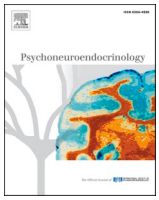
Psychoneuroendocrinology 172 (2025) 107259

Contents lists available at ScienceDirect

Psychoneuroendocrinology

journal homepage: www.elsevier.com/locate/psyneuen



Acute stress differentially influences risky decision-making processes by sex: A hierarchical bayesian analysis☆,☆

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ARTICLE INFO

Keywords:
Acute stress
Risky decision-making
Cumulative prospect theory
Loss aversion
Sex differences

ABSTRACT

How does stress influence our decision-making? Although numerous studies have attempted to answer this question, their results have been inconsistent—presumably due to methodological heterogeneity. Drawing on cumulative prospect theory, we examined how acute stress influenced risky decision-making. To this end, we randomly assigned 147 participants to an acute stress induction or control condition and subsequently assessed participants' risky decision-making. We found that stress increased risky decision-making overall, but more importantly, that stress exerted multiple effects on risky decision-making processes that differed between male and female participants. For female participants, relative to the control condition, stress produced a pattern of decision-making characterized by risk seeking with respect to gains, slightly reduced loss aversion, accurate outcome probability assessment, and greater choice stochasticity. For male participants, stress, relative to the control condition, produced to a pattern of decision-making characterized by very low loss aversion and poorer outcome probability assessment. These results suggest that some of the heterogeneity in existing literature may be explainable by task differences in risk type, risk amount, and outcome certainties, and further that these effects will differ by sex. In short, stress changes how we make decisions, and it does so differently by sex.

1. Introduction

How does stress influence decision-making within the context of financial risk management? Results from the prior literature are mixed, suggesting additional work is needed to bridge the gap between neuropsychology and behavioral economic theory as it relates to financial decision-making (Miendlarzewska et al., 2019; von Helversen and Rieskamp, 2020). This study explores this question via hierarchical Bayesian modeling of component processes underlying risky decision-making for decisions made under acute stress. We then derive utility functions consistent with cumulative prospect theory and explore how sex might moderate the impacts of acute stress on the parameters of the utility function.

Consistent with the behavioral finance literature, *cumulative prospect theory* is a quantitative approach that was developed to account for empirical regularities in patterns of risky decision-making, such as, for example, that people are typically risk-seeking in low-probability gains (e.g., preferring a 5 % chance of winning $100 to a gain of $5), risk-averse in high-probability gains (e.g., preferring a gain of $95 to a 95 % chance of winning $100), risk-averse in low-probability losses (e.g., preferring a loss of $5 to a 5 % chance of losing $100), and risk-seeking in high-probability losses (e.g., preferring a 95 % chance of losing $100 to a loss of $95) (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). This "fourfold pattern of risk" in risky decision-making is extremely reliable and is seen around the world (Ruggeri et al., 2020).

Cumulative prospect theory posits that risky decision-making is based on the conjunction of four[1] parameters: utility curvature, loss aversion, probability distortion, and choice stochasticity (Burke et al., 2018; Tanaka et al., 2010; Toubia et al., 2013; Tversky and Kahneman, 1992). Utility curvature, also called risk aversion, describes subjective decelerations in expected utility that occur as potential outcomes

☆ This work is supported by NSF CAREER 2338789 to Grant S. Shields and a Southern Regional Education Board Doctoral Scholars Fellowship to Zach J. Gray.☆ Data, syntax for analyses, and R output are available at https://osf.io/u5b37/?view_only=1c04a68d369c4f4f9ef01305a3d17243

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[1] Originally, cumulative prospect theory did not model choice stochasticity. We followed most work with this model of decision-making and included choice stochasticity as an estimated parameter (e.g., Toubia et al., 2013).

https://doi.org/10.1016/j.psyneuen.2024.107259
Received 17 August 2024; Received in revised form 16 December 2024; Accepted 17 December 2024
Available online 19 December 2024

increase. For example, the subjective increase in value from receiving $10 versus $0 is typically more than that from receiving $20 versus $10. Loss aversion describes the typically observed greater sensitivity to losses than gains—the asymmetry present if, for example, we are more averse to losing $10 than we are attracted to gaining $10. Probability distortion describes the typically observed overweighting of low-probability outcomes and underweighting of high-probability outcomes—people buy lottery tickets because they think they will win. Finally, choice stochasticity describes the extent to which people deviate from their own strictly optimum expected utility; it can be thought of as pure randomness, or as a tendency to explore versus exploit, among other things.

Although prospect theory is one of the most well-studied topics in the field of behavioral economics, few studies have explored its relationship with acute stress. This is rather surprising, as a single, time-delimited experience of stress (hereafter "acute stress" for brevity) exerts numerous, nuanced effects on a variety of basic cognitive processes (Shields, 2020; Shields et al., 2019a–d, 2020, 2024; Shields and Hunter, 2024), and the confluence of these effects can result in unexpected effects of acute stress on higher-order processes that rely on component cognitive processes, such as risky decision-making (Goldfarb and Phelps, 2017; Shields et al., 2016a). Understanding how stress influences the processes underlying risky decision-making may thus help to explain when and how stress might increase or decrease risky decision-making.

Indeed, much work has found that acute stress robustly increases risky decision-making (for a meta-analysis, see Starcke and Brand, 2016). However, studies on this topic have often obtained conflicting results (e.g., compare Buckert et al., 2014; Clay and Parker, 2018; Margittai et al., 2018; Metz et al., 2020; Nowacki et al., 2019; Porcelli and Delgado, 2009; Raio et al., 2022; Shields et al., 2019b; Sokol-Hessner et al., 2016). For example, sex differences are often obtained in studies examining the effects of stress on risky decision-making (e.g., Kluen et al., 2017; Nowacki et al., 2019), but sex differences in these effects were not obtained at the meta-analytic level (Starcke and Brand, 2016). This heterogeneity may be explainable by insights from cumulative prospect theory, namely, differences between studies in types of risky decision-making assessed (e.g., risks related to potential losses vs. risks related to potential gains). In particular, overall risky decision-making may be differentially influenced by stress if such decision-making tasks measure different forms of risk—depending upon how stress influences processes underlying risky decision-making.

To date, most of the research examining the effects of acute stress on risky decision-making has focused mostly on behavioral outcomes of risk-taking without examining the determinants of that decision-making quantified by cumulative prospect theory. Still, a few studies have examined the effects of acute stress on one or more of these components conceptually or mathematically (e.g., Margittai et al., 2018; Metz et al., 2020; Porcelli and Delgado, 2009; Sokol-Hessner et al., 2016). For example, acute stress has been found by some studies to decrease loss aversion (e.g., Margittai et al., 2018; Starcke and Brand, 2012, 2016; though see Pabst et al., 2013b)—much like it reduces resistance to sunk costs (Schulreich et al., 2022; Shields et al., 2016a). However, the results of studies examining the effects of stress on component risky decision-making processes are inconsistent across studies (e.g., Sokol-Hessner et al., 2016), likely because of different mathematical models and tasks used across studies. For example, some, but not all, studies find sex differences in the effects of stress on loss aversion (e.g., Lighthall et al., 2009, 2012; Molins et al., 2021, 2023). Importantly, to date, no published study has examined how stress affects all components of decision-making described by cumulative prospect theory—despite the interdependence of these components—using the equations of cumulative prospect theory. Recently, a dynamic, adaptive risky decision-making task has been developed that permits reliable estimation of risk aversion, loss aversion, and probability distortion via hierarchical Bayesian modeling within a reasonable number of trials (Burke et al., 2018; Toubia et al., 2013). As mentioned above, however, no work has examined how acute stress affects these parameters concurrently. We address that gap in the current study using hierarchical Bayesian modeling of risky decision-making processes.

1.1. Current research

The present study addressed the gaps described above by examining the effects of stress on risky decision-making and its component processes using hierarchical Bayesian modeling. To this end, randomly assigned 147 participants to an acute psychosocial stress induction ($n = 72$) or its control condition ($n = 75$) and subsequently assessed risky decision-making using a recently developed method that maximally differentiates risky decision-making processes in a small number of trials (see Section 2.2.3 below; see also Toubia et al., 2013).

Drawing on the literature on stress and risky decision-making, we expected to find that stress affected risky decision-making. We further expected that stress would influence component processes underlying risky decision-making, and—drawing on prior inconsistent findings of sex-specific effects on overall risky decision-making (e.g., Kluen et al., 2017; Lighthall et al., 2009, 2012; Nowacki et al., 2019; Starcke and Brand, 2016), which may suggest differential effects of stress on underlying processes by sex—that the effects of stress on risky decision-making processes would differ by participant sex.

2. Method

2.1. Participants

Participants in this study were 147 young adults (randomly assigned to conditions; 75 control, 72 stress) from a large public university in the South Central United States.[2] Individuals were only invited to participate if they did not take psychotropic medication (e.g., antidepressants, stimulants) or medication(s) that can influence stress responses (e.g., immunosuppressants, beta-adrenergic inhalers, corticosteroids), consume excessive amounts of caffeine (e.g., > 8 cups of coffee per day), have severe sleep disturbances within the prior month (e.g., shift work, chronic insomnia), have an autoimmune or major health disorder, or take hormonal contraceptives. Additional exclusion criteria were being currently sick or sick over the past week, or pregnancy. We verified compliance with these inclusion and exclusion criteria at the beginning of the study. Of this sample (M_{age}=19.01, SD_{age}=1.73; 59.2 % assigned female at birth, one transgender male), 83.0 % identified primarily as White, 6.8 % as Hispanic or Latino/a/e, 6.1 % as Asian or Asian American, 3.4 % as Black or African American, 0.7 % as Native Hawaiian or Pacific Islander. Stress and control condition participants did not differ in age ($p = .140$), sex ($p = .296$), or race/ethnicity ($p = .794$).

[2] This was part of a larger study (Shields et al., 2024) recruiting a total of 187 participants. Of the 187 participants, 11 were not able to complete the risky decision-making task due to either time constraints—as the last task within this study, if a participant arrived late and had to go at the scheduled end time, this task was not completed—or miscommunications due to Zoom (e.g., a participant clicked on the wrong icon on the desktop and repeated an earlier cognitive task but skipped the risky decision-making task entirely). Of those 176 participants, 13 were excluded for participating without meeting the stress-related inclusion criteria described below, and 15 more did not complete one or more of the tasks preceding the risky decision-making task due to Zoom-related miscommunications. Only 148 participants who met inclusion criteria completed all measures preceding the risky decision-making task and thus completed the task at the same time post-stressor. Finally, one additional participant responded to the 12 DEEP items in a sum total of less than 10 seconds, and so was excluded, resulting in a final sample for analysis of 147 participants. Analyses including all participants who completed the risky decision-making task produced equivalent inferences related to experimental condition, though some sex differences were distinct. We present the results using the full sample in Supplemental Material.

2.2. Materials

2.2.1. Stress manipulation

The stress manipulation was a Trier Social Stress Test (TSST) (Kirschbaum et al., 1993), or corresponding control condition, that was conducted via Zoom within the lab (with separate room for the participant) due to COVID-related precautions. Prior work has examined Zoom-based TSST manipulations, and the general finding is that these manipulations are successful, albeit weaker than the standard TSST (Gunnar et al., 2021; Meier et al., 2022). Details of this manipulation are provided in Supplemental Material.

2.2.2. Manipulation checks

2.2.2.1. Negative affect. Negative affect was assessed pre- and post-manipulation using the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988). Participants were asked to report the extent to which they currently felt 10 negative and 10 positive emotions (20 items total). Responses to each item were provided on a 1 (*Very slightly or not at all*) to 5 (*Extremely*) scale, and responses to the 10 questions assessing negative affect were then averaged to create an overall index of negative affect, with higher scores indicating more negative affect. Internal consistency for the scale was acceptable both pre- and post-manipulation, αs $\geq$ .77.

2.2.2.2. Cortisol. Participants provided two saliva samples (baseline and post-manipulation) via passive drool. Immediately after collection, the saliva vials were placed in a −20ºC freezer until assayed in duplicate using high-sensitivity Salivary Cortisol ELISA Kits (Salimetrics LLC, State College, PA) according to manufacturer instructions. Eight of the 147 participants did not provide enough saliva for the assay at one or both timepoints and were thus unable to be included in cortisol analyses. Inter- and intra-assay CVs were 6.79 % and 7.34 %, respectively. Assay sensitivity was 0.007 μg/dL. All controls were in the expected ranges. Cortisol concentrations were converted from μg/dL to nmol/L. The Bayesian ANOVAs, which assumed a normal distribution, did not show appropriate conversion without log transforming cortisol (see syntax and data). Therefore, we log transformed cortisol for analyses. Results with untransformed cortisol did not differ from those with log transformed cortisol.

2.2.3. Risky decision-making task

Risky decision-making will be assessed via the recently developed Dynamic Experiments for Estimating Preferences – Risk (DEEP) (Burke et al., 2018; Toubia et al., 2013). The DEEP permits reliable assessment of utility curvature (i.e., risk aversion), loss aversion, and probability distortion with only 12 trials (Toubia et al., 2013). On each trial, participants view two gambles, each containing two possible outcomes with two set probabilities (e.g., Gamble A: 10 % chance to win $2.50 and 90 % chance to win $0.50; Gamble B: 30 % chance to win $50 and 70 % chance to win $10). Participants select which of the two gambles they would prefer to take. From there, the DEEP then dynamically selects the next gamble in such a way to maximally differentiate and thus identify utility curvature, loss aversion, and probability distortion. This branching logic of gambles repeats for each of twelve trials.

2.2.3.1. Parameter estimation for component risky decision-making processes. Parameters described by cumulative prospect theory will be fit to participants' risky decision-making data. Formally, cumulative prospect theory describes the utility of a gamble between x and y (we assume $|x| > |y|$ when x and y have the same sign) shown in the U^A and U^B equations in Fig. 1. Each decision made in the DEEP is a conjunction of two outcomes and their probabilities (x and y); thus, indexing decision-makers as i ($i = 1, \ldots, I$) and trials as j ($j = 1, \ldots, J$) on trial j, participant i must choose between gamble A, $X_{ij}^A = \{x_{ij}^A, p_{ij}^A, y_{ij}^A, q_{ij}^A\}$ and gamble B, $X_{ij}^B = \left\{x_{ij}^B, p_{ij}^B, y_{ij}^B, q_{ij}^B\right\}$. Following Toubia et al., decision-makers are not assumed to always choose the highest expected utility option; choice stochasticity (e.g., response error, randomness, etc.) is fit by parameter θ. Parameters were estimated using hierarchical Bayesian modeling. We fit same-sign cumulative prospect theory, which is an identifiable model with good parameter recovery (Burke et al., 2018; Toubia et al., 2013). Population-level hyperpriors for probability distortion (α), utility curvature (γ), and loss aversion (λ) were means of 0.6, 0.8, and 1.8, given prior work (Burke et al., 2018; Toubia et al., 2013). The Bayesian model specification, including all priors and equations, is shown in Fig. 1.[3] The posterior distribution was obtained via No-U-Turn Sampling (NUTS) across six chains with 2000 warmup and 5000 retained samples. All Rhat values were < 1.01.

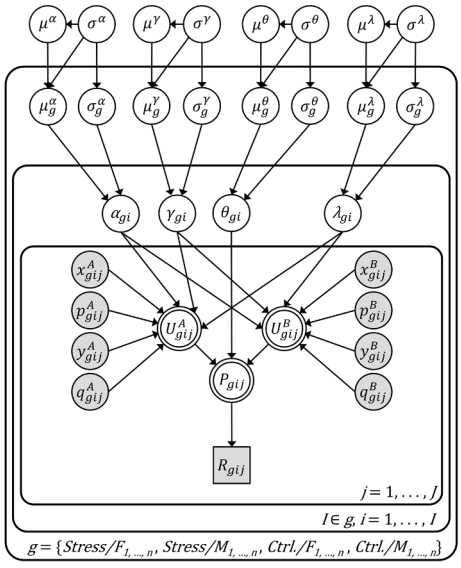
2.3. Procedure

The study procedure is depicted in Fig. 2. Due to low in-person study signups during COVID, we allowed participants to sign up for morning timeslots if needed—we devoted all possible timeslots to running participants. Most participants completed the study in the afternoon: Mean time of completion was 2:19 pm. Sensitivity analyses restricted to afternoon participants alone are reported in the Supplemental Material; results were largely equivalent. Upon arrival at the lab, participants were taken to an isolated room, wherein they completed all measures. The experimenter joined a Zoom call on a second computer in a separate room to guide the participants through the procedures, starting with informed consent. After providing informed consent, participants completed acclimation measures for approximately 10 minutes. Participants then provided the baseline measure of negative affect and baseline saliva sample before completing the stress or control task (depending upon randomly assigned condition). The stress manipulation lasted a total of 18 minutes. Following the manipulation, participants immediately completed the post-manipulation negative affect assessment and subsequently completed filler questionnaires until exactly 10 minutes had elapsed since the stress manipulation had ended. At 10 minutes post-manipulation offset, participants provided the post-manipulation saliva sample. Next, participants then completed three cognitive tasks [two of which have been described elsewhere; (Hunter and Shields, 2023; Shields et al., 2024); the third has not yet been examined or analyzed in any way], which lasted approximately 40 minutes altogether. Participants then completed the DEEP before finally being debriefed and dismissed.

2.4. Data analysis

Bayesian parameter estimation and analyses were conducted using Turing (v0.28.3) via Julia (1.9.2), as well as Stan (v2.26.1) and JAGS (v4.3.1) via R (v4.3.1), with the packages rstanarm (v2.21.4), brms (v2.19.0), BANOVA (v1.2.1), BEST (v0.5.4), and bayestestR (v0.13.1) (Bürkner, 2017; Dong and Wedel, 2017; Kruschke, 2013; Makowski et al., 2019; Muth et al., 2018). Bayesian parameter estimation goes further than providing sample summary statistics in that it estimates population values. Therefore, keeping with convention (Kruschke, 2013), we report Bayesian estimates with their respective Greek symbols—denoting population value estimates. All chains related to Condition (including interactions) converged according to model diagnostics. The effect size δ represents the standardized mean

[3] Truncating the possible values of the parameter population means to $0.35 < \alpha < 1.00$, $0.25 < \gamma < 0.90$, $0.80 < \lambda < 4.00$, and $0.70 < \theta < 5.00$ (probability distortion, utility curvature, loss aversion, and choice stochasticity, respectively) did not alter any of our inferences. Participant parameter estimates in this model and the model presented in the manuscript were correlated with $rs > .997$.



$$\sigma^{\alpha} \sim \text{Uniform}(0.01, 1)$$
$$\sigma^{\gamma} \sim \text{Uniform}(0.01, 1)$$
$$\sigma^{\lambda} \sim \text{Uniform}(0.01, 1)$$
$$\sigma^{\theta} \sim \text{Uniform}(0.01, 2)$$
$$\mu^{\alpha} \sim \text{Gaussian}(0.6, \sigma^{\alpha}),\ 0.05 < \mu^{\alpha} < 2$$
$$\mu^{\gamma} \sim \text{Gaussian}(0.8, \sigma^{\gamma}),\ 0.05 < \mu^{\gamma} < 2$$
$$\mu^{\lambda} \sim \text{Gaussian}(1.8, \sigma^{\lambda}),\ 0.05 < \mu^{\lambda} < 2$$
$$\mu^{\theta} \sim \text{Gaussian}(1.0, \sigma^{\theta}),\ 0.10 < \mu^{\theta} < 10$$
$$\mu_g^{\alpha} \sim \text{Gaussian}(\mu^{\alpha}, \sigma^{\alpha}),\ 0.05 < \mu_g^{\alpha} < 2$$
$$\sigma_g^{\alpha} \sim \text{Gaussian}(\sigma^{\alpha}, 1),\ 0.05 < \sigma_g^{\alpha} < 2$$
$$\mu_g^{\gamma} \sim \text{Gaussian}(\mu^{\gamma}, \sigma^{\gamma}),\ 0.05 < \mu_g^{\gamma} < 2$$
$$\sigma_g^{\gamma} \sim \text{Gaussian}(\sigma^{\gamma}, 1),\ 0.05 < \sigma_g^{\gamma} < 2$$
$$\mu_g^{\lambda} \sim \text{Gaussian}(\mu^{\lambda}, \sigma^{\lambda}),\ 0.05 < \mu_g^{\lambda} < 10$$
$$\sigma_g^{\lambda} \sim \text{Gaussian}(\sigma^{\lambda}, 1),\ 0.05 < \sigma_g^{\lambda} < 10$$
$$\mu_g^{\theta} \sim \text{Gaussian}(\mu^{\theta}, \sigma^{\theta}),\ 0.10 < \mu_g^{\theta} < 10$$
$$\sigma_g^{\theta} \sim \text{Gaussian}(\sigma^{\theta}, 2),\ 0.10 < \sigma_g^{\theta} < 10$$
$$\alpha_{gi} \sim \text{Gaussian}(\mu_g^{\alpha}, \sigma_g^{\alpha}),\ 0.05 < \alpha_{gi} < 2$$
$$\gamma_{gi} \sim \text{Gaussian}(\mu_g^{\gamma}, \sigma_g^{\gamma}),\ 0.05 < \gamma_{gi} < 2$$
$$\lambda_{gi} \sim \text{Gaussian}(\mu_g^{\lambda}, \sigma_g^{\lambda}),\ 0.05 < \lambda_{gi} < 10$$
$$\theta_{gi} \sim \text{Gaussian}(\mu_g^{\theta}, \sigma_g^{\theta}),\ 0.10 < \theta_{gi} < 10$$

$$\text{where } v(x,\gamma) = \begin{cases} x^{\gamma}, & for\ x > 0 \\ -\lambda(-x)^{\gamma}, & for\ x < 0 \end{cases} \quad \text{and} \quad \pi(p,\alpha) = \exp(-(-\ln p)^{\alpha}),$$

$$U_{gij}^{A} \leftarrow \begin{cases} v(y_{gij}^{A}, \gamma_{gi}) + \pi(p_{gij}^{A}, \alpha_{gi})\left(v(x_{gij}^{A}, \gamma_{gi}) - v(y_{gij}^{A}, \gamma_{gi})\right), if\ x > y > 0\ or\ x < y < 0 \\ \pi(p_{gij}^{A}, \alpha_{gi})v(x_{gij}^{A}, \gamma_{gi}) + \pi(q_{gij}^{A}, \alpha_{gi})v(y_{gij}^{A}, \gamma_{gi}), if\ x < 0 < y \end{cases}$$

$$U_{gij}^{B} \leftarrow \begin{cases} v(y_{gij}^{B}, \gamma_{gi}) + \pi(p_{gij}^{B}, \alpha_{gi})\left(v(x_{gij}^{B}, \gamma_{gi}) - v(y_{gij}^{B}, \gamma_{gi})\right), if\ x > y > 0\ or\ x < y < 0 \\ \pi(p_{gij}^{B}, \alpha_{gi})v(x_{gij}^{B}, \gamma_{gi}) + \pi(q_{gij}^{B}, \alpha_{gi})v(y_{gij}^{B}, \gamma_{gi}), if\ x < 0 < y \end{cases}$$

$$P_{gij} \leftarrow \text{logit}^{-1}(\theta_{gi} \times (U_{gij}^{A} - U_{gij}^{B}))$$
$$R_{gij} \sim \text{Bernoulli}(P_{gij})$$

Fig. 1. Hierarchical Bayesian model used for parameter estimation of cumulative prospect theory parameters. Distributions were truncated to facilitate model estimation in some cases. Each Condition×Sex group was modeled as having its own mean and standard deviation, with their priors coming from population values. Participants were then nested within groups, and trials further nested within participants. Options x and y have probabilities p and q (i.e., 1-p), respectively. Parameters provide the probability of choosing option B over option A on choice j for participant i, nested within group g (i.e., P_{gij}). Choices, all having been recoded such that option A was the choice made, are then drawn from a Bernoulli distribution with probability P_{gij}.

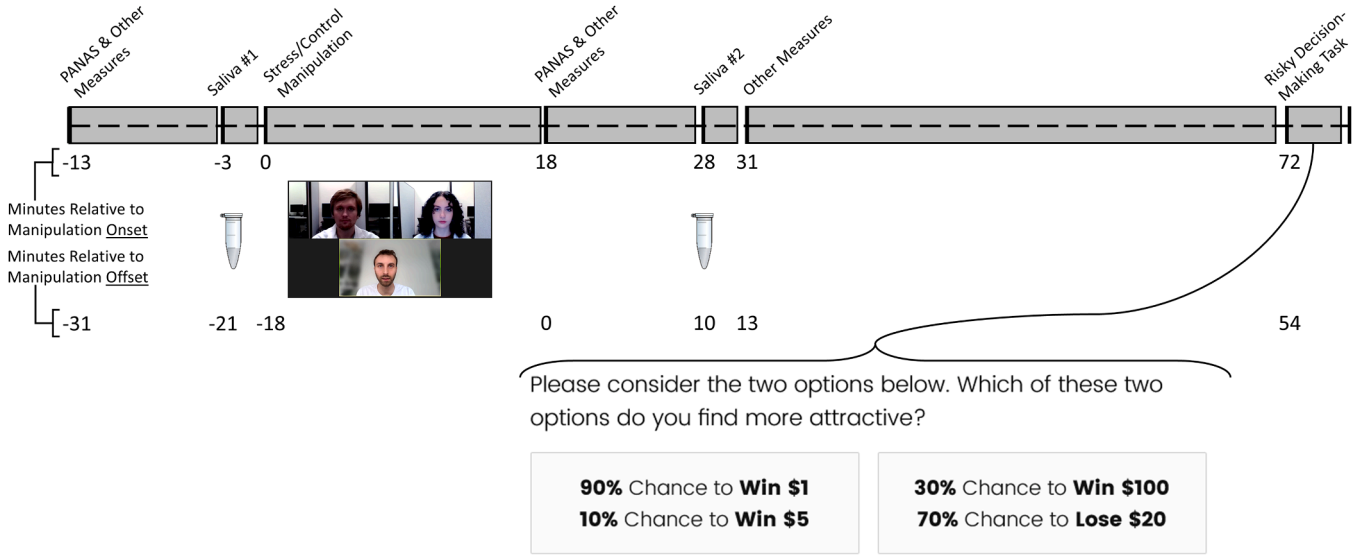


Fig. 2. Study procedure. Picture of the Zoom stressor does not precisely represent the conditions in which participants completed the study. This picture was taken by the PI and two graduate students shortly after study completion, after lab remodeling had occurred. The depicted gamble is the first risky decision-making trial, which every participant completes to begin the branching logic.

difference between groups, and β represents the standardized regression coefficient.

The Bayesian probability of direction (p_d) is typically similarly interpretable to a one-tailed p value—it describes the probability that a distribution is positive or negative, depending upon the median's sign. We present the equivalent of a two-tailed p value with a variant probability of direction, p_{dt}, which indicates the proportion of the posterior distribution including the median and either greater than it (when the median is negative) or less than it (when the median is positive). That is, for the portion of the posterior distribution that ranges from the distribution's 50th percentile to its furthest point from an effect, p_{dt} describes the proportion of that distribution that includes zero or anything further from the median than zero. In short, p_{dt} is interpretable similarly to a two-tailed p value in frequentist statistics.

Results with frequentist statistics were virtually identical; these are presented in Supplemental Material.

As we have done previously (e.g., Shields et al., 2019a), for analyses examining associations with individual differences in cortisol responses, we calculated changes in cortisol by regressing post-manipulation cortisol on pre-manipulation cortisol. Residualized changes were calculated for negative affect in the same way. Residualized changes were used instead of simple change scores because residual change scores are more reliable than simple change scores by better accounting for the influence that basal values have on change scores (Cronbach and Furby, 1970). Using simple change scores (i.e., Δ cortisol) altered the results only slightly: A quadratic association emerged between cortisol and loss aversion. However, upon inspection, this appeared to be driven by a small number of outliers; removing a single observation reduced the quadratic coefficient's significance to marginal. We present our original analyses using residualized change scores below.

3. Results

3.1. Stress responses

Consistent with hypotheses, the Zoom-based stressor increased both negative affect and cortisol relative to control conditions. In particular, we observed a Condition×Time interaction effect in negative affect, η^2_p= .213, p_{dt}< .001, and cortisol, η^2_p= .128, p_{dt}< .001, without significant three-way Sex×Condition×Time interactions, p_{dt}s > .127.

Decomposing the Condition×Time interaction in negative affect (Fig. 3A), we found that participants in the stress condition (μ=1.28, σ=0.22) did not differ from participants in the control condition (μ=1.29, σ=0.24) at baseline, $\delta_{\Delta\mu}$= -0.060, $p_{dt:\ \delta}$= .776, whereas participants in the stress condition reported more negative affect (μ=1.95, σ=0.62) than participants in the control condition (μ=1.21, σ=0.21) post-manipulation, $\delta_{\Delta\mu}$= 1.604, $p_{dt:\ \delta}$< .001.

Decomposing the Condition×Time interaction in cortisol (Fig. 3B), we found that participants in the stress condition (μ_{ln}=1.93, σ_{ln}=0.56) did not differ from participants in the control condition (μ_{ln}=1.77, σ_{ln}=0.62) at baseline, $\delta_{\Delta\mu ln}$= 0.270, $p_{dt:\ \delta}$= .131, whereas participants in the stress condition had higher cortisol levels (μ_{ln}=2.19, σ_{ln}=0.62) than participants in the control condition (μ_{ln}=1.64, σ_{ln}=0.56) post-manipulation, $\delta_{\Delta\mu ln}$= 0.924, $p_{dt:\ \delta}$< .001.

3.2. Stress effects on risky decision-making and component processes

Next, we examined how stress might influence the frequency with which the risky decision (i.e., the decision with the higher variance in expected value) was chosen in a binomial Bayesian ANOVA. We found a small Stress effect, pseudo-η^2_p= .01, $p_{dt:\ \Delta\mu}$= .029, without any significant effect of Sex ($p_{dt:\ \Delta\mu}$=.672) or any Stress×Sex interaction ($p_{dt:\ \Delta\mu\ \times\ \Delta\mu}$ =.715). Probing this Stress effect, stress-condition participants chose the risky option ($\mu_{proportion\ risky\ choices}$=0.55) more frequently than control participants ($\mu_{proportion\ risky\ choices}$=0.49).

We then examined how stress might influence component processes underlying risky decision-making in a series of Bayesian Type III ANOVAs with Stress (Stress, Control) and Sex (Male, Female) as between-subjects factors in each model. All convergence diagnostics passed. Importantly, we found no difference in model fits by stress condition (p_{dt}=.800), sex (p_{dt}=.590), or their interaction (p_{dt}=.819), indicating that inferences related to model parameters were not confounded by differential fits to data across conditions for male or female participants.

With probability distortion as the outcome, we observed a large Stress×Sex interaction, η^2_p= .219, p_{dt}< .001, without a main effect of Stress (p_{dt}=.216) or Sex (p_{dt}=.081) (Fig. 4A). Decomposing this interaction, relative to the control condition, male participants showed greater probability distortion (i.e., greater distance from 1.0) under stress ($\mu_{stress/male}$=0.417, $\sigma_{stress/male}$=0.107; $\mu_{control/male}$=0.583, $\sigma_{control/male}$=0.235), $\delta_{\Delta\mu:\ males}$ = -0.918, $p_{dt:\ \delta}$= .002, whereas female participants showed less probability distortion (i.e., less distance from 1.0) under stress ($\mu_{stress/female}$=0.684, $\sigma_{stress/female}$=0.253; $\mu_{control/female}$=0.439, $\sigma_{control/female}$=0.150), $\delta_{\Delta\mu:\ females}$ = 1.183, $p_{dt:\ \delta}$< .001. Additionally, male participants showed lower variability in probability distortion under stress compared to the control condition (p_{dt}<.001), whereas female participants showed greater variability in probability distortion under stress (p_{dt}=.002). Stated simply, stress increased probability distortion in male participants but decreased probability distortion in female participants.

With utility curvature as the outcome, we observed a small Stress×Sex interaction, η^2_p= .025, p_{dt}= .038, which qualified a significant main effect of Stress, η^2_p= .028, p_{dt}= .030, but no main effect of Sex (p_{dt}=.299) (Fig. 4B). Decomposing this interaction, relative to the control condition, male participants showed no mean difference in utility curvature under stress ($\mu_{stress/male}$=0.522, $\sigma_{stress/male}$=0.130; $\mu_{control/male}$=0.520, $\sigma_{control/male}$=0.063), $\delta_{\Delta\mu:\ males}$ = 0.017, $p_{dt:\ \delta}$= .951, whereas female participants showed a utility curvature that more resembles a linear effect (i.e., less "risk aversion," which entails greater reward sensitivity) under stress ($\mu_{stress/female}$=0.611, $\sigma_{stress/female}$=0.312; $\mu_{control/female}$=0.466, $\sigma_{control/female}$=0.162) with a moderate-sized effect, $\delta_{\Delta\mu:\ females}$ = 0.590, $p_{dt:\ \delta}$= .016. Both sexes showed increased variability under stress versus control conditions (p_{dt}s < .001). Stated simply, stress decreased risk aversion in female participants but did not influence risk aversion in male participants.

With loss aversion as the outcome, we observed a small Stress×Sex interaction, η^2_p= .021, p_{dt}= .050, which qualified a large main effect of Stress, η^2_p= .149, p_{dt}< .001, but no main effect of Sex (p_{dt}=.097) (Fig. 4C). Decomposing this interaction, male participants showed much less loss aversion under stress relative to the control condition ($\mu_{stress/male}$=0.735, $\sigma_{stress/male}$=0.217; $\mu_{control/male}$=1.145, $\sigma_{control/male}$=0.284), $\delta_{\Delta\mu:\ males}$ = -1.634, $p_{dt:\ \delta}$< .001, and the same was true for female

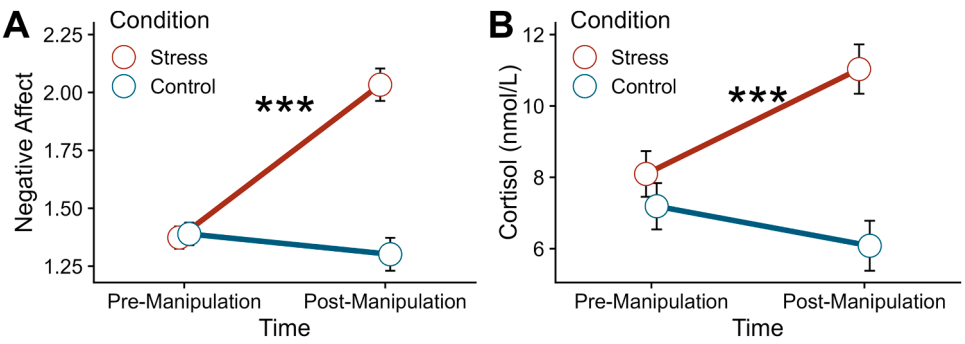


Fig. 3. Effects of the manipulation (i.e., stress vs. control) on negative affect (A) and cortisol (B) over time. The manipulation increased negative affect and cortisol in the stress condition, not the control condition. Depicted means and error bars are marginal means and standard errors from observed data; Bayesian estimates differed and are reported in text.

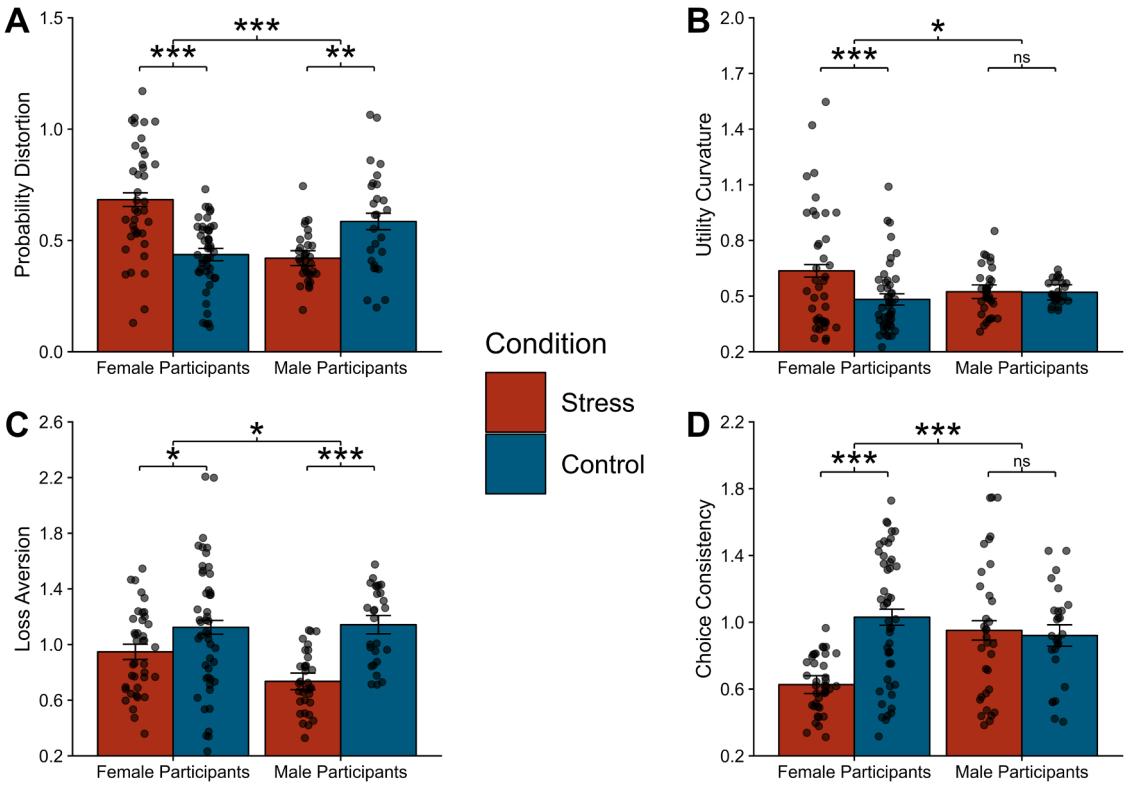


Fig. 4. Effects of stress on each parameter estimate by sex. Stress differentially influenced each parameter estimate by sex, such that the only effect of stress in the same direction across men and women was the effect of stress on loss aversion. Bars illustrate $M \pm SE$.

participants to a lesser extent ($\mu_{stress/female}$=0.947, $\sigma_{stress/female}$=0.304; $\mu_{control/female}$=1.122, $\sigma_{control/female}$=0.460), $\delta_{\Delta\mu:\ females}$ = -0.452, $p_{dt:\ \delta}$= .042. The interaction emerged because the effect of stress on loss aversion was stronger in male participants than female participants. Both sexes showed less variability under stress versus control conditions, but this difference was only significant in female participants (male p_{dt}=.170; female p_{dt}=.013). Stated simply, stress decreased loss aversion in both male and female participants, and it did so more strongly in male participants than it did in female participants.

Finally, with choice stochasticity as the outcome, we observed a significant Stress×Sex interaction, η_p^2= .090, p_{dt}< .001 which qualified a significant main effect of Stress, η_p^2= .067, p = .001, but no main effect of Sex (p_{dt}=.061) (Fig. 4D). Decomposing this interaction, relative to the control condition, male participants showed no difference in choice stochasticity under stress ($\mu_{stress/male}$=0.945, $\sigma_{stress/male}$=0.424; $\mu_{control/male}$=0.922, $\sigma_{control/male}$=0.292), $\delta_{\Delta\mu:\ males}$ = 0.064, $p_{dt:\ \delta}$= .807, whereas female participants showed significantly greater choice stochasticity (i.e., smaller theta values) under stress ($\mu_{stress/female}$=0.627, $\sigma_{stress/female}$=0.167; $\mu_{control/female}$=1.032, $\sigma_{control/female}$=0.397), with a strong effect size, $\delta_{\Delta\mu:\ females}$ = -1.340, $p_{dt:\ \delta}$< .001. Stated simply, stress increased choice stochasticity in female but not male participants.

Altogether, male and female participants showed differential patterns of risky decision-making under stressful and control conditions, depending upon choice probability. For example, stress increased female participants' sensitivity to large, low-probability losses, whereas stress decreased male participants' sensitivity to those same losses. Female participants also showed much greater sensitivity to high-probability gains under stress, especially as the expected value of those gains increased, whereas stress did not increase male participants' sensitivity to those gains—if anything, stress decreased said sensitivity in male participants. These dynamics are illustrated in Fig. 5.

3.3. Individual differences: associations between stress responses and decision-making parameters

Finally, we also examined associations of risky decision-making component processes with negative affect and cortisol responses to stress. In bivariate analyses, we found that greater increases in negative affect predicted a utility curvature that more resembles a linear effect, β= .28, p_{dt}= .001, and less loss aversion, β= -.24, p_{dt}= .003, and greater increases in cortisol also predicted less loss aversion, β= -.25, p_{dt}= .004. To determine whether these associations a) were statistically similar to mechanisms underlying the effects of stress on these parameters (i.e., as mediators, where cortisol or affect would be significantly associated with the outcome[*s*] but neither stress condition nor stress by sex would be), b) were independent of the effects of stress (e.g., as unique associations regardless of condition, where cortisol or affect would be significant along with significant stress condition and/or stress by sex effects), or c) were epiphenomenal (e.g., with the stress condition simply producing associations between variables across conditions because stress by sex influenced cortisol/affect and decision-making parameters concurrently, where cortisol or affect would not retain significance once stress condition and the stress by sex interaction were included in the model), we conducted analyses including sum-contrast-coded factors of stress condition, sex, and the stress condition by sex interaction alongside each centered and scaled continuous predictor (i.e., cortisol or negative affect). In these analyses, both associations with loss aversion became negligible after accounting for the effects of stress by sex (respectively: β= −.04, p_{dt}=.692; β= −.04, p_{dt}=.637), indicating that associations of either increases in cortisol or increases in negative affect with loss aversion appeared to be epiphenomenal to the effects of stress by sex, rather than either mediating effects of stress on loss aversion. Interestingly, though, increases in negative affect remained a significant predictor of utility curvature linearity even when stress condition, sex, and the interaction between stress and sex were included in the model, β= .25, p_{dt}= .011, as did the Stress Condition × Sex interaction,

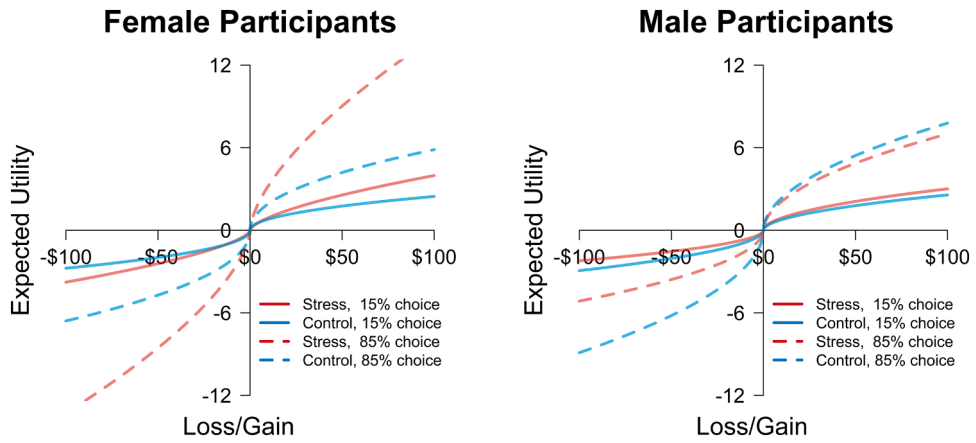


Fig. 5. Expected utility for male and female participants in stress and control conditions with different levels of certainty attached to each potential loss/gain. Except for low-probability gains, which stress influenced equally across male and female participants, stress differentially influenced male and female participants across gains and losses by probability. Such a differential pattern produced a lack of overall sex differences in the effects of stress on risky decision-making behavior at a broad level, despite numerous, nuanced differences depending upon risk type, risk amount, and risk probability.

p_{dt}= .024, indicating that increases in negative affect were associated with a state of decreased risk aversion independent of sex or stress condition effects (Fig. 6). Analyses examining continuous predictor interactions with sex are presented in Supplemental Material.

4. Discussion

Although stress is thought to influence risky decision-making, the pattern of these effects has been difficult to determine. To that end, this study examined, for the first time, how stress influenced all component processes underlying risky decision-making as described by cumulative prospect theory—probability distortion, risk aversion, loss aversion, and choice stochasticity—using hierarchical Bayesian modeling. We found that stress increased risk-taking in decision-making, and at a broad, behavioral level, this effect did not differ by participant sex. At a more granular level, however, stress differentially influenced every estimated parameter by sex, entailing nuanced and distinct effects of stress on risky decision-making that depend upon risk type (e.g., gains vs. losses), risk amount, and risk probability. These results thus support the idea that the effects of stress on risky decision-making are nuanced, and the behavioral effect may differ depending upon task characteristics.

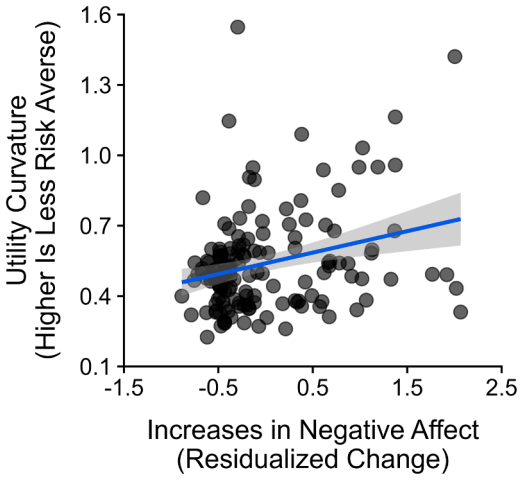


Fig. 6. Greater increases in negative affect predicted less risk aversion. At utility curvature values less than 1.0, expected utility of an outcome tapers off as its absolute value increases; utility curvature values above 1 indicate that the expected utility of an outcome accelerates as its absolute value increases. This association was robust to removal of outliers and held when including stress and sex within the model. Figure depicts observed data, not Bayesian estimates.

The most consistent effect on decision-making we observed was that stress decreased loss aversion. This result is consistent with some (e.g., Molins et al., 2021, 2023) but not all (e.g., Sokol-Hessner et al., 2016) prior work on stress and decision-making. We speculate as to why this result may differ between studies. First, the effect of stress on loss aversion was stronger in men than women. It is possible if a study has predominantly female participants, it may fail to find this effect. Second, the effects of stress on loss aversion may be only detectable when other processes underlying risky decision-making are controlled. Stress influences risk aversion, probability distortion, and choice stochasticity, which together may mask the influence of stress on loss aversion if they are not disentangled. In short, our data support the idea that stress decreases loss aversion.

We also found that stress decreased risk aversion (i.e., increased linearity), and sex moderated this effect: This effect was stronger in female participants than in male participants. This effect of stress increases sensitivity to both rewards and losses as a function of their magnitude. Whereas loss aversion describes the multiplicative difference in expected value between gains and losses of the same dollar amount, risk aversion describes the exponential influence of the dollar amount on expected value. In other words, the influence of risk aversion relative to loss aversion is greater as the magnitude of the gain or loss increases. Together, this confluence makes female participants relatively more averse to taking risks for large potential losses and relatively less averse to taking risks for large potential gains while stressed compared to a control condition.

Another interesting result that we obtained with respect to risk aversion was its association with increases in negative affect. We found that greater increases in negative affect were associated with less risk aversion. This finding is consistent with the literature on "urgency," which finds that in many individuals, high-intensity affective states lead to reward-seeking and impulsive behaviors (Elliott et al., 2023; Johnson et al., 2020; Quinn and Shields, 2023). Our results suggest both a diminishing effect of stress in female participants and an independent inverse association of greater negative affect with risk aversion. Importantly, though, we do not believe this association to reflect a causal effect of stress via negative affect on risk aversion, for two reasons. First, the effects of laboratory acute stress manipulations on negative affect are typically shorter in duration than our stress-to-task delay. Second, our analyses suggested that this association of increases in negative affect with risk aversion was independent of the effects of stress on this parameter. Instead, we believe that negative affect reactivity is simply an indicator of a stable individual difference in affective

stress reactivity. Such a trait may itself be associated with less risk aversion.

We also observed effects of stress by sex on probability distortion: Male participants were particularly likely to overestimate low-probability events under stress, whereas female participants showed little probability distortion under stress. This probability distortion in males may counteract the beneficial effects of stress on forms of risky decision-making where low loss and risk aversion can be helpful, such as investment decision-making (Arkes and Blumer, 1985; Nofsinger et al., 2018; Odean, 1998; Rau, 2014; Weber and Camerer, 1998). A speculative implication of these findings could pertain to changes in household behavior as intra-household decision-making move toward gender parity (Guiso and Zaccaria, 2023; Ozili, 2024). In particular, our findings could be taken to suggest that decision-making in heterosexual, cisgender relationships would most benefit from women being the estimator of outcome probabilities when making decisions under stress, with men providing input on the implications of consequences of potential losses.

Finally, we observed a strong effect of stress by sex on choice stochasticity. In particular, stress increased choice stochasticity (i.e., randomness) in female participants alone. Notably, this effect occurred without any worsening of model fit, entailing that this choice stochasticity effect was not a result of poor model predictions. This result differs from prior work on food choices, which has found no difference in preference consistency following a stress induction (Nitsch et al., 2021), perhaps because food preferences are fairly stable (e.g., Epstein et al., 1987; Ma et al., 2021). Our finding that stress increased choice stochasticity in female participants alone is interesting in light of existing work on the effects of stress on executive functions. In particular, stress often, though not always, has a stronger impairing effect on executive functions in men than women (Gabrys et al., 2019; Kalia et al., 2018; Shields et al., 2016b, 2016c). Our finding with respect to sex differences in the effects of stress on choice stochasticity thus suggests that there are some ways in which stress may reduce goal-directed behavior in women (i.e., through increasing stochasticity rather than through decreasing control abilities).

Although we are not the first to study the effects of stress on decision-making processes long after stressor onset (e.g., Schulreich et al., 2022), the majority of the work on stress and decision-making has placed the decision-making task much closer in time to stressor offset than our study did (e.g., Byrne et al., 2020; Molins et al., 2023; Pabst et al., 2013a; Singer et al., 2017). Currently, it is unknown which of the effects that we observed are those that differ qualitatively from earlier or later effects of stress on risky decision-making processes (e.g., Bendahan et al., 2017; Pabst et al., 2013b), and which effects are qualitatively constant across stress-to-task delays (e.g., Schwabe and Wolf, 2014). However, it is possible to speculate. If physical exercise exerts the same effects as stress on decision-making, then the stress-induced reduction in loss aversion may be time-dependent: Five minutes post-exercise, exercise increases loss aversion (Molins et al., 2021), whereas stress reduces loss aversion by 30 min post-stressor offset (Molins et al., 2023; Schulreich et al., 2022). Risk aversion may also show an opposite time-dependent change, as has been found in one study (Bendahan et al., 2017). Future work should attempt to replicate and extend these results to determine if the effects of stress on these parameters differ by stressor-to-task delays when these parameters are estimated concurrently.

Results related to cortisol should be interpreted with caution for at least two reasons. First, our cortisol response was relatively mild, which may have been due to the Zoom-based stressor. Our cortisol responses did not quantitatively approximate typical stress-related cortisol responses, and we may have had limited power to detect associations with cortisol as a result. Second, we note that by only taking two cortisol samples, we did not characterize the full cortisol response trajectory. As a result, we do not claim that cortisol is not associated with risky decision-making, only that a small part of the cortisol response—as we assessed it—did not relate to our measures beyond the stress condition itself. Prior work has found that cortisol reactivity is related to risky decision-making (e.g., Singer et al., 2017), and our results do not stand in contrast to these findings.

Some discussion of our estimates is warranted. Although our probability distortion and utility curvature estimates are lower than estimates obtained in many studies, they are similar to those obtained by others using this task (e.g., Toubia et al., 2013). However, loss aversion was substantially lower than we expected. To determine how unusual our estimate was, we searched for typical ranges across studies. In this, we found a recent random effects meta-analysis (Walasek et al., 2024) that examined 17 studies using similar mixed-gamble tasks that fit cumulative prospect theory parameters. In this meta-analysis, the authors found that the meta-analytic point estimate of λ was 1.31, 95 % CI [1.10, 1.53]. Notably, this indicates that our control group estimates for men (mean λ=1.15) and women (mean λ=1.12) were unremarkable. We thus believe that some tasks, laboratory conditions, or participant pools (e.g., first-year college students) may simply evidence lower loss aversion than stereotypic or prototypic values, and our study contained the feature(s) leading to such estimates.

These results also have important theoretical implications. In particular, our findings provide relatively strong evidence against the conservation of resources theory of stress (Hobfoll, 1989): This theory unambiguously predicts that under stress, individuals will be more motivated to minimize loss than under nonstressful conditions, but we found that a reduction in loss aversion was the only consistent effect of stress between men and women.

This study has a number of strengths, including an advanced analytic approach and a large sample size. Nonetheless, it has some limitations that should be noted. First, we did not pay participants actual money; their decision-making was hypothetical. Although real and hypothetical rewards identically influence some cognitive processes, including some risky decision-making tasks (e.g., Hinvest and Anderson, 2010; Locey et al., 2011), financial decision-making presumably differs when one is making real versus hypothetical financial decisions. Relatedly, numerous other contextual factors, such as knowledge of how one's decisions influence others (Robison et al., 2020), one's personal preferences (Malone and Lusk, 2018), or the broader regulatory environment in which one makes financial decisions (Malone et al., 2019), modulate decision-making, and those factors were not considered here. Therefore, these results should be interpreted with caution, and future work should replicate these findings in a paradigm with actual financial consequences from participants' decisions. Second, our participants were young and western, educated, industrialized, rich, and democratic (WEIRD) (Henrich et al., 2010; Yuan and Raz, 2014), and our results do not generalize beyond our sampled population. Third, participants completed three cognitive tasks prior to completing the risky decision-making task, and cognitive fatigue interacts with the effects of stress on some cognitive processes (Shields, 2020). Although efforts were taken to mitigate cognitive fatigue in this study (e.g., breaks between tasks), it is possible that stress would have influenced risky decision-making differently had such tasks not been completed first. Future work should attempt to determine whether completing intervening cognitive tasks with breaks between them moderates the effects of stress on risky decision-making at this delay. Fourth, and finally, the effects of stress on multiple cognitive processes, including risky

decision-making, are known to be time-dependent (Bendahan et al., 2017; Joëls et al., 2011; Pabst et al., 2013b; Sarmiento et al., 2024; Schwabe and Wolf, 2014; Shields et al., 2017, 2015; Zoladz et al., 2019), entailing that our results should be interpreted as reflecting the effects of stress on risky decision-making within the late nongenomic and/or early genomic cortisol effects window, not a universal effect.[4]

5. Conclusion

In conclusion, we found that stress exerts multiple effects on component processes underlying risky decision-making, depending upon participant sex. The most consistent effect was on loss aversion, but even this effect was significantly weaker in female participants than male participants. Overall, in female participants, stress contributes to a pattern of decision-making that is characterized by risk seeking in gains, risk avoiding in losses, accurate outcome probability assessment, and greater stochasticity than occurs in nonstress conditions. For male participants, stress contributes to a pattern of decision-making that is characterized by risk seeking in losses and poorer outcome probability assessment than occurs in nonstress conditions. Stress changes how we make decisions, and it does so differently between male and female young adults.

CRediT authorship contribution statement

Zach J. Gray: Writing – review & editing, Methodology. **Trey Malone:** Writing – review & editing, Methodology. **Grant S. Shields:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

None.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.psyneuen.2024.107259.

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[4] We refer to this period as late nongenomic and/or early genomic due to a lack of characterizing this study's specific cortisol response trajectory. Although the cortisol response starts at anticipation, the speech and arithmetic task produce robust cortisol responses, entailing that some of the cortisol response was initiated ~55 min prior to the task. As such, cortisol may still have been elevated and thus exerting nongenomic effects. However, the transition to genomic effects had likely begun, too, due to the cortisol response to the anticipation phase.

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