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EMPIRICAL ARTICLE

Chasing emotional losses: Negative subjective affect is linked to increased risk-seeking behavior both within and between individuals

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Abstract
The literature on emotion and risk-taking is large and heterogeneous. Whereas some studies have found that positive emotions increase risk-taking and negative emotions increase risk aversion, others have found just the opposite. In this study, we investigated this question in the context of a risky decision-making task with embedded high-resolution sampling of participants' subjective emotional valence. Across two large-scale experiments (N = 329 and 524), we consistently found evidence for a negative association between self-reported emotional valence and risk-taking behaviors. That is, more negative subjective affect was associated with increased risk-seeking, and more positive subjective affect was associated with increased risk aversion. This effect was evident both when we compared participants with different levels of mean emotional valence as well as when we considered within-participant emotional fluctuations over the course of the task. Prospect-theoretic computational modeling analyses suggested that both between- and within-participant effects were driven by an effect of emotional valence on the curvature of the subjective utility function (i.e., increased risk tolerance in more negative emotional states), as well as by an effect of within-person emotion fluctuations on loss aversion. We interpret findings in terms of a tendency for participants in negative emotional states to choose high-risk, high-reward options in an attempt to improve their emotional state.

1. Introduction

Human emotions have pervasive effects on cognitive processes, including learning, memory, and decision-making (Bower, 1981; Herz et al., 2004; Lerner et al., 2013). In judgment and decision-making, one question of particular interest is how an individual's emotional valence (i.e., the pleasantness/unpleasantness of their emotional state) influences their risk attitudes. An answer to this question would have implications not only for understanding and predicting real-world risky decision-making (e.g., financial trading; Kramer and Weber, 2012) but also for explaining some of the cognitive symptoms of psychological disorders (e.g., links between mania and risk-taking, and between depression and risk aversion; Leahy et al., 2012; Swann, 2009).

However, in spite of a large body of prior research, there is no consensus as to how emotional valence influences risk attitudes. The literature reports a number of apparently contradictory results (for review, see Prietzel, 2019), and accordingly a disparate set of theories have been proposed to explain the empirical data (e.g., Forgas, 1995; Isen et al., 1988; Lerner et al., 2015; Loewenstein et al., 2001). Below we first review extant findings and theories, emphasizing the diverse approaches that have been taken to the question of emotion and risk-taking. We then introduce an important methodological distinction that is made in the affective science literature between *within-person* and *between-person* variance in emotional valence (Brose et al., 2015; Hamaker et al., 2015). We suggest that this distinction may help explain the heterogeneity of empirical findings in this field, and introduce a behavioral task and analysis method that allows us separately to estimate the between-person effects and the within-person effects of emotional valence on risky decision-making.

1.1. The effects of emotional valence on risk attitudes

A broad survey of the literature on emotional valence and risk attitudes reveals a set of notably inconsistent empirical results. Increases in positive affect have been linked with increases in risk-taking behavior in some studies (Deldin and Levin, 1986; Grable and Roszkowski, 2008; Herman et al., 2018; Johnson, 1986; Mailliez et al., 2020; Otto and Eichstaedt, 2018; Schulreich et al., 2014), but with decreased risk-taking in other work (Colasante et al., 2017; Isen and Patrick, 1983; Juergensen et al., 2018; Zhao, 2006). Likewise, increased negative affect has been linked in separate studies both with increased risk-seeking (Buelow and Suhr, 2013; Raghunathan and Pham, 1999) and with increased risk aversion (Campos-Vazquez and Cuilty, 2014; Colasante et al., 2017; Heilman et al., 2010; Yuen and Lee, 2003).

In line with these discrepant empirical results, theories concerning the effects of emotion on risk attitudes differ in their predictions. Some theories predict that risk-taking will increase as emotional valence becomes more positive (e.g., the Affect Infusion Model; Forgas, 1995), whereas others predict the reverse: increased risk aversion with increased positive emotion (e.g., the Mood Maintenance Hypothesis; Isen et al., 1988). Still other theories can accommodate either direction of effect depending on the cognitive process that is assumed to be altered by changes in emotional valence (Loewenstein et al., 2001).

One factor that has likely contributed to inconsistency in previous findings is the diversity of methods that have been used to address this question. For instance, Grable and Roszkowski (2008) used a correlational method based on self-report measures, and found that individuals who self-reported more positive mood also reported higher levels of risk tolerance. By contrast, experimental studies by Yuen and Lee (2003) and Colasante et al. (2017) each induced positive and/or negative emotion in participants in a controlled laboratory setting and observed the effects of the resulting emotions on behavioral assays of risky decision-making. Another example is given by Otto and Eichstaedt (2018), who analyzed large-scale observational data and found that a city-wide proxy for emotional valence (extracted from sentiment analysis of social media posts, and correlated with factors such as the amount of daily sunshine and performance of local sports teams) was positively associated with a city-wide proxy for risk attitudes (number of lottery tickets purchased) in New York City.

Each of these empirical approaches has its own strengths and weaknesses, and methodological differences may partly account for inconsistencies in the literature. However, we suggest there is an additional factor that has not received substantial attention to date in the judgment and decision-making literature, and which may be an important consideration in understanding the effects of emotional valence on risk attitudes. This additional factor is the distinction between the *within-person* effects of emotion on risk-taking (i.e., the ways in which an individual's risk attitudes tend to change when their emotional state is more or less positive than is usual for them) and the *between-person* effects of emotion on risk-taking (i.e., the extent to which people who are happier on average tend to have different risk attitudes from those who are less happy on average).

1.2. The distinction between within-individual and between-individual variance in emotion

Research on emotion in affective science commonly distinguishes between-person variance in emotions from within-person variance in emotions (see, for example, Brose et al., 2015; Hamaker et al., 2015).

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In this distinction, between-person variance is related to stable differences between individuals in average emotional valence, and within-person variance is related to inter-individual fluctuations around this stable long-term average level. For example, two individuals might have the same average emotional valence but differ in terms of the magnitude of their moment-by-moment emotional fluctuations around this average level; in this case, there would be within-person variance in emotion but no between-person variance in average emotion. By contrast, we can also conceive of two individuals who differ in their average emotional valence (i.e., one tends to be happier than the other), but who experience equivalent of degrees of emotional fluctuation around their respective average levels. In this latter case, there would be between-person differences in emotional valence, but the within-person variance of the two people would be equivalent.

Previous studies have not typically distinguished between between-person and within-person effects of emotion on risk attitudes, and the extant empirical literature is likely to be a mixture of these two effect types in unknown proportions. For instance, it may be the case that emotion only exerts between-person effects on risk attitudes, such that people who experience more positive affect at a trait level have risk attitudes that differ on average from people who experience more negative affect. By contrast, there may be only within-person effects, such that it is moment-to-moment fluctuations in an individual's emotions around their average level that produce moment-to-moment fluctuations in their risk preferences. Of course, these effects are not mutually exclusive: it may be the case that emotions have only between-person effects on risk-taking behavior, only within-person effects, both, or neither.

1.3. Overview of the present study

In the present study, we sought to dissociate the between-person and within-person effects of emotional valence on risk attitudes within a well-controlled cognitive task. In particular, we sought to adjudicate between a number of competing possibilities, all of which have received some degree of support from the previous literature. First, we aimed to test whether more negative emotional valence was associated with increased risk aversion (as would be predicted by the Affect Infusion Model; Forgas, 1995) or more risk-seeking (as would be predicted by the Mood Maintenance Hypothesis; Isen et al., 1988). Second, we aimed to determine whether the effects of emotion on risk-taking were better explained by between-participant differences in mean emotional valence (which would imply that any effects are due to trait-level differences between individuals) or by within-person fluctuations in emotional valence (which would imply that effects are due to state-level fluctuations in emotion).

Our approach made use of two large-scale datasets originally collected for a separate study of emotional reactivity. In these datasets, participants completed a risky decision-making task with an embedded high-resolution sampling of subjective emotional valence. For each participant, we therefore collected a time series of self-reported emotional valence alongside a time series of choice data in the risky decision-making task. We then investigated how risk attitudes as revealed by choice behavior in the task separately covaried with (a) between-person differences in average emotional valence and (b) within-person emotional fluctuations as measured during the task itself.

2. Method

2.1. Design

Here, we report the results of two separate behavioral experiments using an identical study design: exploratory Experiment 1 (N = 329) and confirmatory Experiment 2 (N = 524). Data were collected as part of a separate study of emotional reactivity to reward and nonreward outcomes. By contrast, here we focus on how participants' self-reported emotional states during the task correlated with their momentary risk preferences as revealed through their choice behavior. Because findings were very similar across both studies, we present the results of Experiments 1 and 2 side-by-side and pool data from both experiments together for subsequent computational modeling analyses.

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Data collection procedures (including exclusion criteria) for Experiment 2 were preregistered, but data analysis methods were not preregistered for the analyses reported in this article. Experiment 1 was not preregistered. The preregistration document, as well as all raw data for this study, are openly available in the project Open Science Framework (OSF) repository at https://osf.io/jpv49/.

2.2. Participants

In Experiment 1, we recruited 329 participants (140 men, 188 women, 1 who did not endorse a binary gender). In Experiment 2, we recruited 524 participants (243 men, 263 women, 8 who did not endorse a binary gender). Participants were aged between 18 and 65 years (Exp 1: mean = 35.17, SD = 11.96; Exp 2: mean = 37.50, SD = 11.97), and they were paid a total of US $5.50 for participation. In addition, participants received a performance bonus of up to $1 depending on their choices in the behavioral task (Exp 1: mean = $0.58, SD = 0.31; Exp 2: mean = $0.58, SD = 0.32).

Participants were recruited via the website Prolific and were eligible to participate if they resided in Australia, Canada, New Zealand, the United Kingdom, or the United States of America, were aged between 18 and 65 years, spoke English fluently, and did not have a history of any psychiatric or neurological disorder. All participants provided informed consent, and this study received ethical approval from the Monash University Human Research Ethics Committee (ID 27472). The total time commitment was approximately 30 minutes, and all tasks were completed remotely via a web browser.

2.3. Risky decision-making task

Participants each completed a risky decision-making task that was modeled after tasks previously developed by Mellers et al. (1997) and Rutledge et al. (2014), and a variant of which we have described in more detail elsewhere (Forbes and Bennett, 2023). Briefly, each trial of this task comprised a choice between two face-down 'card' stimuli (Figure 1). Prior to choice, participants were provided with descriptions of the two available outcome amounts and their respective probabilities for each card. The possible probabilities of outcomes for each card were either 50%/50% or 25%/75%, and the possible outcome amounts could be +200, +100, +0, −100, or −200 points (see Supplementary Material, Section S1, for more information on the composition of choice pairs). After selecting a card using the left/right arrow keys, the participant then received feedback on the outcome of both the chosen and the unchosen card. The risky-choice task was presented within participants' web browsers using the jsPsych JavaScript library (De Leeuw, 2015) and custom Python server code. Task instructions as viewed by participants are available within the project OSF repository.

Each trial could be either free-choice (as depicted in Figure 1) or forced-choice. In free-choice trials, participants selected a card freely as described above; by contrast, in forced-choice trials, a card was randomly selected on the participant's behalf. Here our focus was on participants' risk preferences as revealed by their free-choice behavior, and so we do not consider forced-choice trials further in the present study.

To measure participants' subjective emotional valence, we used an affective slider (Betella and Verschure, 2016; see Figure 1). Every 3–5 trials throughout the task (randomly jittered; 56 times in total), participants used the computer mouse to rate the valence of their current subjective emotional state from 'extremely unhappy' (left) to 'extremely happy' (right), with emoji symbols used as anchors.

Each participant completed a total of 212 trials (101 free-choice, 101 forced-choice, 10 attention-check) over 4 blocks of 53 trials each, with the order of trials randomized across participants. The 10 attention-check trials were used to identify inattentive participants; in these trials, one of the two cards was unambiguously better than the other (i.e., the worst possible payout from the correct card was greater than the best possible outcome from the incorrect card). Participants who responded incorrectly to more than one attention-check trial across the experiment were excluded from all further analyses.

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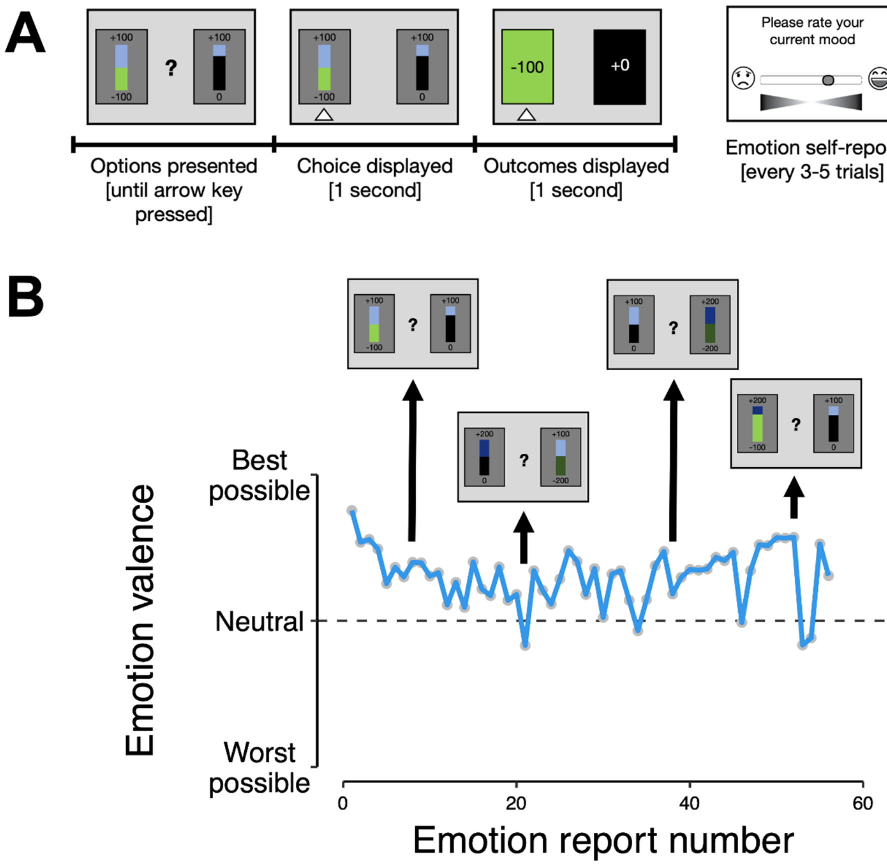

Figure 1. *(A) Trial schematic for the risky decision-making task (free-choice trials). Participants chose between cards that differed in reward magnitude (e.g., +100 points, −100 points) and probability (indicated by the size of the colored bars on each card). During the task, participants reported their subjective emotional valence using a slider response. (B) Analyses of choice data focused on the extent to which participants' risky-choice behavior (here represented by the inset choice screens) covaried with their self-reported emotional valence (here presented in blue for data from one representative participant) on the self-reports preceding each choice.*

2.4. Data analysis

The primary aim of our data analysis was to investigate the extent to which we could predict participants' trial-by-trial choices in the risky decision-making task using the preceding self-reports of their subjective emotional valence. To this end, we first conducted a set of model-agnostic regression analyses using self-reported affect data to predict choice behavior. We then followed up these regression analyses with prospect-theoretic computational modeling analyses.

For computational modeling analyses, we decomposed the observed emotion self-report time series into a between-participant variance component (representing between-participant differences in average emotional valence) and a within-participant variance component (representing the deviations of each momentary self-report from the reporting participant's average emotional valence). This allowed us to investigate the extent to which parameters of a prospect-theory model covaried with each type of variance in subjective emotional valence.

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2.4.1. Model-agnostic regression analyses

For model-agnostic regression analyses, data were analyzed using Bayesian mixed-effects regression analyses as implemented in the brms package for R. Models used a maximal random-effects structure, with random intercepts for participants and random slopes for all within-participant main effects and interactions (Barr et al., 2013). Continuous predictors were z-scored with grand-mean centering. Affect self-report data were analyzed using a mixed-effects Bayesian linear regression analysis, and choice data were analyzed using a mixed-effects Bayesian logistic regression analysis. For analyses of choice data, the dependent variable was whether or not the participant chose the card that was presented on the right of the screen, and the main independent variables of interest were the difference in expected value between cards, the difference in variance between cards, and the interaction of each of these differences with both within-person and between-person difference in emotional state (see Section 2.4.2.2. for a mathematical definition of these variables). For within-person emotional valence, which varied across time during the task, a given emotion rating was assumed to predict choices until a subsequent emotion rating was made. With 101 free-choice trials per participant, this constituted a data set of 83,729 trials in total across the two experiments.

To account for the effects of previous-trial outcomes on risk attitudes (Brooks and Sokol-Hessner, 2020), all regression models also included a z-scored effect of the outcome amount in the previous trial (as well as the interaction of this previous-outcome variable with the current-trial difference in variance and expected value between cards). In this way, we were able to statistically distinguish the effects of previous outcomes on risk attitudes from the effects of emotional valence.

Regression models each used four independent chains of 4000 iterations each, with the first 1000 samples from each chain discarded to prevent dependence on starting values. We analyzed data from the two experiments separately, and coefficient estimates were treated as credibly different from zero if the 95% Bayesian highest density interval (HDI) excluded zero in both Experiment 1 and Experiment 2. Full details of all fixed and random effects included in logistic regressions are available in the Supplementary Material, Section S2, and full *brms* syntax for analyses is presented in Supplementary Material, Section S3. All analyses used default prior specifications as implemented in *brms* version 2.16.3.

2.4.2. Computational modeling analysis

We followed up the model-agnostic regression analyses with prospect-theoretic modeling of choice behavior. Our rationale for adopting this approach was threefold: first, since outcome magnitudes and probabilities varied trial-by-trial, the use of a prospect-theory model allowed for a more nuanced understanding of how the characteristics of each gamble affected behavior compared with the binary outcome variable of the regression analyses. Second, by decomposing emotion self-reports into within-participant variance and between-participant variance, we sought to determine whether the effects of emotional valence on risk preference that we observed in the model-agnostic regression analyses were attributable to between-participant differences in affect, within-participant differences in affect, or both. Finally, using a prospect-theory model allowed us to understand in more detail precisely which aspects of risky decision-making (e.g., risk aversion, loss aversion, etc.) were influenced by changes in emotional valence.

Since the model-agnostic regression analyses revealed consistent behavioral effects across the two experiments, data from both experiments were pooled for computational modeling analyses. Below we first describe the general prospect-theoretic framework that we adopted before summarizing our method for decomposing emotion self-report into the between- and within-participant variance components. We then describe how we integrated the variance decomposition of emotion self-reports within the prospect-theoretic modeling framework to estimate the effects of each kind of variance in emotion self-reports on choice behavior.

2.4.2.1. Underlying prospect theory model

We modeled choice data using variants of a three-parameter prospect theory model (Tversky and Kahneman, 1992). This model assumed that participants chose between cards on each trial by first estimating the expected utility of each card according to

$$V\,(\text{card}) = \sum_{i=1}^{2} \Pr\,(x_i) \times U\,(x_i) \tag{1}$$

where $\Pr\,(x_i)$ and $U\,(x_i)$ respectively denote the (objective) probability and (subjective) utility of the ith possible outcome of the card. Subjective utility was in turn defined as:

$$U(x) = \begin{cases} x^{\rho} & x \geq 0 \\ -\lambda x^{\rho} & x < 0 \end{cases} \tag{2}$$

In Equation 2, the parameter λ affects the degree of loss aversion, whereas the ρ parameter affects the degree of curvature of the utility function (i.e., risk aversion as produced by diminishing marginal utility; values closer to 0 produce greater curvature). We did not measure subjective probability distortion as implemented in the full five-parameter prospect theory model, because only two probability levels were assessed in our behavioral task (50%/50% or 25%/75%). As a result, we did not have sufficient variance in objective probabilities to identifiably measure probability distortion alongside risk and loss aversion. Similarly, we did not allow the degree of curvature of the utility function to vary separately for gains and losses because parameter recovery analyses indicated that data from our task would not have allowed us to simultaneously identify both the λ parameter and separate ρ parameters for the gain and the loss domain. We therefore constrained the model by assuming an identical ρ parameter for prospective gains and losses.

Participants were assumed to select between the two cards according to probabilities provided by a logistic function of the difference in the cards' expected utilities (with slope parameter β):

$$\Pr\,(\textit{choose right}) = \frac{1}{1 + e^{\beta(V(\text{left}) - V(\text{right}))}} \tag{3}$$

2.4.2.2. Decomposing within- and between-participant variance in emotion

To separately estimate the between-participant and within-participant effects of emotional valence on risky decision-making, it is necessary to decompose the variance in each participant's emotional self-reports into a between-participant variance component and a within-participant variance component. To do this, we took advantage of the fact that any random variable can be re-expressed as a function of its mean, its standard deviation, and a z-scored transformation of the variable. For emotional valence self-reports, for example, it is possible to re-express each raw measurement of a participant's emotional valence self-reports as follows:

$$\text{Emotion}_n = \mu_i + Z_{\text{within}}(\text{Emotion}_n) \times \sigma_i \tag{4}$$

where Emotion_n is the nth measurement of emotional valence, μ_i and σ_i are respectively the mean and (participant-level) standard deviation of emotional valence self-reports for the ith participant, and $Z_{\text{within}}(\text{Emotion}_n)$ is the person-centered z-score of the nth data point. That is,

$$Z_{\text{within}}(\text{Emotion}_n) = \frac{\text{Emotion}_n - \mu_i}{\sigma_i} \tag{5}$$

This gives us an expression for the within-participant variance component $Z_{\text{within}}(\text{Emotion}_n)$. To obtain the orthogonal between-participant variance component, we can then normalize the

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Table 1. *Model comparison results.*

Model #	Parameter(s) affected by emotion	WAIC	ΔWAIC (SE)
1	None	72,856.22	31.8 (8.9)
2	λ	72,831.7	5.2 (3.9)
3	ρ	72,850.2	28.9 (8.5)
4	λ, ρ	72,792.6	0 (0)

per-participant emotional valence means $\mu_1, \mu_2, \mu_3, \ldots \mu_N$ with respect to the mean $\overline{\mu}$ and standard deviation $\overline{\sigma}$ of participant-mean emotion self-reports across the entire sample:

$$Z_{\text{between}}(\text{Emotion}_n) = \frac{\mu_i - \overline{\mu}}{\overline{\sigma}} \tag{6}$$

Z_{between} therefore has a relatively straightforward interpretation: it is a normalized measure of mean affect levels across participants. In other words, a positive Z_{between} term denotes a participant who expressed a more positive affect on average than the grand mean of the overall sample, and vice versa for a negative Z_{between} term. For this reason, it is important to note that as well as average emotional valence, the Z_{between} term may partially capture variance due to between-participant differences in interpretation of the affective slider (e.g., differences between participants in interpretation of the emotional state corresponding to the 'neutral' midpoint of the scale). However, by the same token, an advantage of using within-person z-scores to quantify within-participant emotional valence is that this metric effectively controls for individual differences in the interpretation of the endpoints of the affective slider.

As a result of this reparameterization, every self-report of emotional valence can be re-expressed in terms of two independent variance components: the between-participant component Z_{between}, which quantifies the extent to which a given participant's average self-reported emotion is higher or lower than the average emotional valence in the overall sample, and the within-participant component Z_{within}, which quantifies the extent to which a given data point is higher or lower than the participant's own average emotional valence.

Mathematically, we should expect the variance components Z_{between} and Z_{within} to be statistically orthogonal. We confirmed that this was the case for our data by estimating the correlation between Z_{between} and Z_{within}. We found that these time series were indeed uncorrelated in our data (Pearson $r = -.0006$, $p = .86$), indicating that this method can successfully decompose participants' emotional self-reports into independent between-participant and within-participant variance components.

2.4.2.2. Modeling the effects of emotional valence on choice behavior

We next sought to identify how each component of variance in emotion self-reports was separately related to different aspects of risky decision-making. To do so, we formulated a series of models in which different parameters of the basic prospect-theory framework described above were permitted to vary as a function of within-participant and between-participant variance in emotion self-reports. We compared a total of four computational models (detailed in Table 1) in which different combinations of the prospect-theory parameters λ and ρ were permitted to vary as a function of both between-participant and within-participant variance in emotional valence. Alongside these models, we also estimated a 'null' model in which no parameters changed as a function of emotional valence. In addition, to control for the effects of previous-trial outcomes on model parameters (Brooks and Sokol-Hessner, 2020), each of Models 2–4, which included an emotion-related change in model parameters, also allowed for an effect of the previous trial's outcome (z-scored across participants) on the same model parameters.

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In Model 2, for instance, onlyλ was permitted to vary as a function of emotional valence. In this model, the effective λ value for the participant's choice at trial n was computed as

$$\lambda_{\text{effective}} = \lambda_i + \Delta\lambda(\text{between}) \times Z_{\text{between}}(\text{Emotion}_n) + \Delta\lambda(\textit{within}) \times Z_{\text{within}}(\text{Emotion}_n) + \Delta\lambda\,(\text{prev\_outcome}) \times \text{prev\_outcome} \quad (7)$$

Here, λ_i is the average λ parameter for the ith participant, and $\Delta\lambda(\text{between})$ and $\Delta\lambda(\text{within})$ are two additional and separate free parameters that respectively quantify the extent to which λ covaries with between-participant and within-participant variance in emotional valence. Similarly, $\Delta\lambda(\text{prev\_outcome})$ is a free parameter that estimates the effect of previous-trial outcomes on the λ parameter, independent of the effects of emotion. An estimate overlapping with 0 for any of these $\Delta\lambda$ parameters indicates no meaningful covariance between λ and the predictor in question. By contrast, a $\Delta\lambda$ estimate greater than (/less than) 0 would indicate a positive (/negative) association between λ and the variance component in question. Similar computations were carried out for the equivalent modulation of other parameters in Model 3, Model 4, and so forth. All Δ parameters were estimated once for the entire sample (i.e., as fixed effects) because parameter recovery analyses indicated that separate per-participant Δ parameters would not have been identifiable.

2.4.3. Model fitting and comparison

Computational models were fit using Hamiltonian Monte Carlo as implemented in Stan (Stan Development Team, 2022). For each model, we used four independent sampling chains of 2250 samples each and discarded the first 1000 samples from each model, producing a total of 5000 posterior samples for analysis. There were no divergent transitions in any model, and all models fully converged ($\widehat{R} < 1.1$). Models were fit using partial pooling, such that participant-level parameters were assumed to be drawn from a Gaussian group-level distribution with a mean and standard deviation estimated freely from the data. Parameters with finite support were sampled from an unconstrained latent space and then transformed to the appropriate domain. To maximize sampling efficiency, group-level means and standard deviations were sampled using weakly informative noncentered parameterizations (McElreath, 2020).

Models were compared using the widely applicable information criterion (WAIC; Watanabe and Opper, 2010). We computed each model's WAIC, Δ WAIC (difference from WAIC of the best-fitting model), and the standard error of Δ WAIC using the *loo* package in R. Models with a Δ WAIC within one standard error of 0 were taken to be statistically equivalent to the best-fitting model, with ties broken according to model complexity (measured as number of parameters per model). Model and parameter recovery analyses (reported in Supplementary Material, Sections S4 and S5) indicated that all models had good recoverability.

3. Results

3.1. Data exclusions

A total of 24 participants (9 in Experiment 1, 15 in Experiment 2) were excluded for incorrect responding to attention checks, leaving 829 participants for analysis (320 in Experiment 1, 509 in Experiment 2).

3.2. Regression results

3.2.1. Self-reported emotion data

The mixed-effects Bayesian linear regression analysis indicated that participants' self-reported emotional valence was significantly more positive than the neutral mid-point (0.5) of the scale (Exp 1: mean = .55, [.54, .57]; Exp 2: mean = .52 [.51, .53]). In both experiments, there was also a small but

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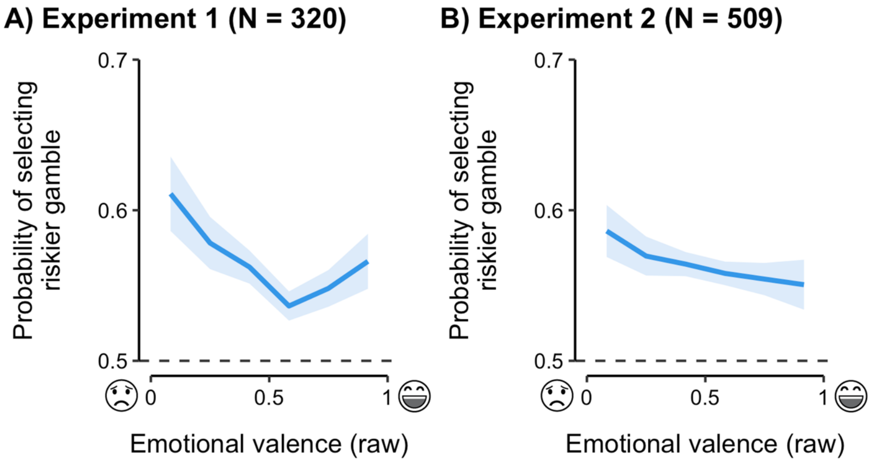

Figure 2. *Probability of selecting higher-risk gambles as a function of self-reported emotional valence in Experiment 1 (A) and Experiment 2 (B). Emotional valence is presented in the raw measurement space of the affective slider (0 = negative extreme, 1 = positive extreme, 0.5 = neutral). Error ribbons represent the 95% confidence interval of the mean.*

significant negative effect of time-on-task, such that participants tended to report slightly more negative affect as time went on (Exp 1: $\beta = -0.01$ [−0.02, −0.003]; Exp 2: $\beta = -0.01$ [−0.01, −0.001]).

3.2.2. Choice data

A mixed-effects Bayesian logistic regression indicated that participants were slightly risk-seeking on average, choosing the higher-risk choice option in 55.5% of trials in Experiment 1 ($\beta_{\text{variance}} = 0.41$ [0.32, 0.50]) and in 56.2% of trials in Experiment 2 ($\beta_{\text{variance}} = 0.48$ [0.41, 0.55]). Participants also had a strong tendency to choose cards with higher expected values (Exp 1: 75.5% of trials, $\beta_{\text{EV}} = 1.71$ [1.63, 1.80]; Exp 2: 75.9%, $\beta_{\text{EV}} = 1.81$ [1.74, 1.89]).

Crucially, in both experiments, we found a significant interaction between within-participant emotional valence and option variance (Exp 1: $\beta = -0.06$, 95 [−0.09, −0.03]; Exp 2: $\beta = -0.04$ [−0.06, −0.01]; see Figure 2, which shows the overall effect of raw emotional valence on the proportion of risk-seeking choices). This interaction indicates that participants tended to show a weaker preference for choosing the riskier card if they had reported a more positive emotional valence in the most recent self-report, and a stronger preference for the riskier card if they had reported a more negative emotional valence in the most recent self-report. These results suggest that within-person fluctuations in emotional valence had a reliable effect on their risk attitudes: more positive emotional valence was associated with increases in risk aversion and more negative emotional valence was associated with increases in risk-seeking. We did not find any significant evidence for the effects of *between-person* emotional valence on risk attitudes in logistic regression analyses. However, consistent with previous literature (e.g., Brooks and Sokol-Hessner, 2020), we also found an effect of a previous-trial outcome on choice behavior, with participants showing more risk-seeking behavior after worse previous-trial outcomes. Full regression tables for both experiments are presented in the Supplementary Material (Section S2), as is the *brms* syntax used for analysis (Supplementary Material, Section S3).

However, since most choice pairs presented to participants involved gambles with both gain- and loss-domain potential outcomes (see Supplementary Material, Section S1), it remains unclear whether the effects of emotional valence evident in the regression results above exerted their influence via changes in risk aversion, changes in loss aversion, or both. To answer this question, we next turned to computational modeling of the data.

Table 2. *Median parameter estimates from Model 4.*

Parameter	Median	95% HDI	Credible effect?
λ	0.80	[0.76, 0.84]	–
ρ	0.68	[0.67, 0.70]	–
β	0.16	[0.15, 0.17]	–
$\Delta\lambda(\text{between})$	0.03	[−0.02, 0.07]	No
$\Delta\lambda(\text{within})$	0.02	[0.01, 0.03]	Yes
$\Delta\lambda$ (prev outcome)	0.03	[0.02, 0.04]	Yes
$\Delta\rho(\text{between})$	−0.01	[−0.02, −0.003]	Yes
$\Delta\rho(\text{within})$	−0.005	[−0.01, −0.001]	Yes
$\Delta\rho(\text{prev outcome})$	−0.005	[−0.009, −0.001]	Yes

3.2.3. Computational modeling results

The results of a formal comparison of the different computational models are presented in Table 1. The best-fitting model overall was Model 4, in which emotion modulated both risk aversion (i.e., the degree of curvature of the utility function, ρ) and loss aversion (λ).

Group-level parameter estimates from Model 4 are presented in Table 2. These parameter estimates elucidate several aspects of our behavioral results. Parameter estimates indicated that, on average, participants in these experiments were risk-averse (i.e., mean ρ parameter credibly less than 1) but not loss averse (i.e., the mean λ parameter was less than 1, rather than being greater than 1 as is typically observed). The combination of these effects explains why, despite evidence of risk aversion, participants tended to choose higher-risk gambles at rates above chance (as detailed in Section 3.2.2). Specifically, because riskier gambles in our task were more likely to involve both gains and losses, the tendency for participants to be loss-seeking outweighed their underlying risk aversion.

For the effects of emotion on these parameters, we found that the risk aversion parameter ρ was significantly moderated by *both* between-participant differences in emotional valence (group-level mean $\Delta\rho(\text{between}) = -.01$, 95% HDI = [−0.02, −0.003]) *and* within-participant differences in emotional valence (group-level mean $\Delta\rho(\text{within}) = -.005$, 95% HDI = [−0.01, −0.001]). By contrast, for the loss aversion parameter λ we found evidence only for a significant effect of within-participant differences in emotional valence (group-level mean $\Delta\lambda(\text{within}) = 0.02$, 95% HDI = [0.01, 0.03]), with no significant effects of between-participant differences in emotional valence on λ. Separately, we found that preceding outcomes also significantly affected both risk and loss aversion, with receipt of more positive outcomes associated with increased risk aversion and increased loss aversion on the immediately subsequent trial.

In interpreting the effects of emotional valence on risk and loss aversion, however, it is important to consider the utility curves implied by these parameter estimates holistically, rather than focusing on the interpretation of any one parameter. Importantly, the ρ parameter governs the curvature of the risk aversion parameter in both the gain domain and the loss domain; as a consequence, the shape of the utility function in the loss domain depends on both ρ and the loss aversion parameter λ. In interpreting the effects of emotional valence on the subjective utility of different prospects, therefore, it is important to consider the total effect of both ρ and λ on the shape of the utility function. To do so, we have estimated the subjective utility curves that are implied by the mean estimated parameter values from our computational model; these are presented in Figure 3 for between-person (A) and within-person variance in emotional valence (B). Importantly, taken together these results suggest that the within-person effects of negative emotion on both risk aversion and loss aversion may have tended to 'cancel out' one another in the loss domain (Figure 3B), with within-person effects of negative emotion therefore primarily evident in the gain domain. By contrast, between-person effects of negative emotion on the curvature of the utility function were evident in both the gain and the loss domain (Figure 3A).

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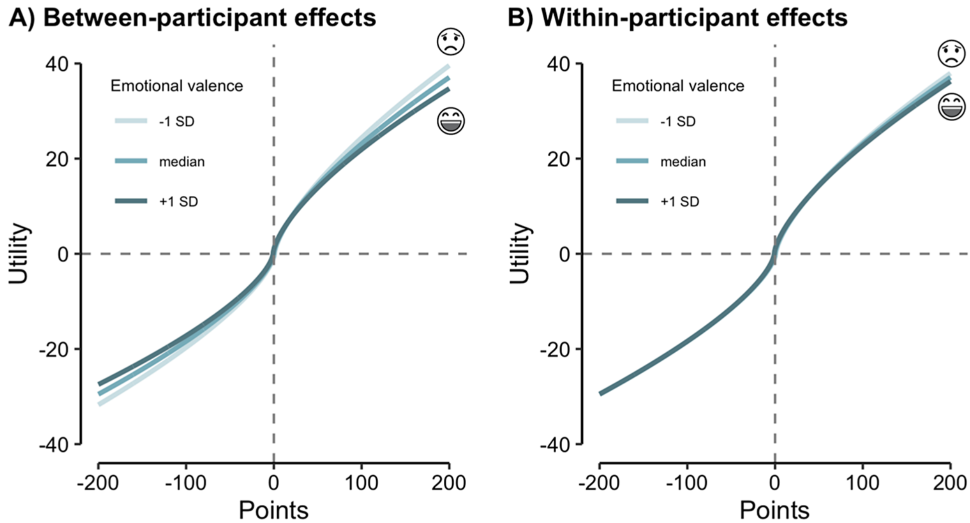

Figure 3. *Estimated subjective utility curves from Model 4. More positive emotion was associated with increased curvature of the utility function for gains (i.e., increased risk aversion) both at a between-participant level (A) and a within-participant level (B). Plotted values correspond to the median values of the group-level posterior distribution for all model parameters. Different line colors denote parameter values for median emotion self-reports ± one standard deviation in each domain (also represented by emoji symbols).*

4. Discussion

A long-standing question in judgment and decision-making is how individuals' emotional states influence their risk attitudes. Despite a long history of study, however, previous research on this question has produced markedly inconsistent results (Prietzel, 2019). In the present study, we adopted a novel approach to this question, emphasizing the distinction between within-individual and between-individual effects of emotional valence on risky decision-making (Brose et al., 2015; Hamaker et al., 2015). We analyzed data from two large-scale datasets of participants completing a risky-choice task with an embedded high-resolution sampling of subjective emotional valence. This design allowed us to investigate how risky-choice behavior covaried with participants' subjective emotional valence, both at a between-participant level (i.e., differences in risk attitudes between participants who experienced a more positive affect on average and those who reported a more negative affect on average) and at a within-participant level (i.e., changes in risk attitudes over time within each participant as their emotional valence fluctuated during the task).

Across both experiments, our initial model-agnostic regression analyses indicated that participants' subjective emotional valence was significantly negatively associated with their risk tolerance; we then used prospect-theoretic computational models of choice to further dissect this overall effect. This computational modeling analysis uncovered two findings of note. First, modeling results indicated that the overall negative association between emotional valence and risk attitudes was driven by emotion-related changes in the ρ parameter of the model, which controls the curvature of the subjective utility function. As such, we can conclude that more negative emotional valence was associated with decreased curvature of the utility function (i.e., less risk aversion for prospective gain outcomes in more negative emotional states), whereas more positive emotional valence was associated with increased curvature of the utility function (i.e., more risk aversion in more positive emotional states). That is, participants tended to assign greater subjective utility to high-value prospective gains when they were in a more negative emotional state, and less utility to prospective gains in a more positive emotional state. We did

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not find any evidence for an effect of subjective emotional valence on other prospect-theory parameters such as loss aversion or curvature of the utility function for prospective losses.

A second important finding from our computational modeling analysis was that the effect of emotion valence on risk aversion described above was present *both* at a between-participant level *and* at a within-participant level. In other words, at the between-participant level, we found that participants who reported more negative emotional valence on average were more risk-seeking than those who reported more positive emotional valence on average. Analogously, at the within-participant level, we found that individual participants tended to become more risk-seeking for gains on trials in which their emotional valence was more negative than was usual for them, and more risk-averse for prospective gains in choices where they felt more positive than usual. Moreover, since our analysis method ensured that within-participant variance in emotional valence was orthogonalized with respect to between-participant variance, we can conclude that these two effects were statistically independent of one another (though the standardized effect size of the between-participant effect was approximately twice that of the within-participant effect).

Broadly speaking, our results are in keeping with a subset of the empirical literature that has reported increases in risk-seeking with increases in negative affect. Consistent with our findings, previous research has reported this effect both at a between-participant level using correlational studies (Buelow and Suhr, 2013) and at a within-participant level using experimental affect-induction methods in the laboratory (Colasante et al., 2017; Juergensen et al., 2018; Raghunathan and Pham, 1999; Zhao, 2006). However, our results are inconsistent with a separate subset of the literature in which, by contrast, more positive emotional valence has been linked with increased risk-seeking both in correlational studies (Grable and Roszkowski, 2008; Otto and Eichstaedt, 2018) and with respect to within-participant changes in emotion in controlled laboratory settings (Schulreich et al., 2014; Vinckier et al., 2018; Yuen and Lee, 2003).

In addition to the effects of subjective emotional valence, the computational models that we used in the present study allowed for risk aversion and loss aversion to vary as a function of the outcome of the previous trial. These previous-trial effects were included in the model because previous work has shown that immediately preceding outcomes can shift risk and loss aversion (Brevers, He, Xue and Bechara, 2017; Brooks and Sokol-Hessner, 2020; Imas, 2016; Suhonen and Saastamoinen, 2018; Thaler and Johnson, 1990). Accounting for these effects in our models was crucial since it allowed us to ensure that the effects of emotional valence on choice are unconfounded by the effects of previous-trial outcomes on emotional valence. Consistent with this logic, we found that the effects of emotion on risk-taking were present even after accounting for previous trial outcomes. In line with findings previously reported by Brooks and Sokol-Hessner (2020), we found that more positive previous-trial outcomes produced greater loss aversion (but also decreased risk aversion, in line with studies of the 'house money' effect; Suhonen and Saastamoinen, 2018, Thaler and Johnson, 1990).

Among theories of emotion and risk-taking, our results are most consistent with the Mood Maintenance Hypothesis (Isen et al., 1988). This hypothesis posits that individuals have preferences over their own emotional states, such that people feeling negative emotions are motivated to take actions that will repair their emotional state (e.g., buying oneself chocolate after a bad day at work), whereas those feeling positive emotions are motivated by a desire to prolong their pleasant emotional state. Under this framework, the effect of emotional valence on the curvature of the utility function that we observed in the present study might reflect the greater perceived capacity of high-reward outcomes for repairing participants' negative emotions (Juergensen et al., 2018) when they were comparatively unhappy. By contrast, the same high-reward outcomes may have had reduced subjective utility for participants in positive emotional states because these participants were already relatively satisfied with their current emotional states, and were not motivated to win a large reward to improve their emotional state further.

Under this interpretation, the effects of emotion on risk attitudes that we observed were determined by participants' expectations about their future emotional states after observing the outcomes of their

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decisions. Two interesting corollaries follow from this interpretation: first, we would predict that the overall effect of emotional valence on risk-taking that we observed might only be present in settings where individuals receive immediate feedback on behaviors. When decision outcomes are delayed or hidden, participants cannot anticipate an immediate post-feedback change in their emotional state, and may therefore be less likely to factor their expected emotional responses into their decision calculus. This distinction between tasks with immediate versus tasks without immediate feedback may help to explain the heterogeneity of effects in the literature, given that some studies that found contradictory effects to ours used risky-choice tasks in which feedback was not provided to participants (Grable and Rozkowski, 2008, Schulreich et al., 2014; but see also Maillez et al., 2020). For example, our findings disagree with the results of Otto and Eichstaedt (2018), who found that city-level proxies for emotional valence extracted from sentiment analysis of social media posts predicted city-level variance in lottery ticket purchases. However, although buying a ticket in a lottery is a canonical risk-seeking action, it is also an action for which outcome feedback is not expected until days after the decision to purchase the decision. We would not therefore predict participants to consider a mood-repair function of risk-seeking in this setting in the same way as they might when outcome feedback is immediate, as in the present study.

A second related corollary of interpreting our findings in terms of the Mood Maintenance Hypothesis is that the effects of emotion on risk-taking may be mediated by affective forecasting. Affective forecasting refers to individuals' ability to predict their emotional reactions to future events, and has been previously shown to play a role in choice behavior (Wilson and Gilbert, 2005). In our study, for instance, increased risk-taking in negative emotional states might be especially prominent among participants who forecast more mood repair for themselves after a large win outcome. This would be conceptually consistent with results on affective forecasting and decision-making previously reported by Charpentier et al. (2016).

It is important to note several limitations to our research approach. First, we measured risk-taking using prospect-theoretic gambles differing in outcome magnitude and probability; this is a common laboratory measure of risk preferences but by no means the only one. Risk-taking is a heterogeneous cognitive construct (Mamerow et al., 2016), and it is an open question whether our results would generalize to other laboratory and real-world assays of risk-taking. Second, in the present study, we focused on variation in the valence of emotions along a bipolar positive–negative continuum. Although valence is commonly considered to be one of the fundamental dimensions of human affect (Russell, 2003), other taxonomies of emotion may also hold explanatory power for risk-taking behavior. In particular, one prominent approach studies categorical differences in basic emotions (e.g., fear, sadness, anger; Lerner and Keltner, 2000, 2001), which we were not able to separately investigate using the data collected in this study. Harmonizing the valence-specific results of the present study with a basic-emotion perspective is an important task for future research into emotion and risk-taking behavior. Similarly, another influential perspective on emotional valence holds that positive affect and negative affect are not mirror opposites of one another on a bipolar scale, as we have assumed. Instead, this perspective contends that positive affect and negative affect are distinct dimensions of emotional experience that may be independent of one another (Cacioppo et al., 1997; Villano et al., 2020; Watson et al., 1999). Under this perspective, the present study leaves unanswered whether the effects of (bipolar) emotion on risk attitudes that we observed were driven by positive affect, negative affect, or both. Further research separately measuring subjective positive affect and negative affect during risky decision-making is required to answer this question. Finally, prospect theory is a descriptive model of choice, not a process model; as such, our findings do not necessarily provide any insight into the underlying cognitive (or neural) mechanisms by which negative emotional valence might decrease risk aversion.

Overall, our results shed new light on a well-studied but not well-understood aspect of judgment and decision-making. We find that emotional valence is negatively associated with participants' risk tolerance and present modeling results that suggest that this effect is mediated by changes in the curvature of a subjective utility function. In addition, whereas previous research on this question has not typically considered the distinction between within-person and between-person effects of emotional valence on risk attitudes, we find that the observed effects are independently present when we separately consider within-person and between-person variance in participants' subjective emotional states.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/jdm.2024.29.

Data availability statement. De-identified raw data are available without restriction at the project OSF repository (https://osf.io/jpv49/).

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Competing interest. The authors declare none.

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