# Examining the Influence of Stress and Anxiety on Visual Working Memory and Decision-Making

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**Abstract**

This study investigates how stress and anxiety influence the interplay between visual working memory and decision-making in human participants. Using the Socially Evaluated Cold Pressor Test (SECPT) to induce acute stress, we examined cognitive performance on a computerized behavioral paradigm (the Marble Jar Task) requiring the storage, manipulation, and utilization of visual information. Results revealed that while experimentally induced stress did not significantly affect overall accuracy, higher self-reported state anxiety was correlated with both lower decision-making accuracy and poorer visual memory performance. Interestingly, higher state anxiety was also correlated with increased attention towards high-value outcomes in decision-making. This work highlights the importance of understanding how stress and anxiety affect the interaction between interconnected cognitive functions, rather than studying isolated cognitive phenomena.

**Keywords:** representation learning; visual working memory; decision-making; stress; state anxiety

## Introduction

In our daily lives, we encounter far more information than our senses can process, constrained by limited memory and attention capacity. Yet, we still manage to act quickly and make rapid decisions. To handle this information overload, our brains form mental representations by attending to features most relevant to achieving our goals and manipulating the representations with input from memory (Niv, 2019; Radulescu et al., 2021). Ignoring irrelevant aspects of the environment enables us to generalize from one experience to inform future decision-making in similar situations. Crucially, representation formation is a multifaceted cognitive process involving attention, working memory, long-term memory, decision-making, and learning.

However, this intricate cognitive balancing act does not occur in isolation. Daily life is often accompanied by acute stressors and anxiety, such as racing to meet a deadline or being stuck in traffic. Stress is a physiological or psychological reaction triggered by a perceived stressor (Ness & Calabrese, 2016; Schwabe & Wolf, 2013). Acute stressors trigger responses in three interacting components: a neuroendocrine response (e.g., an increase in cortisol), an autonomic response (e.g., an increase in heart rate), and a behavioral response (e.g., reporting having difficulty concentrating)(Sapolsky et al., 2000). Similarly, state anxiety—a temporary emotional reaction to adverse situations (Saviola et al., 2020; Spielberger, 1972)—can affect cognitive processes and is characterized by feelings of apprehension, nervousness, and physiological changes, such as increased heart rate or respiration (Spielberger, 1979).

Research on stress and state anxiety has primarily focused on their effects on cognitive processes in isolation. However, due to the interconnected nature of representation formation, disruptions from stress or state anxiety in one process, such as working memory, could have downstream effects on other processes, such as decision-making.

Working memory is a system for temporarily storing and manipulating information (Ma et al., 2014; Oberauer, 2019) that includes executive control functions responsible for switching attention between tasks, selective attention, and inhibition (Baddeley, 1986; Eysenck et al., 2007; Miyake et al., 2000). Two attentional systems jointly influence mental representations (van Ede et al., 2020): one in which we attend to items relevant to our goals (e.g., deliberately scanning a crowded room for a friend) and an involuntary system in which we attend to salient stimuli (Eysenck et al., 2007; van Ede et al., 2020) (e.g., our gaze shifting to a flash of light).

Prior work has shown that state anxiety reduces the influence of the goal-directed attentional system and increases the influence of the stimulus-driven attentional system, which subsequently impairs the ability of individuals to inhibit task-irrelevant information and switch between tasks (Eysenck et al., 2007). This shift is likely due to anxious individuals allocating their limited attentional resources to threat-related stimuli, whether internal (e.g., worrisome thoughts) or threatening task-irrelevant distractors (Derakshan & Eysenck, 2009; Eysenck et al., 2007).

Another aspect of limited attentional and memory resources is evident in decision-making, where people choose between two alternatives to maximize utility or reward. Even under non-stressful decision-making, people overrepresent infrequent outcomes over less important, but more probable, outcomes (Lieder et al., 2018). This utility-weighted decision-making can be regarded as resource-rational, given that people have limited cognitive resources and time to make decisions (Lieder et al., 2018). However, high stress levels can lead to an abrupt decision before all potential outcomes are fully evaluated (Starcke & Brand, 2012).

Decision-making can be modeled as accumulating decision-relevant information over time until a threshold is reached and an option can be chosen (Khoudary et al., 2025; Ratcliff et al., 2016; Ratcliff & Rouder, 1998). The information governing the decision can originate from external sensory input (e.g., seeing a tree) or internal working memory representations (e.g., storing features of a tree in working memory) (Bornstein et al., 2023; Khoudary et al., 2022; Kumle et al., 2025). Neural evidence demonstrates that


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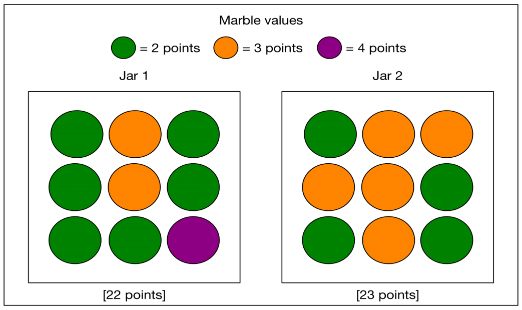

Figure 1. A sample of the Marble Jar Task at the start of each trial. The point values in square brackets were not shown to participants.

decisions about the visual identity of an internal working memory representation rely on this information accumulation process (Ede & Nobre, 2024), highlighting that mental representations do not exist passively in memory, but rather guide decision-making.

Despite evidence linking working memory representations to decision-making, and research showing the effects of stress and anxiety on each of these processes, most studies have examined them in isolation. There remains a lack of understanding of how stress and anxiety affect the interaction between these interconnected cognitive processes.

To address this gap, we used the Socially Evaluated Cold Pressor Task (SECPT; Schwabe et al., 2008) to induce stress and then examined its effects on a computerized behavioral task (the Marble Jar Task) where performance depended on how mental representations stored in visual working memory influenced decision-making. We hypothesized that the SECPT would induce stress and anxiety as measured through self-reports, impacting visual memory representations, which would in turn influence decision-making.

## Methods

### Participants

52 healthy participants (23 females, 29 males) were recruited through flyers posted around campus and on social media. Participants were paid $22, plus an additional bonus based on Marble Jar Task performance (up to $30). Participants were at least 18 years old, had no clinical diagnosis related to stress and anxiety disorders, and had no color blindness or color deficiency. The study was preregistered on the Open Science Framework (https://osf.io/h9bxr) and approved by the Rensselaer Polytechnic Institute Institutional Review Board. Written informed consent was obtained from all participants.

### Design

**Stress Manipulation.** Stress was induced by exposing participants to the SECPT (see Schwabe et al., 2008 for full methodological details). The SECPT is a widely used and safe tool for inducing short-term stress in a laboratory. It combines physiological stress by immersing the hand and wrist in ice water for three minutes, with psychosocial stress by being video recorded and evaluated by the experimenter. In the control condition, participants immersed their dominant hand and wrist in warm water for three minutes and were not videotaped nor evaluated by the experimenter.

**Marble Jar Task.** The Marble Jar Task (see Malloy & Sims, 2024) is a computerized task that examines the mental representation of visual information needed for visual working memory and decision-making. On each trial of the experiment, participants were shown two jars of "marbles" side by side for 2 seconds (Figure 1). There were three marble colors: green, orange, and purple. Marble colors were assigned point values (2, 3, or 4; mapping counter-balanced across participants), and participants were instructed on the mapping between marble color and point value. When generating the stimuli, each marble color's probability of being sampled was determined by its point value: the 2-point marble had a 50% chance, the 3-point marble had a 33% chance, and the 4-point marble had a 17% chance.

After the jars were shown for 2 seconds, the display was cleared, and then the participant was prompted to complete one of two types of trials. In the *decision-making trials*, participants chose either the left or right jar, after which a single marble was randomly sampled from the selected jar. The participant earned the number of points determined by the marble's color. In the *visual working memory trials*, participants were instead shown a probe stimulus on either the right or left side that was either identical or different from the respective jar on the corresponding side. The participants answered whether the probe jar was the same or different, and correct responses were awarded points.

Importantly, both types of trials started with 2 marble jars displayed and occurred randomly with 50% probability. Thus, participants had to form mental representations efficient enough to answer correctly on visual working memory trials (i.e., actively storing and utilizing visual information about the marbles for change detection) and to maximize points on decision-making trials (i.e., choosing one of two jars with higher expected value or utility). Before starting the experiment, participants were told they would receive a monetary bonus based on accumulated points. Participants had 3 seconds to respond in each trial.

**Measurement of stress and anxiety.** The 10-question Perceived Stress Scale (PSS-10: Cohen et al., 1983) was used to assess participants' recent stress levels (e.g., "In the last week, how often have you felt nervous or stressed?"). To measure trait anxiety (typical anxiety levels) and state anxiety (anxiety levels after the SECPT or control condition), participants completed the State-Trait Inventory for Cognitive and Somatic Anxiety (STICSA; Ree et al., 2008). Participants answered items in the STICSA, such as "Indicate the extent that at this moment, this statement is true for you: I cannot concentrate without irrelevant thoughts intruding." The STICSA includes questions assessing cognitive and somatic markers of anxiety, resulting in four "sub-scores": state cognitive, trait cognitive, state somatic, and trait somatic anxiety.

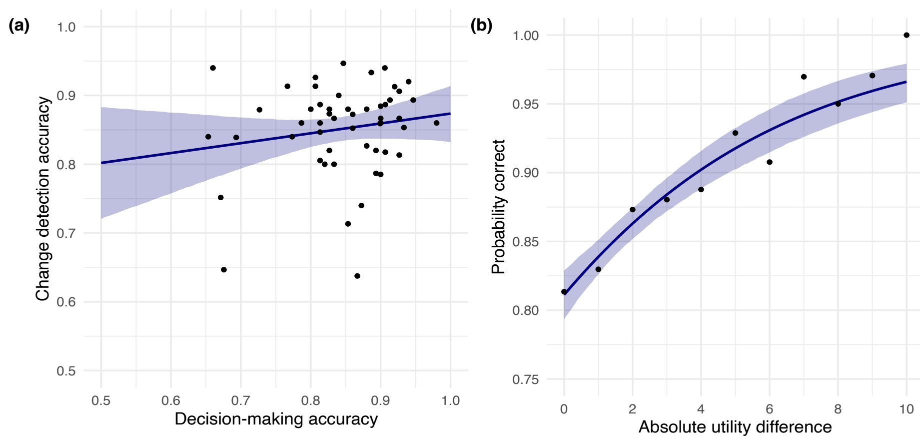


Figure 2. (a) Overall performance on decision-making and change detection trials. Each plot marker corresponds to a different participant. The solid blue line shows the posterior mean linear regression; the shaded region indicates the 95% highest density credible interval (HDCI). (b) Performance on change detection trials, as a function of the magnitude of difference in utility between the original and probe stimulus. Plot markers show mean performance at each difference level. The blue curve shows the posterior mean of a logistic regression; shaded region indicates 95% HDCI.

## Procedure

Upon arrival to the laboratory, participants were given 15 minutes to acclimate. Participants were informed of their random assignment to one of two conditions: SECPT (n = 26) or control (n = 26). After providing informed consent, participants self-reported their recent stress levels using the PSS-10. Participants then experienced either the SECPT or the control condition, followed by the first half of the Marble Jar Task. During a 5-minute break, participants self-reported their anxiety levels at the moment using the STICSA (state anxiety). After completing the Marble Jar Task, participants self-reported their general anxiety levels using the STICSA (trait anxiety). Heart rate variability was also measured throughout the experiment, but the results are beyond the scope of this paper.

## Statistical analysis

All statistical analyses were conducted within a Bayesian framework using Stan (Carpenter et al., 2017) version 2.32.2, via the RStan package in R. Posterior distributions were obtained using four Markov chains, each run for 20,000 iterations (including 10,000 warm-up iterations). Convergence was assessed using the $\hat{R}$ statistic (all $\hat{R} < 1.01$) and effective sample size (ESS).

# Results

## Overall task performance

Figure 2(a) shows the performance of each participant in the experiment in terms of the proportion of trials answered correctly in the decision-making ($x$-axis) and change detection (i.e., visual working memory) trials ($y$-axis). For decision-making, correct responses were defined as choices that maximize expected utility.

We utilized a Bayesian linear regression model to examine the relationship between change detection and decision-making accuracy. The posterior mean estimate for the slope (β) was 0.14, with a 95% highest density credible interval (HDCI) of $(-0.09, 0.38)$. As the credible interval includes zero, there is not strong evidence for a relationship between performance on the two tasks. Under one hypothesis, change detection and decision-making might draw upon shared cognitive abilities, which would predict a positive correlation in performance. Alternatively, given limited cognitive resources and time, people might prioritize one task over another, leading to a negative correlation. However, the current results do not allow us to unambiguously distinguish between these alternatives, raising the possibility that the observed performance reflects a combination of both.

A key feature of the Marble Jar Task—unlike typical experiments on visual working memory—is that visual information is not just passively stored, but rather must be manipulated and utilized to make decisions between two jars to maximize points. Therefore, we hypothesized that the mental representations utilized by participants would be influenced by the dual demands on visual memory. To test this hypothesis, we examined whether utility information (useful for decision-making) biased performance on change detection trials. The results of this are shown in Figure 2(b). For this analysis, we examined only trials where the probe differed from the original stimulus.

We utilized a Bayesian logistic regression to examine the relationship between utility and change detection accuracy. The model was specified as:

$$y_t \sim \text{bernoulli\_logit}(\alpha + \beta x_t)$$

where $x_t$ indicates the absolute value of the difference in marble jar value on trial $t$, and $y_t$ is the binary response on that trial (0 = no change, 1 = change). Bernoulli_logit refers to a Bernoulli distribution with a logit-transformed success parameter to ensure that the parameter lies in the interval $(0,1)$. The posterior mean estimate for the slope ($\beta$) was 0.19, with a 95% HDCI of $(0.14, 0.24)$, indicating a significant

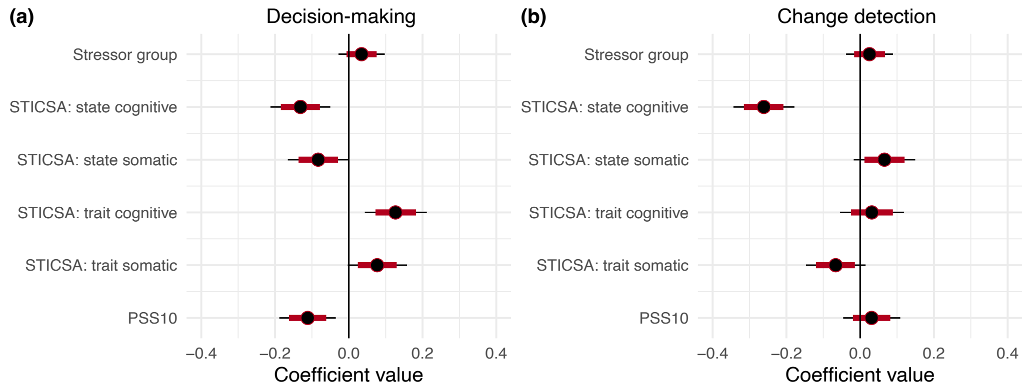


Figure 3. (a) Estimated predictor coefficient values for performance on decision-making trials. (b) Estimated predictor coefficient values for performance on change detection trials. In each plot, thick red lines indicate the 80% HDCI, outer black lines indicate the 95% HDCI.

positive relationship. In other words, people were more likely to notice a change had occurred when it implied a larger change in utility, replicating findings from previous experiments using the Marble Jar Task (Malloy & Sims, 2024). We also compared this logistic regression model to an alternative that used the number of marbles that changed color as a predictor, rather than the magnitude of the utility difference. We compared the two models using leave-one-out cross-validation (LOO-CV; Vehtari et al., 2017). The model using utility difference had a higher expected log predictive density (ELPD), with an elpd_diff of 14.1 (SE = 8.5) compared to the alternative. These results support our hypothesis that memory representations were altered by utility information: with limited resources, people formed mental representations that facilitated performance on both behavioral tasks.

## Impact of stress and anxiety on task performance

Our primary interest in this experiment was to examine the influence of stress and anxiety on cognitive performance, using the Marble Jar Task to look at these effects on different aspects of cognition simultaneously within the same person.

To that end, we utilized a series of Bayesian general linear models (GLMs) to examine the influence of 6 different predictors on task performance. The predictors were:

- Stressor group: A binary variable = 1 for the stressor condition, 0 for the control condition.
- Four sub-scores from the STICSA, including state anxiety (anxiety experienced in the moment) and trait anxiety (an individual's general tendency to experience anxiety over time), experienced as cognitive and somatic symptoms.
- Responses to the PSS-10, assessing stress in the past week.

We checked the correlation between predictor variables and found the largest correlation was between STICSA state and trait somatic anxiety ($r = 0.63$). As a rule of thumb, multicollinearity becomes problematic if $r >\sim 0.9$ (McElreath, 2018). In separate analyses, we examined the influence of these predictors on change detection accuracy and decision-making. Both analyses utilized the same model structure:

$$y_s \sim \text{binomial\_logit}(n_s, \alpha + \mathbf{X_s} \cdot \boldsymbol{\beta})$$

where $y_s$ indicates the number of correct responses from participant $s$, out of $n_s$ trials; $\mathbf{X}_s$ is a $(1 \times 6)$ row vector of predictor values for participant $s$; $\boldsymbol{\beta}$ is a $(6 \times 1)$ vector of coefficient values; and α is the intercept term in the model. The predictor matrix $\mathbf{X}$ was standardized such that each column (predictor) had zero mean and unit standard deviation. The parameters α and $\boldsymbol{\beta}$ were given standard $\text{Normal}(0,1)$ priors.

Results for decision-making trials are shown in Figure 3(a). Negative values indicate worse performance, in terms of making fewer choices that maximized expected utility. Contrary to our hypotheses, the stress manipulation had no impact on performance [posterior mean = 0.03; 95% HDCI = $(-0.03, 0.10)$]. Possible reasons for this are discussed in the Discussion section. However, perceived stress as measured by the PSS-10, and state cognitive and somatic anxiety as measured by STICSA sub-scores, all correlated with performance [STICSA: state cognitive 95% HDCI = (–0.21, –0.05); STICSA: state somatic 95% HDCI = (–0.17, 0.00); PSS-10 95% HDCI = (–0.19, –0.04)]. In brief, people with higher reported stress or anxiety performed worse at decision-making.

Intriguingly, people with higher self-reported *trait* anxiety (via both cognitive and somatic symptoms) exhibited higher decision-making performance [STICSA: trait cognitive 95% HDCI = $(0.04, 0.21)$; trait somatic 95% HDCI = $(0.00, 0.16)$]. We interpret this to suggest that people experiencing chronic elevated anxiety (e.g., due to academic pressure) may have adapted to this baseline, such that they found the Marble Jar Task itself less stressful or taxing.

Figure 3(b) shows the results of applying the same statistical analysis to performance on change detection trials. In this case, high levels of state anxiety reported as cognitive symptoms were strongly associated with worse performance [posterior mean = $-0.26$; 95% HDCI = $(-0.34, -0.18)$].

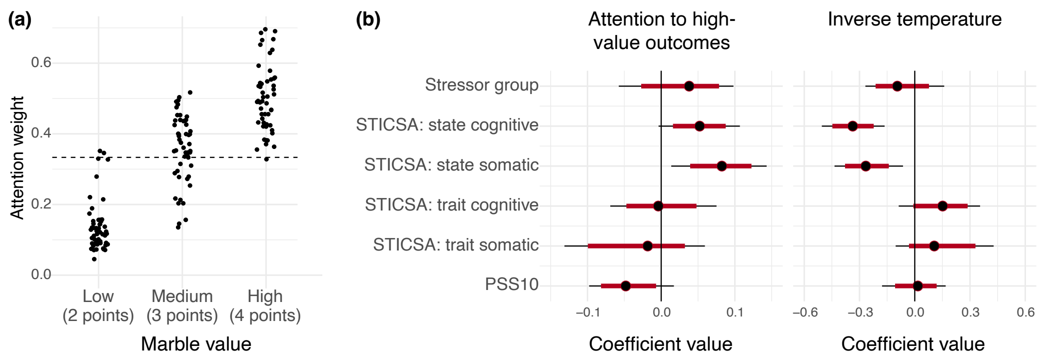


Figure 4. (a) Estimated attention weights to each possible outcome on decision-making trials. Each plot marker corresponds to a different participant. The horizontal dashed line indicates the values consistent with rational choice behavior. (b) Left panel: Estimated coefficient values when using a general linear model to predict the parameter controlling attention to high-value outcomes. Right panel: Estimated coefficient values for the inverse temperature parameter.

Coefficient values for all other predictors cannot be reliably distinguished from zero.

## Attention-weighted decision model

While the results discussed in the previous section looked at a crude measure of performance—the total number of correct choices—this does not tell us *how* cognitive performance was impacted by stress and anxiety. We therefore fit a simple utility-based choice model to the data. Viewing decision-making trials as a choice between lotteries, we define the expected utility $U$ of a marble jar as

$$U = \sum_{k=1}^{3} w_k \cdot p_k \cdot u_k$$

where $u_k$ is the value of each possible outcome (i.e., marble color; in our experiment $u_k \in \{2,3,4\}$ points), and $p_k$ is the probability of each outcome. In our model, $p_k$ and $u_k$ were directly determined by the stimuli (i.e., they are not free parameters in the model). We also introduce an 'attention weight' parameter $w_k$ for each possible outcome, where $w_k \geq 0$ and $\sum_k w_k = 1$. This is intended to model the possibility that participants might attend to or represent only certain marble colors. When $w_k = 1/3$ for each outcome, the model is equivalent to normative expected utility theory (i.e., all marbles are equally attended to). In the extreme limit where the attention weight is 1 for one of the outcomes, marble jars are compared solely on the basis of a single marble color. This allows the model to, for example, capture behavior where participants might focus exclusively on the high-value marbles in decision-making.

Given the (weighted) expected utility of each marble jar, the probability of choosing one of the two jars is modeled using the softmax function:

$$p(\text{choice} = A) = \frac{\exp(\tau \cdot U_A)}{\exp(\tau \cdot U_A) + \exp(\tau \cdot U_B)}$$

where $\tau$ is the inverse temperature parameter; as $\tau \to 0$ choices approach uniform random selections.

We first estimated parameters independently for each participant using Bayesian parameter estimation. $\tau$ was given a Normal(0,5) prior, truncated to ensure values are non-negative. The vector of weights $w_k$ define a simplex and were given a Dirichlet({1,1,1}) prior.

Figure 4(a) shows the estimated attention weights for each outcome for each participant. Notably, people deviated systematically from rational choice: their decisions were influenced by high-value outcomes to a greater degree than would be expected by an optimal decision-maker. For example, when faced with the choice between marble jars illustrated in Figure 1, a rational agent would select the right jar (a total value of 23 versus 22 points). However, using the mean attention weights observed in our participants, decision makers would prefer the left marble jar instead. Even though it has a lower expected utility, the possibility of a high-value outcome increases its subjective value.

While we find that people deviated from strict rational choice in our experiment, our participants had limited time to process the marble jar stimuli and presumably were not computing expectations incorporating all outcomes and objective probabilities. Our attention-weighted decision model is intended to be a tool for characterizing decision behavior, rather than a process model. Notably, the results are consistent with other theoretical accounts of decision-making (Lieder et al., 2018): Under strict limits on time and working memory capacity, focusing preferentially on high-value outcomes can be seen as a resource-rational strategy.

We next examined how the parameters of the model were influenced by stress and anxiety. To achieve this, we used the same GLM structure to estimate parameter values for each participant rather than fitting the model parameters independently. The inverse temperature parameter $\tau$ was defined as:

$$\tau = \exp(\tau_0 + \mathbf{X}\boldsymbol{\beta}_\tau)$$

where $\mathbf{X}$ is the same predictor matrix used previously. The exponentiation ensures that the parameter value is non-negative. Because of the constraints on the attention weights (non-negative, must sum to one), we parameterized the model as follows:

$$\alpha = \alpha_0 + \mathbf{X}\,\boldsymbol{\beta}_{\alpha}$$
$$[w_1, w_2, w_3] = \mathrm{softmax}([-\alpha, 0, \alpha]).$$

In the above, $\alpha$ controls the attention to high-value outcomes, and conversely $-\alpha$ determines attention to low-value outcomes. When $\alpha = 0$, we have $w_1 = w_2 = w_3 = 1/3$. We found that a more complex model that allowed separate attention weights for high- and low-value outcomes struggled with parameter identifiability issues; hence, we assume a single parameter here.

The results are shown in Figure 4(b). We found that people with higher state anxiety showed an increased attention to high-value outcomes [STICSA: state cognitive posterior mean = 0.05, 95% HDCI = $(0.00, 0.11)$; STICSA: state somatic posterior mean = 0.08, 95% HDCI = $(0.01, 0.14)$].

At the same time, participants with higher reported state anxiety exhibited a lower inverse temperature parameter, resulting in noisier (more random) choices [STICSA: state cognitive posterior mean = –0.34, 95% HDCI = $(-0.5, -0.16)$; STICSA: state somatic posterior mean = –0.26, 95% HDCI = $(-0.44, -0.06)$].

## Discussion

In this study, we examined the influence of stress and anxiety on how mental representations stored in visual working memory influence decision-making. We hypothesized that the SECPT would induce stress and anxiety, impacting visual memory representations which would in turn influence decision-making.

Contrary to our expectations, the SECPT manipulation had no impact on task accuracy. This could be due to a few reasons that need to be directly explored in future studies. First, because of the commonality of stress and anxiety faced by college students, it is possible that the effects of the SECPT were not large enough to noticeably raise stress levels. Second, the delay between the SECPT and when participants completed the Marble Jar Task could have been too long, causing any potential effects of the SECPT to be short-lived. While our study does not identify a definitive reason for this null effect, several studies (e.g., Blankstein et al., 1989, 1990; Calvo et al., 1990) have similarly reported no difference in task accuracy between low- and high-anxious individuals. Importantly, however, prior work suggests that individuals with high anxiety may display similar task accuracy as those without anxiety, yet the high-anxiety group may exhibit longer reaction times and display differences in attentional allocation (Eysenck et al., 2007). These metrics highlight a distinction between performance *effectiveness* (measured by task accuracy) and processing *efficiency* (e.g., reaction time, attentional allocation). Using two other relevant findings in our study, we hypothesize that the SECPT and control groups may have differed in terms of processing efficiency.

First, individuals with higher state anxiety showed greater attention to high-value outcomes in decision-making. It is possible that attention to the highest-valued marble among individuals experiencing anxiety was due to the increased influence of the stimulus-driven attentional system (Eysenck et al., 2007). Under this view, the highest-valued marble acted as a distractor that disrupted participants from attending to the more common but lower-valued marbles that would have likely increased performance on the visual working memory trials. Given that there was no difference in task accuracy between the SECPT and control conditions, the greater attention to high-value outcomes could reflect a difference in processing efficiency.

Further supporting differences in processing efficiency, participants with higher state anxiety made more stochastic choices on the decision-making trials. This could be due to the impaired ability to inhibit distractors and shift attention (Derakshan & Eysenck, 2009; Eysenck et al., 2007) between the decision-making and visual working memory trials. Internal distractions (i.e., worrying thoughts) (Hitchcock et al., 2022) and/or task-irrelevant stimuli could have contributed to increased stochasticity in choice behavior. While the two groups had similar task accuracy, the SECPT group displayed greater attention to the highest-valued marble and behaved more stochastically in decision-making trials, highlighting potential differences in processing efficiency.

Finally, since both the visual working memory and decision-making trials in the Marble Jar Task occurred with 50% probability, participants had to form a mental representation of the marble jars to maximize points on both the visual working memory trials and decision-making trials. However, addressing an important distinction in literature, the act of forming mental representations or allocating attention (i.e., greater attention to the highest-valued marble) is not necessarily of conscious volition. Participants in the Marble Jar Task may have chosen a strategy such as prioritizing one task over another or purposefully allocating their attention toward high-valued marbles, which may reflect a resource-rational approach given limited time and attentional resources. In turn, this strategy selection could impact how their visual representations were formed, but this is distinct from participants *choosing* their mental representations. Conversely, people may not have deliberately chosen a strategy, but under higher anxiety, had more difficulty in task switching and inhibiting external information, such as the salient high-value marbles on the change detection task or internal distractors on the jar selection task. Although our results do not directly address whether participants were aware of their task strategies or mental representations, this raises an important avenue for future research: examining how individuals evaluate their own perceptual capacities (Fleming et al., 2012; Rong & Peters, 2023) and how perceptual metacognition influences representation formation under conditions of stress and anxiety.

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