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# Negative Interpretation Bias Connects to Real-World Daily Affect: A Multistudy Approach

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Negative interpretation bias, the tendency to appraise ambiguous stimuli as threatening, shapes our emotional lives. Various laboratory tasks, which differ in stimuli features and task procedures, can quantify negative interpretation bias. However, it is unknown whether these tasks globally predict individual differences in real-world negative (NA) and positive (PA) affect. Across two studies, we tested whether different lab-based negative interpretation bias tasks predict daily NA and PA, measured via mobile phone across months. To quantify negative interpretation bias, Study 1 ($N = 69$) used a verbal, self-referential task whereas Study 2 ($N = 110$) used a perceptual, emotional image task with faces and scenes. Across tasks, negative interpretation bias was linked to heightened daily NA. However, only negative interpretation bias in response to ambiguous faces was related to decreased daily PA. These results illustrate the ecological validity of negative interpretation bias tasks and highlight converging and unique relationships between distinct tasks and naturalistic emotion.

***Public Significance Statement***

Negative interpretation bias, the tendency to interpret ambiguous stimuli as threatening, shapes our emotional lives. Individual differences in negative interpretation biases are usually measured in the lab, but it is unclear how one's laboratory behavior relates to everyday emotion. Replicating our findings across two studies, using distinct lab tasks of interpretation bias, we demonstrate that a negative interpretation bias is linked to heightened daily negative emotion. These results highlight that how one tends to interpret ambiguous information is linked to their daily emotional lives and may be implicated in risk for psychopathology.

*Keywords:* ambiguity, emotion, individual differences, negative interpretation bias, ecological momentary assessment

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Humans face a barrage of ambiguous information and events in daily life. Ambiguous stimuli, such as an acquaintance's laughter after something you said, can lack clear meaning and require contextual information to resolve. With limited contextual information, individuals exhibit trait-like tendencies in the appraisal of the valence and meaning of emotionally ambiguous stimuli (Kim et al., 2003; Neta et al., 2009; Neta & Whalen, 2010). Some display a bias toward evaluating ambiguous information as negative, which has been linked with a broad range of psychiatric symptoms (Hirsch et al., 2016). Yet, the various behavioral tasks that measure negative interpretation bias have scarcely been tested for ecological validity, and the likely mechanisms by which they lead to psychiatric symptoms have not been fully explored. It has been hypothesized that laboratory assessments of negative interpretation biases reflect how ambiguous events are appraised in everyday life (Beard & Amir, 2010; LeMoult & Gotlib, 2019), with a greater negative bias leading to heightened daily negative affect (NA) and the development of emotional disorders (Beck, 1967). However, the degree to which judgments about various types of ambiguous stimuli in highly controlled laboratory tasks are linked with our daily experiences of positive and negative emotions is unknown.

Laboratory tasks assessing negative interpretation bias typically present ambiguous stimuli and record participants' behavior (making a choice or rating) and response times (Hirsch et al., 2016). However, despite these commonalities, negative interpretation bias tasks often differ on numerous dimensions (Schoth & Liossi, 2017). Most studies use only a single negative interpretation bias task and thus cannot address whether the specific task features account for the observed relationships. However, it has been suggested that there are two key dimensions on which laboratory negative interpretation bias tasks differ (Schmuckler, 2001; Schoth & Liossi, 2017): the first pertains to the type of stimuli that are presented (e.g., words vs. images) and the second pertains to the specific decision and behavioral response required by the task (e.g., the acceptability of a single possible interpretation vs. a forced choice between two possible interpretations). Because our goal was to determine the generalizable links between laboratory-assessments of negative interpretation bias and real-world, daily emotion, we chose two widely employed negative interpretation bias tasks that differ from one another on these two critical dimensions. Investigating multiple tasks that stratify these dimensions help to establish a connection between real-world emotion and task-based negative interpretation bias.

One widely used task is the word sentence association paradigm (WSAP; Beard & Amir, 2009; Gonsalves et al., 2019). In each trial of this task, a single word precedes an ambiguous, self-referential scenario (e.g., "you ask for directions"). The word is either negative, given the context of the specific scenario, (e.g., "weak") or benign (e.g., "resourceful"). Then, the participant categorizes whether the word and sentence are related. With regard to the dimensions of interest, this task presents *semantic* stimuli with a *relatedness* decision for one possible interpretation. Trait-like individual differences in negative interpretation bias can be derived from the percentage of negative words endorsed as matching the ambiguous sentence (Beard & Amir, 2009). Although developed to target negative interpretation bias, this task also captures individuals' degree of benign interpretation bias from the percentage of benign words endorsed on those trials. A thorough systematic review of more than 40 studies employing the WSAP demonstrated that it has good internal consistency (αs from .71 to .85, see table 4 in Gonsalves et al., 2019), test–retest reliability ($r = .71$; Martinelli et al., 2014) and is sensitive at discriminating those with and without psychopathology (Gonsalves et al., 2019). Further evidence that the WSAP captures negative interpretation bias comes from intervention studies demonstrating that bias modification training shifts an individuals' bias as quantified by the WSAP (across 15 studies, Cohen's $d$ ranging from 0.94 to 2.84 for change in negative interpretation bias; Gonsalves et al., 2019). Overall, there is compelling evidence that the WSAP is a psychometrically sound assessment of interpretation bias.

Another well-validated negative interpretation bias task, the emotional image task (Neta & Brock, 2021; Neta et al., 2009), presents different stimuli and decisions from the WSAP. In this task, emotionally clear (e.g., a smiling face) and emotionally ambiguous (e.g., a surprised face) facial expressions and scenes are presented to participants. Then, they categorize whether the image is positive or negative. Negative interpretation bias is quantified by the percentage of ambiguous stimuli an individual categorizes as negative (Kim et al., 2003; Neta et al., 2009; Neta & Whalen, 2010), and can be calculated separately for face and scene stimuli. Unlike the WSAP, trials of this task present a *visual* stimulus with a forced choice between interpretation options spanning the full valence spectrum (Neta & Brock, 2021; Neta et al., 2009). Due to the forced choice nature of the task, negative interpretation bias and positive interpretation bias are the two ends of a single dimension. However, like the WSAP, there is strong evidence that scores on this task are stable over various timespans (1 week, Neta et al., 2018; 6 months, Harp et al., 2022; and 1 year, Neta et al., 2009). Moreover, task scores converge with other meaningful measures, such as depression symptoms, state and trait anxiety, neuroticism, and more (Neta & Brock, 2021). Therefore, it appears that both the emotional image task and the WSAP indeed fall under the umbrella of negative interpretation bias.

In addition to measuring participants' choices about the valence of ambiguous stimuli, both of these tasks also assess the speed of these choices. Reaction times (RT) for binary choices reflect a process by which an individual gathers information, arrives at their decision, and executes their choice behavior (Voss et al., 2013). In the context of negative interpretation bias tasks, the faster an individual endorses ambiguous stimuli as negative, the more intense, habitual, or easier to access the negative interpretation bias is believed to be. RT metrics are thought to provide additional information about one's degree of negative interpretation bias, in part, because they may be less sensitive to response biases and demand characteristics than explicit choice behavior (Blanchette & Richards, 2010). Sometimes referred to as indirect metrics (Everaert et al., 2017), RT measures often show only partial overlap with choice measures of negative interpretation bias (Beard et al., 2017; Cowden Hindash & Rottenberg, 2017; O'Connor et al., 2021), suggesting such RT measures may capture a unique aspect of negative interpretation bias. Yet, whether both choice and RT measures of negative interpretation bias have utility in predicting naturalistic affective outcomes remains an open question.

Although the WSAP and emotional image task measure negative interpretation bias broadly, their differences in stimulus and decision type may have implications for real-world functioning. For example, Hirsch and Mathews (1997) suggested that, compared with static images or single words, verbal descriptions of ambiguous scenarios (e.g., "You have visitors round for a meal and they leave sooner than expected"), like those used in the WSAP, may uniquely capture the complexity of real-world events. These verbal descriptions invite participants to imagine themselves in a scenario, a process which induces affective states (Schubert et al., 2020) and thus, heightens the emotional consequences of negative interpretations of ambiguous information (Holmes et al., 2009). Further, generating mental images engages a similar, but partially independent, set of neural circuits (Schacter et al., 2007) that are distinct from bottom-up perceptual processing of ambiguous stimuli (Andrews-Hanna et al., 2014; Burrows et al., 2017).

Even among tasks that present ambiguous visual stimuli, processes for resolving ambiguity across stimulus types, such as emotional facial expressions and complex scenes, may differ. Indeed, faces and scenes differ based on perceptual complexity as well as conceptual dimensions. As highly social beings, humans have developed a specialized and prioritized processing capacity for the human face (McFadyen et al., 2017). Distinct neural pathways are recruited for processing and appraising face versus non-face stimuli (Davis & Whalen, 2001) and these differences may be exaggerated for affect-laden stimuli (Hariri et al., 2002; Sabatinelli et al., 2011). Such differential neural processing of emotional faces also appears to produce distinct downstream physiological responses, including faster orienting to faces, but smaller facial electromyography responses to faces versus scenes (Mavratzakis et al., 2016). Compared with faces, scenes often contain more perceptual information and more diverse and abstract concepts, which yields greater latency for processing and evaluation (Hariri et al., 2002; Neta et al., 2013). These differences could contribute to ambiguous faces typically being rated more negatively than ambiguous scenes (Harp et al., 2021; Neta et al., 2013) and highlight the need to further explore their potentially divergent real-world, emotional consequences.

Moreover, the behavioral choices within these tasks differ greatly. Whereas trials of the WSAP only present one possible interpretation alongside the ambiguous stimuli (in this case a word, such as "embarrassing"), the emotional image task presents two interpretation options with each image (happy or angry, positive or negative). It is possible that determining whether a negative word (one possible interpretation) is related to the ambiguous scenario, may only partially reflect real-world judgments of ambiguous information, which often include multiple possible interpretations evaluated simultaneously. While the emotional image task indeed provides multiple options, it does force a choice between a negative or positive judgment about each image without allowing the participant to generate their own set of alternatives. Thus, it is necessary to test whether these differences in decision and stimulus type have baring on the relationship between negative interpretation bias and day-to-day emotion.

As highlighted above in the example about an acquaintance's laughter, interpretation biases can shape our daily emotional experience. However, the ecological validity of laboratory negative interpretation bias paradigms, or the impact of certain task features on real-world negative and positive affect is not known. Key assumptions about the specific mechanisms by which interpretation biases manifest in our affective lives can be tested by using ecological momentary assessment (EMA). EMA can provide assessments of naturalistic, daily affect and thus enables the testing of links between emotional states (across time and diverse contexts) and individual differences in these negative interpretation bias tasks. Specifically, given empirical (Eldar et al., 2016; Puccetti et al., 2021) and theoretical (Davidson, 1998) assertions that stimulus-driven emotional responses contribute to enduring moods, it is imperative to test whether negative interpretation biases predict heightened NA, and/or perhaps reduced PA, in daily life. Finally, cognitive models of psychopathology have long posited that negative interpretation biases confer risk for mood and anxiety disorders by creating persistent, heightened negative moods (Beck, 1967). This assertion that negative interpretation bias and daily affect are connected has yet to be tested, even in non-clinical samples. Demonstrating an empirical connection between individual differences in negative interpretation bias and naturalistic emotion would be a novel, preliminary test of Beck's claims.

Further, it is crucial to test whether the connection between negative interpretation bias and daily emotion is modulated by valence because of the differential role of NA and PA in the development and maintenance of internalizing disorders (Clark & Watson, 1991). While greater negative interpretation bias is theorized to be associated with heightened NA in daily life (Beck, 1967), it is less clear whether this bias is also linked to variation in daily PA. This is, in part, because PA and NA are not opposing constructs, but appear to vary independently within individuals (Dejonckheere et al., 2021; Tellegen et al., 1999). Examining valence specificity has important implications for understanding the real-world impact of interpretation biases. For instance, while high NA and low PA are both linked to internalizing symptoms cross-sectionally (Heller et al., 2021; Scott et al., 2020), high daily NA predicts the future development of internalizing symptoms (Conway et al., 2016; Hettema et al., 2006; Kendler et al., 2004). Moreover, specific skills and interventions are often prescribed to ameliorate high NA vs increase low PA (Bryant, 2021; Dimidjian et al., 2011; Kaczkurkin & Foa, 2015). Thus, investigations into the real-world, affective correlates of negative interpretation bias should examine valence specificity.

To that end, in two studies employing different laboratory-based negative interpretation bias tasks, we tested the hypothesis that negative interpretation biases, are related to profiles of daily positive and negative emotions. In Study 1, 69 young adults completed every-other-day EMA of PA and NA for approximately 2 months. Participants also completed the WSAP to measure negative interpretation bias to ambiguous verbal scenarios. In Study 2, 110 young adults completed a similar EMA protocol and the emotional image task that measures negative interpretation bias to face and scene stimuli. For both studies, we hypothesized that greater negative interpretation bias, as assessed in the laboratory, would be related to higher daily NA. As an additional exploratory aim, we tested whether daily PA would be associated with the negative interpretation bias tasks and how the magnitude of these connections differ from daily NA.

## Study 1

### Method

#### *Participant Characteristics*

One hundred three participants were recruited across two cohorts (Fall 2017 and Fall 2018) from an Introduction to Psychology course to participate in a study that included self-report questionnaires and behavioral tasks across two laboratory visits. Independent data from these participants were published in Stamatis et al. (2020) and Heller et al. (2021). From the 103 participants recruited, 77 participants completed the second laboratory visit at the end of the academic semester. A subset of participants was excluded from group analyses for poor negative interpretation bias task performance (see below) and/or too few EMA responses, which yielded a final analysis sample of 69 participants who provided data at both time points. Mean age = 18.58, $SD = 0.55$. Among multiple choice racial identity options, 55% of participants endorsed Caucasian or White, 20% Asian or Asian American, 9% African American or Black, 7% identified with multiple races, and 9% identified as "other" with an option to write in their race. When presented with a forced choice ethnicity item, 20% of the sample endorsed Hispanic or Latino ethnicity and 80% endorsed non-Hispanic or Latino ethnicity. When presented with a forced choice sex item, 59% identified as female and 41% as male. Using the MacArthur Scale of Subjective Social Status (Adler et al., 2000), participants place themselves on rungs of a ladder (range = 1–10) relative to others nationally. The average placement was 6.51 ($SD = 1.5$, range = 2.5–10).

#### *Study Procedure*

Study procedures were approved by the Institutional Review Board of the authors' home institution, and participants provided written consent. During the first laboratory visit, participants completed a battery of psychiatric symptoms, not analyzed here, and received instructions for completing EMA surveys throughout the semester. Participants were compensated with course credit and/or cash for their participation proportional to the percentage of EMAs completed. During the second laboratory visit, approximately 2 months later, participants repeated the questionnaire battery and completed the WSAP task. Additional behavioral tasks were completed during both lab visits but are beyond the scope of this report.

#### *Word Sentence Association Paradigm (WSAP)*

Participants completed the computerized WSAP developed by Beard and Amir (2008, 2009). This task assesses negative interpretation bias as the tendency to interpret ambiguous phrases as having negative meaning. For each trial, participants see a fixation cross for 500 ms, then either a benign or threatening word (e.g., funny or embarrassing, respectively) for 500 ms. Then, an ambiguous sentence (e.g., "People laugh after something you said") is displayed for 1,250 ms before being removed from the screen. Participants are prompted to "press 1 if the word and sentence are related or 3 if the word and sentence are unrelated." There is no time limit to make this response; however, participants are instructed to go as quickly as they can when making their responses.

Participants responded to each of 70 phrases two times—once with a benign word and once with a threatening word—for a total of 140 trials. Thirty trials (15 phrases) targeted general threat-related concerns (e.g., "You receive a call from a loan officer," paired with either "approved" or "declined"); 30 trials (15 phrases) targeted social threat-related concerns (e.g., "You make small talk with people at a wedding reception," paired with either "polite" or "awkward"); and 80 trials (40 phrases) presented negative self-referential statements (e.g., "You get a new job," paired with either "qualified" or "unqualified"). For the purpose of this analysis, all trials presenting negative or threatening words were included in the calculation of a single negative interpretation bias metric. Data from benign trials were collected but not included in the primary analyses (see Results in Table S1 in the online supplemental materials).

Prior to performing the task, participants completed six practice trials that contained unambiguous sentence-word matches. For example, when the phrase "The waiter brought our food to the table," was paired with the word "appetizer," participants were expected to indicate that the sentence and phrase did match. Conversely, when the same sentence was paired with the word "tiger," participants were expected to respond that they did not match. The practice trials allowed the participants to become familiar with the task and demonstrate that they understood the instructions.

#### *WSAP Data Cleaning*

Data cleaning and analyses were conducted using the R programming language (R Core Team, 2017). Six participants were excluded for completing two or more of the six practice trials incorrectly. This criterion was set because the practice stimuli were easy and obvious. We elected to include participants who had one error, however, participants that made two or more errors more than likely did not understand the objective of the task or were not attending to, or applying sufficient effort, on the task. For the remaining 71 participants, each person's mean RT was calculated and trials involving a RT > 3 standard deviations (*SD*; Berger & Kiefer, 2021) above their own mean RT were removed to prevent extreme outliers from influencing the participant's mean. This resulted in the removal of 167 trials total across 68 of 71 participants ($M = 2.45$, $SD = 1.09$, and range = 1–5 trials removed per person). After censoring within-person outliers, we computed the average RT across the whole sample and removed an additional two participants who had an average RT that was >3 *SD* above the sample mean ($M = 982.41$ ms, 3 *SD* cutoff = 2,243.63 ms). This resulted in 69 participants for the final analysis.

For these participants, negative interpretation bias was operationalized as the percent of negative interpretations endorsed. In line with previous research (Beard & Amir, 2009; Beard et al., 2017), we also calculated negative word RT bias, by subtracting mean RT for endorsing negative interpretations from mean RT for rejecting negative interpretations.

#### *EMA Surveys of Daily Affect*

Participants received EMA surveys of momentary affect one time, every other day, throughout the semester, beginning 1–2 days after the initial laboratory session. EMA surveys were distributed via SMS messages at pseudo-randomly determined times between 10:00 a.m. and 8:00 p.m. (per Villano et al., 2020; see Figure S2 in the online supplemental materials for the distribution of times surveys were submitted). These text messages contained a link to an online self-report survey hosted on Qualtrics (2019). This survey did not expire after a certain time elapsed, however, the data were cleaned to retain only a single submission in response to the text message prompt. Moreover, regardless of whether participants completed the survey 1 min or 1 hr after receiving the text message, the EMA items were worded to elicit the participant's *current* experience. Sampling this way, once per two days across months, allowed us capture longitudinal patterns of affect that are less susceptible to temporary events and stressors. Thus, rather than just experiences limited to a few days or one week, this sampling procedure permits identification of enduring trait-like levels of PA and NA for individuals.

Six emotion items derived from the Positive Affect/Negative Affect Schedule (Watson et al., 1988) were assessed, specifically "happy," "excited," "content," "upset," "irritable," and "anxious." This set of emotions was chosen to broadly sample the dimensions of affective valence and arousal while minimizing participant burden. Participants rated the degree to which they were *currently* experiencing each emotion (e.g., "How anxious are you feeling right now?") on separate visual analog scales (i.e., slider bars; range: 0–100). The internal consistency among these three positive emotions was good (Cronbach's $\alpha = .87$), as was the internal consistency of the negative emotions (Cronbach's $\alpha = .89$).

### EMA Compliance and Data Cleaning

Pooling all participants together, the *median* time to complete a survey was 63 s. There were outliers that appeared to shift the mean and standard deviation of survey completion times. Of the 1,712 total EMA responses, 1,655 or 96.67% were completed in under 5 min. The distribution of surveys with completion durations beyond 5 min is very positively skewed (skew = 2.80) highlighting that vast majority of EMA responses were completed within a few moments (see Figure S1 in the online supplemental materials for outlier distribution). For the sake of presenting representative descriptive statistics, we set aside the 57 EMA responses that were completed in greater than 5 min, finding that the average completion duration was 74.77 s ($SD = 42.08$ s, range = 24–300) with a median time to complete of 62 s.

The total number of EMA surveys sent varied by each individual's start and end date in the study. The mean number of EMA surveys completed across the semester was 27.51 ($SD = 9.29$, range = 3–45). The average completion percentage, or compliance rate, for each participant was 90.60 ($SD = 15.40$, range = 11.11–100; see Figure S1 in the online supplemental materials for the distribution). We accounted for the variability in number of responses in two ways. First, our main analyses employed hierarchical regression models with a random effect of participant so that each individual participant's contribution to fixed effect parameter estimates was weighted by their number of responses.

Second, we confirmed our main analyses using only participants who completed >14 EMA responses (see Figure S3 in the online supplemental materials). To determine this cutoff, we used a data-driven analysis (similar to Jaso et al., 2021) to determine the number of EMA responses required to compute stable within-participant estimates of NA and PA. In brief, NA and PA means were calculated iteratively using different numbers of randomly sampled EMA responses (range: 5–35) and the rank-order correlation between resampled NA and PA estimates was calculated. We observed an asymptote of rank-order stability ($\rho = 0.90$) at around 8 or more observations for NA mean and 14 or more for PA mean (Figure S1 in the online supplemental materials). The confirmation analyses, which included a subset of 62 participants with 14 or more EMA responses, produced a similar pattern of results as presented below with the full sample (see Table S2 in the online supplemental materials).

### Data Analytic Plan

Pearson product-moment correlations were estimated between WSAP task outcomes, specifically, the percent of threat-related word-sentence pairs endorsed and RT and mean NA and PA derived from EMA measures (see Table S1 in the online supplemental materials). These correlations were corrected using the false discovery rate (Benjamini, 2010) to control for multiple comparisons. For the primary aim, we used a hierarchical linear regression (*lme4* in R; Bates et al., 2021). The outcome for this model was EMA-derived affect with separate observations (rows) containing NA and PA scores. A separate binary "valence" predictor variable (coded as NA = 0, the intercept, and PA = 1) was added to index whether the EMA value was a positive or negative emotion score. Interactions between valence and task predictors of interest—negative interpretation bias and negative word RT bias on daily affect—were tested. We reverse scored the PA values to ensure PA and NA were on the same scale. Specifically, PA scores were subtracted from 100 (the maximum possible value) so that higher values reflected lower PA. As a result, the interaction term tested whether negative interpretation bias was more strongly related to greater NA than it was related to lower PA. This coding scheme meant that main effects of the model reflect the relationship between bias and *negative affect* only. For each interaction, we computed simple slopes to examine whether the relationships between task and PA were significant. Data and analysis code are available at: https://osf.io/kfu8j/ (Puccetti, 2022).

## Results

### WSAP Descriptive Statistics

Descriptive statistics for affect and WSAP task behavior are presented in Table 1. On the WSAP, the negative interpretation bias mean was 0.24 ($SD = 0.08$, range = 0.09–0.44). Mean RT on trials endorsing negative words was 887.70 ms ($SD = 334.60$ ms, range = 341–1,740 ms) and mean RT on trials rejecting negative words was 947.80 ms ($SD = 413.30$ ms, range = 306–1,740 ms). The mean negative word RT bias was 60.14 ms ($SD = 334.60$ ms, range = 341–1,740 ms). Negative interpretation bias and negative word RT bias were significantly correlated ($r = .59$, $p < .001$; Table S1 in the online supplemental materials).

### Daily Affect Descriptive Statistics

Daily affect descriptive statistics are displayed in Table 1. The interclass correlation, or ICC, for EMA-assessed NA was 34.94%. This means that approximately 35% of the variance in NA scores are attributable to the grouping factor of participant and the remaining 65% of variance reflecting within-person fluctuations. For PA, the ICC is 24.95%. These numbers confirm that the EMA sampling captured a wide range of experiences within individuals. Between

**Table 1**
*Study 1 Descriptive Statistics*

| Variable | *M* | *SD* | Min | Max |
|---|---|---|---|---|
| WSAP indices | | | | |
| Negative interpretation bias (negative word endorsement) | 0.24 | 0.08 | 0.09 | 0.44 |
| Negative word endorsement RT | 887.7 | 334.6 | 340.53 | 1.739.53 |
| Negative word rejection RT | 947.8 | 413.3 | 306.03 | 2.584.54 |
| Negative word RT bias | 60.14 | 271.24 | −456.18 | 1.308.38 |
| Daily affect | | | | |
| Mean NA | 34.48 | 13.47 | 4.83 | 65.74 |
| Mean PA | 56.91 | 10.95 | 34.1 | 93 |

*Note.* n = 69. NA = negative affect; PA = positive affect; SAP = word sentence association paradigm; RT = reaction times; Negative interpretation bias = negative endorsement, or the rate of negative words determined to be related to the subsequent ambiguous phrase. Negative word bias RT = negative word rejection RT − negative word endorsement RT. Range of possible values for daily affect means was 0–100.

participants, the average of participants' mean NA was 34.48 ($SD$ = 13.47, range = 4.83–65.74 out of 100). The average of participants' mean PA was 56.91 ($SD = 10.95$, range = 34.10–93.00. Between-participants, mean NA and PA were inversely related ($r = -.39$, $p = .006$). Moreover, the number of EMA responses submitted was not related to either mean NA ($r = -.075$, $p = .545$) or mean PA ($r = -.015$, $p = .903$).

### *Negative Interpretation Biases to Verbal, Self-Referential Stimuli Are Related to Daily NA but not PA*

We tested whether negative interpretation biases, assessed using self-referential, language-based stimuli, were related to daily NA and PA in a hierarchical linear model (Table 2). Specifically, EMA-derived affect (both positive and negative) was the dependent variable with a binary "valence" predictor variable (NA = 0 and PA = 1) that interacted with the task predictors, negative interpretation bias and negative word RT bias. PA scores were reverse scored so that the interaction term tested whether negative interpretation bias was more strongly related to greater NA than it was related to lower PA.

The main effect of negative interpretation bias from this model indicated that negative interpretation bias significantly predicted daily NA ($b = 0.65$, $SE = 0.20$, $p = .002$; Figure 1). Further, there was a significant interaction between negative interpretation bias and EMA affect valence ($b = -0.39$, $SE = 0.10$, $p < .001$). Analysis of simple slopes confirmed that negative interpretation biases did not significantly predict daily PA ($b = 0.25$, $SE = 0.20$, $p = .208$, reverse scored, Figure 1). Effects were specific to the direct measure of choice data; negative word RT bias was not significantly related to daily NA ($b = -0.006$, $SE = 0.006$, $p = .295$), nor did it interact with valence ($b = -0.002$, $SE = 0.003$, $p = .487$). Simple slopes analysis confirmed negative word RT bias was also unrelated to daily PA ($b = -0.008$, $SE$ = 0. 0.006, $p = .161$).

**Table 2**
*Hierarchical Linear Model of Daily Affect Regressed on Negative Interpretation Bias From the WSAP Task*

| Predictor | *B* | *SE* | *t* | *p* |
|---|---|---|---|---|
| Main effects | | | | |
| Valence | 8.93 | 0.66 | 13.60 | <.001*** |
| Negative interpretation bias | 0.65 | 0.20 | 3.25 | .002** |
| Negative word RT bias | −0.006 | 0.006 | −1.06 | .295 |
| Interaction effects | | | | |
| Valence × negative interpretation bias | −0.39 | 0.10 | −3.75 | <.001*** |
| Valence × negative word RT bias | −0.002 | 0.003 | −0.70 | .487 |
| Simple slopes for interactions | | | | |
| NA ∼ negative interpretation bias | 0.65 | 0.20 | 3.25 | .002** |
| PA ∼ negative interpretation bias | 0.25 | 0.20 | 1.27 | .208 |
| NA ∼ negative word RT bias | −0.006 | 0.006 | −1.06 | .295 |
| PA ∼ negative word RT bias | −0.008 | 0.006 | −1.41 | .161 |

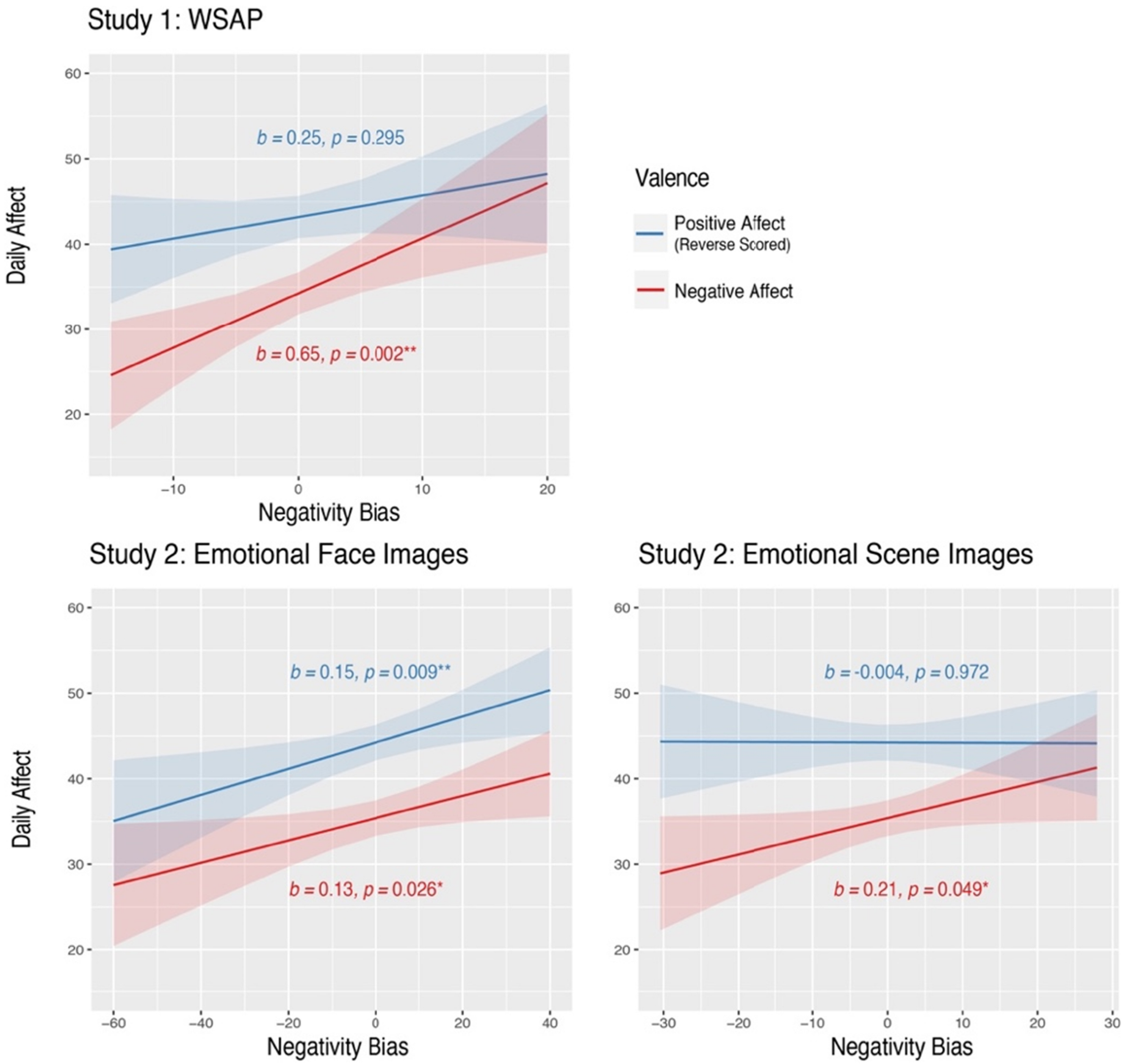
*Note.* Model included 3,328 observations across 69 participants. NA = negative affect; PA = positive affect; RT = reaction time; WSAP = word sentence association paradigm. Valence is coded with NA = 0 and PA = 1. PA scores were also reversed scored so that larger values reflect less PA. This was done so that negative interpretation bias effects would be positive for both positive and negative affect and interaction terms could compared the magnitude of the linear relationships between positive and negative affect. Main effects are interpreted when valence = 0 (for negative affect specifically).
$^{**}p < .01$. $^{***}p < .001$.

## Study 1 Discussion

Study 1 demonstrated that individual differences in self-referential negative interpretation bias, as indexed by the WSAP, are related to real-world NA but not PA. To our knowledge, this is the first investigation connecting the WSAP, a widely used negative interpretation bias task (Gonsalves et al., 2019), to naturalistic measures of daily affect. These results confirmed our hypothesis that laboratory-assessed negative interpretation bias would be linked to greater NA in daily life. This relationship suggests that those who match more negative words with ambiguous phrases in the laboratory may similarly evaluate ambiguous events as negative in their daily life, which could, in turn, heighten their average level of NA across time and contexts.

Interestingly, negative interpretation bias was not related to lower daily PA. This suggests that the affective consequences of negative interpretation bias may be at least partly independent between NA and PA. This valence effect may be a product of negative interpretation bias, regardless of the task used to measure it. For example, it may be that individuals with greater negative interpretation biases, when evaluating unclear or ambiguous information, are still able to evaluate more "clearly positive" information, such as a good grade on an exam, as indeed positive. This could yield comparable levels of PA across those with higher versus lower negative interpretation bias. In contrast, however, it appears that characteristics of the WSAP might produce a negative interpretation bias "score" that is not sensitive to variation in average levels of daily PA. For instance, WSAP trials specifically probe whether an ambiguous, self-referential scenario matches a single negative word presented at the start of the trial. Possible negative interpretations are not displayed alongside an alternative neutral or positive word within that trial. Thus, this procedure may not allow individuals to generate and simultaneously evaluate multiple alternative interpretations (including more positive interpretations) for a given ambiguous event. Subjective experiences of PA in daily life may be more tightly linked with generating and selecting positive interpretations that are in competition with more negative interpretation of ambiguous stimuli in the real world, which is not measured by the WSAP.

**Figure 1**
*Negative Interpretation Bias Is Related to Daily Affect*




*Note.* N = 69 for Study 1 and 110 for Study 2. Shown here are the expected values of daily affect from the hierarchical linear regression models that used negative interpretation bias as a predictor (see Tables 2 and 4 for Study 1 and Study 2 models, respectively). Significant interactions between EMA valence and negative interpretation bias from the WSAP and scene images are shown: negative interpretation bias across all three types of stimuli is related to increased daily NA, while only negative interpretation bias to ambiguous faces is related to less daily PA. PA scores were reversed so that larger values reflect less PA. This was done so that negative interpretation bias effects would be positive for both positive and negative affect and interaction terms could compared the magnitude of the linear relationships between positive and negative affect. For the WSAP, negative interpretation bias is determined by the rate at which participants matched ambiguous phrases with negative words. For the emotional image task, negative interpretation bias is calculated as the percentage of surprised face or ambiguous scene trials that were categorized as negatively valenced. See the online article for the color version of this figure.

Further, the RT metric of negative interpretation bias (the difference in mean RT for rejecting and endorsing negative interpretations) was not significantly related to daily NA or PA. O'Connor et al. (2021) similarly found that, unlike WSAP choice outcomes, individual differences in reaction time were not linked to depression symptoms. They suggested that response time measures may not capture the same analytic processes that are required by more direct, self-report measures of negative interpretation bias (Everaert et al., 2017; Hirsch et al., 2016; O'Connor et al., 2021). Another possibility is that the RT bias score itself is not an ideal measure, as aggregate response times, particularly "scores" taken from the difference between means of two conditions, have been criticized as unreliable (Hedge et al., 2018; O'Connor et al., 2021; Rouder & Haaf, 2019).

Critically, it is an open question whether other tasks that measure negative interpretation bias would show the same pattern of relationships with daily affect. Previous research on the degree of convergence across negative interpretation biases have been inconsistent, with some studies showing moderate correlations across tasks indexing negative interpretation bias (Harp et al., 2021; O'Connor et al., 2021), and others finding few significant correlations between tasks (Lee et al., 2016). As mentioned above, the WSAP measures a particular type of verbal, self-referential negative interpretation bias. It is plausible that resolving ambiguity presented in emotional images may not completely overlap with WSAP-elicited processes. Moreover, whereas the WSAP presents a single possible interpretation (one word) for the ambiguous scenario, a task that simultaneously allows for multiple competing interpretations—ranging from negative to positive—for a single stimulus could yield different relationships with daily affect. Given this, it is crucial to investigate the relationship between negative interpretation bias and daily affect using additional behavioral tasks.

## Study 2

Study 2 examined whether negative interpretation bias toward ambiguous faces and scenes (Neta et al., 2013) is associated with individual differences in naturalistic, EMA-derived daily affect. Here, by using a different negative interpretation bias task from Study 1, we were able to compare whether the relationship between negative interpretation bias and daily PA and NA is conditional upon critical task differences in stimulus and decision type. As mentioned above, implementing multiple tasks that vary in stimulus type and decision type is necessary to realize our goal of determining generalizable links between laboratory assessments of negative interpretation bias and real-world emotion.

Whereas the WSAP in Study 1 presented individuals with brief written, self-referential situations as ambiguous stimuli, the task in Study 2 presented static images of faces and scenes. Happy or angry expressions convey relatively clear positive and negative information, respectively, however surprised expressions are more ambiguous and open to interpretation. When presented with this ambiguity, some individuals consistently categorize surprised expressions as positively valenced, while others categorize them as negatively valenced (Kim et al., 2003; Neta et al., 2009; Neta & Whalen, 2010). Thus, in this study, interpretation bias can be seen as a single dimension on which individuals tend towards more negative interpretation *or* more positive interpretations. Similarly, scenes from the IAPS database (Lang et al., 2008) are positive or negative, or ambiguous. Negative interpretation biases between these stimulus types are significantly correlated ($r = .50$, Neta et al., 2013), such that the same people that tend to categorize surprised faces as negative also categorize ambiguous scenes as negative. However, there are also documented differences in negative interpretation biases to faces versus scenes, with individuals, on average, tending to consistently categorize ambiguous faces as more negative than ambiguous scenes (Harp et al., 2021; Neta et al., 2013).

Compared with scenes, faces are perceptually simpler and more purely social than scenes (only 50% of scene stimuli were allowed to contain one or more humans). The facial expression stimuli may also be perceived as more self-referential than scene stimuli as the emotional facial expression is directed at the participant. On one hand, it may be that negative interpretation bias when rating the face stimuli may serve as a stronger predictor of daily affect due to the ubiquity of human facial processing in the real-world, relative to specific scenes in the IAPS database (Lang et al., 2008). On the other hand, it may be that complex scene stimuli more closely resemble the rich environments that we encounter in day-to-day life, thus providing a more sensitive metric of negative interpretation bias to connect from profiles of real-world emotion. The richness of the scene stimuli may also provide more affordances for reappraisal (Suri et al., 2018), which could reflect real-world regulatory processes and shift affective correlates of scenes relative to the face stimuli. Still another possibility is that the broad construct of negative interpretation bias manifests similarly across these tasks resulting in few, if any, differential links to daily affect.

### Method

#### *Participant Characteristics*

One hundred and eighty-eight participants were recruited from an Introduction to Psychology course in three separate protocols. Each of these protocols included the emotional image task and then a similar EMA protocol to that of Study 1 (see protocol details below in *EMA Surveys of Daily Affect*). Study 2 included a subset of 29 participants from Study 1, This small amount over overlap precluded substantial within-person comparison of the negative interpretation bias tasks in Study 1 and Study 2. Of the participants enrolled, a subset were excluded for poor task performance (see below). Thus, the final analysis sample included 110 participants. The mean age = 18.64, $SD = 1.18$. Among multiple choice racial identity options, participants endorsed 54% Caucasian or White, 29% Asian or Asian American, 10% African American or Black, 3% mixed race, and 4% choose other with option to write in their race. When presented with a forced choice ethnicity item, 21% of the sample endorsed Hispanic or Latino ethnicity and 79% endorsed non-Hispanic or Latino ethnicity. When presented with a forced choice sex item, 75% identified as female and 25% as male. Seventy-two of these participants completed the MacArthur Scale of Subjective Social Status (Adler et al., 2000) and their average placement on the ladder was 6.44 ($SD = 1.71$, range = 1–10). The remaining 38 participants did not complete a measure of socioeconomic status.

#### *Study Procedure*

All study procedures were approved by the Institutional Review Board of the authors' home institution, and participants provided written consent. During an initial laboratory visit, participants completed a task to quantify negative interpretation bias (Neta et al., 2013), a battery of self-report questionnaires not analyzed here, and received instructions for completing EMA surveys for the semester. Participants were compensated with course credit and/or cash for their participation proportional to the percentage of EMAs completed. A subset of participants completed a second laboratory visit with additional behavioral tasks that are beyond the scope of this study.

### Emotional Image Task

Participants completed a computerized emotional faces and scenes task developed by Neta et al. (2009, 2013), assessing negative interpretation bias, or the tendency to interpret emotionally ambiguous faces and scenes as having negative meaning. Twenty-four face stimuli were taken from the NimStim set (Tottenham et al., 2009; 14 unique individuals, 7 female) and 20 from the Karolinska Directed Emotional Faces dataset (Lundqvist et al., 1998; 20 unique individuals; 10 female). Twenty-four scenes were taken from the IAPS database (Lang et al., 2008) based on previous ratings of valence.

Participants completed four experimental blocks. Each block consisted entirely of facial or scene stimuli. Each experimental block consisted of 24 unique images: 12 of which were of ambiguous valence (surprised faces or ambiguous scenes) and 12 of which were of clear valence with six positive (happy faces or positive scenes) and 6 negative (angry faces or negative scenes). The ambiguity of IAPS scenes was determined by high variability in ratings across individuals, such that some categorized specific pictures as negative while others categorized them as positive (Neta et al., 2013).

Each trial, participants made a forced choice speeded decision, categorizing the valence (i.e., positive or negative) of each facial expression or scene. Each stimulus was presented for 500 ms, followed by a 1,500 ms inter-stimulus interval containing a fixation cross. Negative interpretation bias was operationalized as the percent of trials for which ambiguous stimuli were categorized as negative (Neta et al., 2013). In line with previous literature, we also calculated participants' response time on ambiguous trials (Neta & Tong, 2016).

### Emotional Image Task Data Cleaning

Analyses were conducted using the R programming language (R Core Team, 2017). Of the 188 participants enrolled in the study, 8 were excluded because of technical difficulties (i.e., their task responses were not recorded or they completed the incorrect version of the task) and 2 did not complete any EMA surveys. For the remaining 178 participants, the mean RT during the emotional image task across all participants was calculated and trials involving a RT > 3 standard deviations (*SD*) above the mean RT across all participants were removed (group mean RT = 700.43 ms, 3 *SD* cutoff = 1,745.88 ms). This resulted in the removal of 112 trials across 71 participants ($M = 1.5$, $SD = 1.15$, and range = 1–8 trials removed per person). From the included trials, we computed participant accuracy in classifying happy and angry faces as positive or negative, respectively. Low accuracy on clearly valenced trials weakens the validity and interpretation of negative interpretation bias. Thus, in line with extensive prior research (Neta et al., 2009, 2013; Petro et al., 2018), participants ($N = 65$) were excluded if they were unable to reliably classify clearly valenced expressions and scenes with at least 60% accuracy. For the remaining participants, negative interpretation bias scores were calculated as the percentage of surprised faces categorized as negative (faces bias) or the percentage of ambiguous scenes categorized as negative (scenes bias).

### EMA Surveys of Daily Affect

The EMA procedure for Study 2 was similar to Study 1 in that participants completed surveys every other day throughout the semester at pseudo-random times between 10:00 a.m. and 8:00 p.m. (per Villano et al., 2020; see Figure S5 in the online supplemental materials for the distribution of times surveys were submitted in Study 2). For these participants, the focal emotion items of our analysis (specifically "happy," "excited," "content," "upset," "irritable," and "anxious") were measured alongside other emotion items (e.g., "nervous," "jittery"). Items unique to this cohort were omitted from the present analyses in order to have comparable NA and PA composites for each EMA survey. The same visual analogue scales were used as in Study 1 (i.e., slider bars; range: 0–100).

### EMA Data Compliance and Cleaning

Similar to Study 1, 97.85% of surveys were completed in under 5 min and surveys with completion durations longer than 5 min (66 of 3,062 or 2.16%, of surveys) were very positively skewed (skew = 3.60; see Figure S4 in the online supplemental materials). This further illustrates that the vast majority of EMA responses were indeed capturing momentary ratings. Trimming those 66 surveys, the average completion duration was 75.01 s ($SD = 46.51$ s, range = 23–300) with a median time to complete of 60 s. Also like Study 1, the total number of EMA surveys sent varied by the start and end date of the study. The mean number of EMA surveys completed across the semester was 26 ($SD = 8.09$, range = 3–43) and the mean percentage of surveys completed was 80% ($SD = 22.91$, range = 9.30100). See Figure S4 in the online supplemental materials for the distribution. We accounted for this variability similarly to Study 1, by (a) using hierarchical regression models with a random effect of participant, which weights participant-specific effects by their number of responses and (b) confirming our main analyses after excluding those completing few EMA responses (fewer than 14 EMAs; see Figure S3 in the online supplemental materials). These analyses (with $N = 104$) yielded a similar pattern of results as the results reported below (see Table S4 in the online supplemental materials).

### Data Analytic Plan

The analytic plan for Study 2 was very similar to that of Study 1. First, FDR-corrected Pearson product-moment correlations were estimated between task parameters and daily affect means from EMA (see Table S3 in the online supplemental materials). Then, we tested a hierarchical linear model nearly identical to Study 1: EMA-derived affect, with separate observations containing NA and PA scores, was the outcome variable with a binary "valence" predictor variable (coded as NA = *0*, the intercept, and PA = *1*) to index whether the EMA value was a positive or negative emotion score. Interactions between valence and task predictors of interest: negative interpretation bias and RT for negative choices on daily affect, were tested. As in Study 1, we reverse scored the PA values to ensure PA and NA were on the same scale. Specifically, PA scores were subtracted from 100 (the maximum possible value) so that higher values reflected lower PA. As a result, the interaction term tested whether negative interpretation bias was more strongly related to greater NA than it was related to lower PA. This coding scheme meant that main effects of the model reflect the relationship between bias and *negative affect* only. For each interaction, we computed simple slopes to examine whether the relationships between task and PA were significant. Data and analysis code are available at: https://osf.io/kfu8j/.

## Study 2 Results

### *Emotional Image Task Descriptive Statistics*

The descriptive statistics for the task parameters are displayed in Table 3. To confirm the ambiguity of the stimuli, repeated measures ANOVAs probed for differences between clear and ambiguous trials to confirm the ambiguity of the stimuli. Specifically, consistent with previous work (e.g., Neta et al., 2013), we found a main effect of valence, $F(2, 654) = 67.70$, $p < .001$, which demonstrated that participants' mean RTs to clearly valenced stimuli were significantly faster than for the ambiguous stimuli. This supports the ambiguity of the valence of surprised faces and ambiguous scenes.

Consistent with prior work (Neta et al., 2013), we found a main effect of stimulus type (faces vs. scenes) on RT, such that participants were slower to respond to scene trials in general, $F(1, 654) = 135.81$, $p < .001$, which suggests that the scene stimuli were perceived as more complex than the face stimuli. In addition, negative interpretation bias was higher for the surprised face trials compared with the ambiguous scene trials, $t(109) = 8.67$, $p < .001$, as in prior work (Harp et al., 2021; Neta et al., 2013). There was also a significant correlation between negative interpretation bias for surprised faces and for ambiguous scenes ($r = .28$, $p = .003$).

### *Daily Affect Descriptive Statistics*

Daily affect descriptive statistics are displayed in Table 3. The ICC for EMA-assessed NA was 37.45% and 25.49% for PA. This means that about 37.5% of the variance in NA scores and 25.5% of the variance in PA scores are attributable to the grouping factor of participant and the remaining variance reflecting within-person fluctuations. Similar to study 1, these numbers confirm that the EMA sampling captured both variability within and between participants emotions. The average of participants' mean NA was 35.24 ($SD = 14.78$, range = 4.83–74.81 out of 100). The average of participants' mean PA was 55.65 ($SD = 11.95$, range = 24.19–93.00 out of 100). As in Study 1, Pearson's zero-order correlations indicated that, between-participants, NA and PA mean were moderately negatively correlated ($r = -.36$, $p < .001$). Moreover, the number of EMA responses submitted was not related to either mean NA ($r = .096$, $p = .323$) or mean PA ($r = .016$, $p = .865$).

**Table 3**
*Study 2 Descriptive Statistics*

| Variable | *M* | *SD* | Min | Max |
|---|---|---|---|---|
| Emotional picture task indices | | | | |
| Ambiguous RT | | | | |
| Faces | 761.95 | 158.81 | 495.26 | 1,207.82 |
| Scenes | 932.83 | 170.39 | 597.65 | 1,397.48 |
| Clearly Valenced RT | | | | |
| Faces | 659.22 | 108.15 | 460.76 | 1,025.39 |
| Scenes | 765.50 | 132.76 | 544.68 | 1,187.5 |
| Clearly valenced accuracy | | | | |
| Happy face | 86.44 | 11.05 | 66.67 | 100.00 |
| Angry face | 85.30 | 10.70 | 66.67 | 100.00 |
| Positive scene | 92.35 | 8.97 | 66.67 | 100.00 |
| Negative scene | 86.97 | 9.41 | 66.67 | 100.00 |
| Negative interpretation bias | | | | |
| Faces | 58.83 | 19.52 | 8.33 | 91.67 |
| Scenes | 42.80 | 10.54 | 12.50 | 70.83 |
| Daily affect metrics | | | | |
| NA mean | 35.24 | 14.78 | 4.83 | 74.81 |
| PA mean | 55.65 | 11.95 | 24.19 | 93.00 |

*Note.* $N = 110$ for all variables. RT = response time; NA = negative affect; PA = positive affect; RT = reaction time. Clearly valenced RT and accuracy refers to values collapsed across clearly negative and clearly positive stimuli.

### *Negative Interpretation Biases to Visual Stimuli Are Differentially Related to Daily NA and PA*

We used a hierarchical linear model that jointly examined the effects of face and scene negative interpretation bias on daily emotion (Table 4). EMA-derived affect was the dependent variable and PA values were reverse scored. This model revealed that negative interpretation bias for both faces *and* scenes predicted daily NA (Table 4; Figure 1), as indicated by significant positive coefficients for the main effects of face negative interpretation bias ($b = 0.13$, $SE = 0.06$, $p = .026$) and scene negative interpretation bias ($b = 0.21$, $SE = 0.11$, $p = .049$). Only scene negative interpretation bias significantly interacted with valence of EMA-derived emotion ($b = -0.22$, $SE = 0.05$, $p = .009$), such that the relationship between negative interpretation bias towards scenes and daily NA was significantly different from the relationship between negative

**Table 4**
*Hierarchical Linear Model of Daily Affect Across Valence Regressed on Negative Interpretation Bias from Both Image Types*

| Predictor | *b* | *SE* | *t* | *p* |
|---|---|---|---|---|
| Main effects | | | | |
| Valence (positive) | 8.85 | 0.51 | 17.46 | <.001*** |
| Face negative interpretation bias | 0.13 | 0.06 | 2.25 | .026* |
| Scene negative interpretation bias | 0.21 | 0.11 | 1.99 | .049* |
| Ambiguous face RT | −0.001 | 0.01 | −0.13 | .897 |
| Ambiguous scene RT | −0.01 | 0.01 | −0.58 | .565 |
| Interaction effects | | | | |
| Valence × face negative interpretation bias | 0.02 | 0.03 | 0.80 | .426 |
| Valence × scene negative interpretation bias | −0.22 | 0.05 | −4.00 | <.001*** |
| Valence × ambiguous face RT | 0.01 | 0.01 | 2.00 | .045* |
| Valence ambiguous scene RT | −0.01 | 0.01 | −1.07 | .286 |
| Interaction simple slopes | | | | |
| NA ~ face negative interpretation bias | 0.13 | 0.06 | 2.25 | .026* |
| PA ~ face negative interpretation bias | 0.15 | 0.06 | 2.64 | .009** |
| NA ~ scene negative interpretation bias | 0.21 | 0.11 | 1.99 | .049* |
| PA ~ scene negative interpretation bias | −0.004 | 0.11 | −0.04 | .972 |
| NA ~ ambiguous face RT | −0.002 | 0.01 | −0.13 | .897 |
| PA ~ ambiguous face RT | 0.01 | 0.01 | 0.85 | .398 |
| NA ~ ambiguous scene RT | −0.01 | 0.01 | −0.58 | .565 |
| PA ~ ambiguous scene RT | −0.01 | 0.01 | −1.11 | .270 |

*Note.* Model included 6,180 observations across 110 participants. NA = negative affect; PA = positive affect; RT = response time. Valence is coded with NA = 0 and PA = 1. PA scores were also reversed scored so that larger values reflect less PA. This was done so that negative interpretation bias effects would be positive for both positive and negative affect and interaction terms could compared the magnitude of the linear relationships between positive and negative affect. Main effects are interpreted when valence = 0 (for negative affect specifically).
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

interpretation bias towards scenes and daily PA (Table 4; Figure 1). Analysis of the simple slopes demonstrated that negative interpretation bias for scenes was only related to daily NA and *not* daily PA ($b = -0.004$, $SE = 0.11$, $p = .972$; Figure 1). In contrast, negative interpretation bias for faces was significant not only for daily NA but also PA ($b = 0.15$, $SE = 0.06$, $p = .009$, reverse scored; Figure 1).

The reaction time metric of negative interpretation bias was not predictive of daily affect (Table 4). The null main effects of ambiguous face RT and ambiguous scene RT indicated that neither significantly predicted daily NA. Further, although RT to ambiguous faces significantly interacted with EMA affect valence, simple slopes analysis revealed that daily PA was also not significantly related to RT for ambiguous scenes.

## Study 2 Discussion

Study 2 extended the findings from Study 1 by demonstrating that individual differences in negative interpretation bias derived from the emotional image task also map onto real-world daily affect. Specifically, greater negative interpretation bias for ambiguous emotional faces and scenes was related to higher daily NA in the subsequent 2 months. An alternative interpretation of this result could be that *less positive interpretation bias* for ambiguous emotional faces and scenes is related to higher daily NA, because this task quantifies negative and positive interpretation bias along a single dimension.

Despite the differences between the face and scene stimuli, the type of image did not appear to impact the relationship between negative interpretation bias and daily NA. Interestingly, face and scene negative interpretation bias were only moderately correlated ($r = .28$), consistent with prior work (Harp et al., 2021; Neta & Brock, 2021; Neta et al., 2013). This suggests that while they share some common variance, they may also be measuring different aspects of negative interpretation bias. Both face and scene interpretation bias were included in a single model, further solidifying that face and scene negative interpretation bias uniquely relate to greater NA.

However, only negative interpretation bias for faces was significantly related to lower PA. There are a number of reasons why this unique relationship may have emerged. In our sample, negative interpretation bias scores were higher on average for ambiguous faces than scenes ($M$ difference $= 16.32$, $p < .001$). This is in line with previous research that has found the same pattern (Neta et al., 2013) and work demonstrating that longer decision times are linked to a shift towards more positive ratings of ambiguous stimuli (Neta & Tong, 2016). Thus, it may be possible that the negative interpretation bias indexed by faces recruits a speedier, perhaps more automatic, process of evaluating emotional faces (compared with the complexity of the scene stimuli). This automatic bias could preclude more flexible, potentially positive, interpretations. Thus, if this more automatic metric indeed reflects one's "go-to," habitual appraisal processes in daily life, it would be related to both heightened NA as well as dampened PA.

The unique connection between negative interpretation bias for faces and daily PA may also be due, in part, to the strong social element inherent in interpreting others' facial expressions. Social interactions are ubiquitous in daily life and positive social relations are a strong predictor of positive mood and psychological well-being (Ishii-Kuntz, 1990). It could be that a higher negative interpretation bias for faces may impact interpersonal processes that are important for maintaining positive relationships, which could lead to lower PA and higher NA. However, a more detailed investigation of the factors that drive NA and PA in daily life is needed to test this possibility.

## General Discussion

Our lives are filled with emotional ambiguity, such as a colleague's pensive facial expression during a presentation, or a missed call from a family member. Prior research suggests that some individuals have a propensity to consistently interpret ambiguous information as negative (Gonsalves et al., 2019; Neta et al., 2013; Neta & Whalen, 2010), which may ultimately impact daily emotional experience. However, this connection between the laboratory and the real world has not previously been tested. The two studies presented here provide empirical support for the notion that judgments about ambiguous stimuli in the laboratory map onto our broader daily emotional landscape. Moreover, the current results indicate that distinct negative interpretation bias tasks show both converging and unique relationships to real-world affect assessed via longitudinal EMA.

As hypothesized, we showed that greater negative interpretation bias across different behavioral tasks predicted greater NA in daily life. This result challenges critiques that laboratory tasks measuring cognitive processes lack ecological validity and may not reflect real-world behavior, perhaps due to the controlled or simplified stimuli or the "sterile" or unnatural laboratory environment (Holleman et al., 2020). We demonstrate specifically that individual differences in negative interpretation bias index variation in real-world NA, suggesting that negative interpretation bias tasks may reflect processes deployed in daily life (Beck, 1967; Disner et al., 2011). Using EMA to measure daily affect across time and contexts allowed us to capture a rich set of emotional experiences to relate to task-derived negative interpretation bias. Thus, negative interpretation biases are linked to one's experience of NA in everyday life.

Moreover, the consistency of effects between daily NA and various negative interpretation bias tasks in largely independent samples is in line with previous research suggesting that the various negative interpretation bias tasks tap a common, latent, negative evaluation process (Everaert et al., 2017; Hirsch et al., 2016; O'Connor et al., 2021). We found that the daily NA-negative interpretation bias relationship exists regardless of whether negative interpretation bias is calculated from verbal, self-referential evaluations or from categorizing the valence of ambiguous visual stimuli. Such convergence suggests that the dimensions on which these stimuli differ, such as perceptual complexity or personal relevance, may not be important for relating negative interpretation bias to daily NA, in particular.

This consistent pattern of results can be contextualized within schema theory (Beck, 1964, 1967; Piaget, 1926), which defines schemas as systems of beliefs and assumptions that influence how we perceive and evaluate our environment (Dozois & Beck, 2008). A critical characteristic of schemas is that they often become broad, through a process of generalization (Beck, 2002), and can be activated in response to a wide range of events. From this perspective, the "lens" of negative interpretation bias is used to evaluate a myriad of ambiguous information, including the verbal scenarios and emotional images of faces and scenes presented in these studies. In support of this claim, affective neuroscience research has identified neural circuits underlying emotional stimulus valuation, which cut across types of stimuli (Montague & Berns, 2002;

Winecoff et al., 2013). These stimulus-independent neural processes may be more important than the stimulus-specific neural circuitry (McFadyen et al., 2017) in understanding the broad effects of negative interpretation bias on negative emotion in daily life.

While these studies provide evidence for a stimulus-independent negative interpretation bias connection to daily NA, they also point to unique effects of negative interpretation bias on daily PA. Across Studies 1 and 2, only negative interpretation bias for ambiguous emotional faces was predictive of lower day-to-day PA. As noted, the surprised facial expressions were inherently more social and self-referential than the scene stimuli, and were categorized more quickly and more negatively overall. In addition, whereas each WSAP trial only allows participants to judge a threatening interpretation as relevant or not, the emotional image task trials allow the participant to select between equally valid negative and positive response options simultaneously. Taken together, this suggests that a speedy, perhaps more automatic or habitual, negative interpretation bias while evaluating social and self-referential information, even in the face of a positive alternative, is the most indicative metric of dampened PA in daily life.

Moreover, we did not find evidence that RT measures of negative interpretation bias are linked to daily affect. Across both studies, we generally found that "direct" measures (e.g., the rate of categorizing ambiguous stimuli as negative rather than positive) were more strongly associated with daily emotion than RT measures. This pattern of results aligns with some previous literature that links choice measures of negative interpretation bias to affective outcomes, such as depression, more strongly than RT measures (O'Connor et al., 2021). A meta-analysis concluded that choice outcome measures (95% CI [0.77; 0.99]) significantly predicted depression whereas RT measures did not ($g = 0.04$, 95% CI [−0.14; 0.22]; Everaert et al., 2017). Importantly, longitudinal daily NA is distinct from self-reported depression symptoms, and thus, comparisons with these studies may be limited. This is the first study, to our knowledge, that has investigated the connections between real-world affect and both choice and RT measures of negative interpretation bias. Overall, despite RT measures being hypothesized to complement choice measures by reducing response biases and demand characteristics (Blanchette & Richards, 2010), our results suggest that daily affect is more strongly related to explicit choice measures of negative interpretation bias.

We believe that connecting brief laboratory tasks of negative interpretation bias to variation in daily affect has potential implications for clinical affective science. In 1967, Beck hypothesized that a tendency to appraise ambiguous information as negative is a central precursor to the development of internalizing disorders. It is proposed that greater negative interpretation bias brings about clinical disorders by contributing to a persistent, heightened negative mood, a cardinal symptom of depression (American Psychiatric Association, 2013; Beck, 1967). Similarly, Joormann and Quinn (2014) also suggest that negative interpretation biases impair everyday emotion regulation. The present study connecting negative interpretation bias tasks and heightened day-to-day NA is the first to our knowledge to begin testing Beck's claims using naturalistic measurement of emotion. Finding this connection in a *non-clinical* sample with a range of psychiatric risk may limit conclusions that can drawn about clinical disorders. However, it is well-established that college students experience a higher prevalence of psychological challenges than the general population and reflect a full range of psychiatric risk and functioning (Heller et al., 2021; Pedrelli et al., 2015). Therefore, the current study does provide important, preliminary support for the connection between negative interpretation bias and real-world emotion that should be tested in clinical and high-risk samples. Certainly, longitudinal work that follows individuals over time and records the development of psychiatric conditions would be necessary to definitively test Beck's assertions that patterns of day-to-day affect could serve as a mediator between cognitive bias and psychological conditions.

This study is not without limitations. The EMA paradigm employed here assessed momentary NA and PA, but it lacked information about the driving source(s) of these emotions or the contexts in which they arose (Lapate & Heller, 2020; Villano et al., 2020). Future studies should use EMA to simultaneously index daily events, their emotional ambiguity, and their affective consequences to better understand contextual factors impacting the relationship between negative interpretation bias and daily affective functioning. In addition, while the sampling paradigm (one survey every other day) was a strength in that it allowed us to measure across months while minimizing participant burden, it limited our ability to assess fine-grained temporal patterns of emotion. The effect of the timescale on which EMA measures are collected is an understudied area that should be explored by future research (Adolf et al., 2021; Frijda, 2009). Although we view the relative independence of the samples in the two studies as a strength, it is crucial that future studies administer multiple negative interpretation bias tasks in the same sample to determine their relative contributions to predicting psychological outcomes, such as daily affect, depression, and well-being. Finally, our results are limited by our college-aged sample, pointing to a need to replicate these findings in clinical samples. At the same time, a strength of our sample was its diversity across both demographic (e.g., race, ethnicity, and socioeconomic status) and affective (e.g., bias scores and emotional ratings) dimensions.

In summary, we showed that two laboratory-based tasks of negative interpretation bias related to heightened day-to-day NA across a span of months, regardless of the task or type of stimuli presented. In contrast, a unique relationship emerged between negative interpretation bias to faces and dampened daily PA. These effects bolster the ecological validity of these tasks as well as provide initial support for cognitive models of psychopathology. Connecting controlled, behavioral indices of ambiguity appraisal with longitudinal assessment of daily affect, we have identified possible real-world impacts of information processing biases. Ultimately, this is a crucial step to understand the development of enduring and cognitively complex psychological conditions.

## Broader Context

The idea for this manuscript was born from larger studies in our lab examining cognitive risk for depression and anxiety. We wondered whether our lab-based behavioral tasks measuring cognitive risk factors, such as negative interpretation bias, truly captured how people navigate ambiguity in the real world. Do these controlled stimuli and decisions reflect how people function in their day-to-day lives? This question seemed to us crucial given that Beck has theorized that such information processing biases lead to clinical disorders because of their impact on day-to-day emotion. We have been excited to find that our analyses provide preliminary evidence that lab-based negative interpretation bias could reflect more naturalistic processes, given their connection to real-world negative affect. We view this as a first step towards testing this connection more directly by developing and testing creative EMA-paradigms that could capture individuals' in-the-moment response to naturally occurring ambiguous stimuli in daily life.

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