-trial variation.

This finding has two important implications to be considered. First, as previously noted, accounting for intra-individual variation in experimental research can help address differences in individual response patterns and improve inferences about relationships between hypothesized variables (Jensen, 1992; Nesselroade & Ram, 2004). Specifically, in the context of the belief updating paradigm, Marks and Baines (2017) previously demonstrated that traditional methods of analyzing the belief update procedure, including the main analyses in the present study, failed to identify relationships between their variables of interest (e.g., whether trials used positive or negative events) and belief updating. The fact that our findings demonstrate clear interaction and main effects for induction in LMM suggest that LMM offers more precise and clean analysis of experimental data while accounting for trial-by-trial variation relative to previously used generalized linear and ANOVA modeling.

Of note, our LMM did not indicate a significant main effect of information type (i.e., desirable versus undesirable) on belief updates, despite the extensive history of findings supporting this effect and the presence of this effect in our primary analysis.

There was no presence of this effect due to the presence of EE as a covariate in the LMM models. While information type indicates the direction of the information (i.e., whether or not it is desirable or undesirable), EE indicates both the direction and magnitude of the difference between the initial estimate and the aBR. Including EE is crucial to include in the LMM, as the magnitude of the difference between initial estimates and the aBR should be closely related to the magnitude of the BU, particularly in a trial-by-trial analysis. Therefore, the significant effect of EE on BU in the LMM negated the main effect of information on the model, while information needed to be included to understand the interaction effect between the direction of information with induction group.

Second, the presence of a significant interaction between information desirability and induction group suggest that emotional states are related to the cognitive processes involved in the prediction of the likelihood of future negative events. The observed interaction indicates that belief updates following the negative mood induction were greater for undesirable information relative to desirable information. This is consistent with our hypothesized effect and due to the temporal relationship established between the experimental mood induction and changes in response to belief updates for desirable versus undesirable information suggest that this relationship may be causal. In other words, because the differences in responding to belief updates followed the mood inductions, it can be inferred that the change in affect likely caused the changes in cognitive processes related to belief updating.

This finding is important for a number of reasons. First, it indicates that individuals' judgements about the likelihood of future negative events are affected by emotional states. Because individual decision-making is partially based on anticipated emotions about future events and outcomes of those decisions (DeWall, Baumeister, Chester, & Bushman, 2016; Mellers & McGraw, 2001), the present study suggests how current affective states may interact with cognitions about the future to affect decision-making. Furthermore, the cognitive-affective interaction identified in this study could demonstrate how dysphoric or acutely sad individuals may experience altered cognitive processes that lead to engagement with behaviors that could in turn worsen these affective states. This would result in a cognitive-affective-behavioral feedback loop consistent with the cognitive triad proposed by Hollon and Beck (1979). In their formulation, depressive symptoms are developed and maintained through a process where dysphoric emotions lead to altered cognitions which in turn lead to behaviors that maintain this loop. The present study explores the first association indicated in this model and provides support for the cognitive theory of depression.

Second, it is important to note that the present study does not indicate that sadness is associated with a cognitive bias toward more pessimistic appraisals of future events, but instead that neutral moods are associated with an optimism bias that is not associated with acute sadness. This is consistent with the proposed "psychological immune system," which posits the presence of a psychological system that prioritizes the assimilation of information that will support psychological health and the de-prioritizes the assimilation of information that is detrimental to well-being (Mandelbaum, 2018). In the present study, this manifests as a failure to effectively integrate bad news (undesirable information) that could be potentially damaging to one's psychological well-being (by causing feelings of distress related to potential future negative events and outcomes) and vice versa. However, in the presence of acute sadness, individuals appeared to demonstrate “immune neglect” or the failure to assimilate information in systematically biased way that is protective of one’s psychological health (Gilbert, Pinel, Wilson, Blumberg, & Wheatley, 1998; Wilson & Gilbert, 2005).

This research has several clinical implications based on these findings. By supporting the connection between emotional states and cognitions about the likelihood of future negative events, this research is consistent with therapeutic interventions based on the cognitive-behavioral model (Hollon & Beck, 1979). However, because the biased cognitions identified in this study appear to be related to psychological immunity and follow affective changes temporally, traditional cognitive-behavioral strategies, such as challenging cognitive distortions, may not be beneficial to the patient. Instead, it may be more helpful to target these states themselves by developing skills to improve distress tolerance, emotion regulation, and mindfulness during acute affective states (Linehan, 2020) to reduce the impact of these cognitions on daily functioning and decision-making, thus disrupting the cognitive triad. It may also be beneficial to educate patients about the psychological immune system and the relationships between affective states and biased cognitions (Rosenzweig, 2016). Because psychological immunity is inconsistent with realistic appraisals of future negative events and challenging realistic appraisals would likely be counterproductive and unintuitive, some patients may find value in understanding the relationship between mood, belief updating biases, and decision-making. By understanding the connections between emotions and biased cognitions, individuals may be empowered to accept these differences and rely on more objective reasoning to engage in healthy behaviors that can strengthen the psychological immune system and reduce focus on cognitions that could exacerbate negative emotional states.

4.1.1 Limitations and Future Directions

The present study includes several limitations that may reduce generalizability and inferences about these findings. First, the present study used a population of undergraduate students who were completing this study for course credit, reducing the ability to generalize findings to other populations. Importantly, we did not assess effects within a clinical population, specifically individuals with depression. Because depressive symptoms have been found to be associated with reduced optimism bias, future research should incorporate these populations. Potential directions could include testing whether being taught specific strategies to mitigate acute feelings of sadness or distress are associated with alterations to belief updating patterns. Second, the measure of acute hopelessness employed in the study has been used in EMA research but has not been extensively validated as a measure for hopelessness and therefore findings regarding the second hypothesis are inconclusive. Future research using more robust measures should be used to assess relationships between hopelessness and optimistic belief updating.

CHAPTER V – CONCLUSION

The present study investigated the relationships between acute sadness, hopelessness, and belief updating. Results replicated prior findings regarding optimism bias when presented with desirable information relative to undesirable information. Additionally, while primary analyses did not find an association between induced sadness and belief updating biases, follow-up analyses that accounted for intra-individual and trial-by-trial variation indicated that experiencing a sadness mood induction interacted with the type of information received (i.e., desirable versus undesirable) to reduce optimism bias. These findings are consistent with relationships proposed by the cognitive theory of depression and psychological immunity. Future research should explore clinical implications of these findings and how affective states can be managed to reduce focus on future negative events.

APPENDIX A – IRB Approval Letter

Office *of*
Research Integrity

THE UNIVERSITY OF SOUTHERN MISSISSIPPI

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NOTICE OF INSTITUTIONAL REVIEW BOARD ACTION

The project below has been reviewed by The University of Southern Mississippi Institutional Review Board in accordance with Federal Drug Administration regulations (21 CFR 26, 111), Department of Health and Human Services regulations (45 CFR Part 46), and University Policy to ensure:

- The risks to subjects are minimized and reasonable in relation to the anticipated benefits.
- The selection of subjects is equitable.
- Informed consent is adequate and appropriately documented.
- Where appropriate, the research plan makes adequate provisions for monitoring the data collected to ensure the safety of the subjects.
- Where appropriate, there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of all data.
- Appropriate additional safeguards have been included to protect vulnerable subjects.
- Any unanticipated, serious, or continuing problems encountered involving risks to subjects must be reported immediately. Problems should be reported to ORI via the Incident template on Cayuse IRB.
- The period of approval is twelve months. An application for renewal must be submitted for projects exceeding twelve months.
- Face-to-Face data collection may not commence without prior approval from the Vice President for Research's Office.

PROTOCOL NUMBER: IRB-21-36
PROJECT TITLE: Assessing the effect of sadness on valence-dependent belief updating
SCHOOL/PROGRAM: Psychology
RESEARCHER(S): Aleksandrs Karnick, Daniel Capron

IRB COMMITTEE ACTION: Approved
CATEGORY: Expedited

7. Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

PERIOD OF APPROVAL: February 17, 2021

Donald Sacco, Jr.

Donald Sacco, Ph.D.
Institutional Review Board Chairperson

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