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Death-Related Anxiety Associated with Riskier Decision-Making Irrespective of Framing: A Bayesian Model Comparison

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Abstract

A commonly reported finding is that anxious individuals are less likely to make risky decisions. However, no studies have examined whether this association extends to death-related anxiety. The present study examined how groups low, moderate, and high in death-related anxiety make decisions with varying levels of risk. Participants completed a series of hypothetical bets in which the probability of a win was systematically manipulated. High-anxiety individuals displayed the greatest risk-taking behavior, followed by the moderate-anxiety group, with the low-anxiety group being most risk-averse. Experiment 2 tested this association further by framing outcomes in terms of losses, rather than gains. A similar pattern was observed with both positive and negative framing. In contrast to findings with trait anxiety, the present results suggest that death-related anxiety is positively associated with risky decision-making – an effect that holds regardless of how options are framed. Furthermore, the present study demonstrates that Bayesian modeling can provide very accurate predictions for economic decision-making behavior.

Keywords: risk, decision making, individual differences, Bayesian modeling

1. Introduction

1.1 Factors affecting decision making

When it comes to making decisions with an associated degree of risk, individuals generally display a greater tendency to avoid losses than seek gains. This bias is commonly known as *loss aversion* (Tversky & Kahneman, 1991). For instance, individuals have shown reluctance to take a bet when there is a 50% chance of winning $200 and a 50% chance of losing $100 (Kermer, Driver-Linn, Wilson, & Gilbert, 2006). Even though one stands to gain twice as much from winning as they would lose, people generally do not agree to such a bet. Furthermore, loss aversion tendencies may be modulated by the way that choices are framed. For instance, in a two-choice decision task, Tversky and Kahneman (1981) found that participants were more likely to choose an outcome when it was framed in terms of gains (i.e., "*200 people will be saved*") than when the same outcome was framed in terms of losses (i.e., *"400 people will die*"). These findings may suggest that individuals adopt risk-taking strategies. Specifically, when a choice is framed in terms of a gain, people will adopt a risk-aversion strategy. When choices are framed in terms of a loss, people will adopt a risk-taking strategy (Kahneman, 2003).

Subsequent research has shown that additional factors, such as emotions (Lerner, Small, & Lowenstein, 2004), previous decisions (Post, Assem, Baltussen, & Thaler, 2008), expected outcomes (Kerner et al., 2006; Wilson & Gilbert, 2003), and context (Shen, Rabinowitz, Geist, & Shafir, 2010) can influence decisions. Collectively, such findings suggest that people do not make decisions based on probabilities alone, but also the psychological impact of their choices, the framing of the choice, and the external circumstances in which the decision is made. In addition to examining the effects of external (i.e., circumstantial) factors on decision-making, a large collection of studies has examined the influence of internal factors, such as personality traits (Byrne, Silasi-Mansat, & Worthy, 2015; Lauriola & Levin, 2001), age (Defoe, Dubas, Figner, & Aken, 2015; Delaney, Strough, Parker, & Bruine de Bruin, 2015), gender (Delaney et al., 2015; Weller, Ceschi, Hirsch, Sartori, & Constantini, 2018), and cognitive traits (Lauriola, Panno, Levin, & Lejuez, 2013; Weller, Ceschi, & Randolph, 2015) on decision-making processes. Certain traits have shown to influence the efficiency of decision-making for better or worse. Individuals high in neuroticism have been shown to perform worse on decision-making tasks (Byrne et al., 2015; Lauriola & Levin, 2001), whereas individuals high in conscientiousness have been shown to perform particularly well on decision-making tasks. For instance, in a time-sensitive card selection task individuals higher in neuroticism tended to make decisions that provided immediate benefits, but less than optimal long-term gains (Byrne et al., 2015). The observation of vast individual differences in decision-making efficiency, based on a variety of factors, has prompted researchers to propose a psychological construct, *decision-making competency* (DMC), thought to reflect an individual's ability to make rational decisions. Decision-making competency has shown to covary with many individual traits, including personality traits and appraisal of risk. For instance, Weller, Ceschi, and Randolph (2015) found a small negative association between DMC and risk-taking tendencies. It has been observed that older individuals, individuals with higher income and higher education tend to be more risk averse (Gachter, Johnson, & Herrmann, 2007). The implication from this collection of findings is that not all individuals are equally susceptible to decisional biases, such as loss aversion or framing effects.

Despite the large literature assessing the relationship between individual traits and decision-making, relatively few studies have examined how anxiety influences decision-making. Even fewer studies have examined the specific relationship between anxiety and risk in decision-making. While the relationship between anxiety and behavior has been studied intensively, to gain a thorough understanding of this relationship it is necessary to examine the cognitive processes, such as risk-assessment and choice-framing, that modulate behavioral outcomes. In this way, we can understand the intermediate factors at play between emotional states and behaviors and inform interventions targeting these factors to reduce maladaptive decision-making behavior. A correlation between mental health measures and risk perception has been consistently shown. For instance, individuals with anxiety and depression often display greater distortion regarding perceptions of risk relative to controls (Gao, Fan, Xia, Soondrum, Lin et al., 2021; Li, Bornheimer, Fernandez, & Dagher, 2021; Pailing & Reniers, 2018; Leahy, 1997).

The work that has been done provides a starting point for examining this question further. Initial findings suggest that anxious individuals are generally more risk-averse than non-anxious individuals (Maner, Cromer, Mallott, Lejuez, Joiner, et al., 2007; Wray-Lake & Stone, 2005). However, more recent findings are inconsistent with this view (Gu, Wu, Broster, Yang, Xu et al., 2017; Howlett & Paulus, 2017). For instance, Gu et al. (2017) suggest that anxious individuals are not more risk averse, but more strongly affected by negative framing. Researchers have also noted that attitudes concerning risk should be viewed as domain-specific rather than general (Weller et al., 2015). For instance, an individual may display considerable risk in a gambling or financial context, while being risk-averse when it comes to potentially dangerous behaviors (e.g., skydiving). Additional findings suggest that different forms of anxiety may produce different effects on decisions. In on interesting study, researchers found that trait (i.e., dispositional) anxiety had an adverse effect on decision-making, whereas state (i.e., situational) anxiety had a positive effect on decisions (Pajkossy, Dezso, & Paprika, 2009). This suggests that decision behavior may vary depending on the type of anxiety in question.

Most studies examining the relationship between anxiety and decision-making have focused on trait anxiety. Trait anxiety refers to “a stable tendency to attend to, experience, and report negative emotions such as fears, worries, and anxiety across many situations” (Gellman & Turner, 2013b, p. 29). This form of anxiety is believed to be a subcomponent of neuroticism, a dimension of personality, and recent studies show a positive correlation between death anxiety and depression in various populations and across several cultures (Oker, Schmelowszky, & Reinhardt, 2021; Marrogiorgou, Haller, & Juckel, 2020; Thiemann, Quince, & Benson, 2015). As discussed above, there are mixed findings regarding whether anxiety influences risk-taking in decision-making, and if so, what the exact relationship is. The present study expands on this topic by examining the influence of death anxiety on decision-making; specifically, the risk displayed in decision-making. Death anxiety refers to the “fear and anxiety related to anticipation and awareness, of dying, death, and nonexistence” (Gellman & Turner, 2013a, p. 32). Death anxiety may be experienced either consciously or unconsciously. Cognitive aspects of death anxiety may include awareness of death and a variety of attitudes, beliefs, images, and thoughts concerning death, the process of dying, and what happens after death (Lehto & Stein, 2009). By examining the influences of death anxiety on risk in decision-making, we can gain a broader understanding of the possible relationship between anxiety and decision processes.

1.2 The present study

There were two main goals in the current study. The first goal was to us a model-based approach to describe decision behavior as a function of risk across different groups of varying levels of anxiety. To achieve this goal, the variable ‘risk’ must be quantified and systematically manipulated. The major challenge with this objective is that it requires a design that enables one to systematically manipulate risk across repeated trials *in the same individual*. Thus, the present study draws on principles of signal detection theory (SDT) to achieve this end. SDT is a theory that maps decision behavior to a psychological decision space. Individual choice behavior is represented by a distribution in the decision space and one can examine how experimental manipulations affect the characteristics of the response distribution. For instance, one can assess how easily an individual can discriminate new faces from previously seen faces, how loud a tone needs to be before 50% of participants detect the tone, or, in the present case, what the odds of winning a bet need to be before a participant accepts the bet. The present study posed participants with a series of hypothetical wagers where the probability of a win for the participant varied (i.e., from 0.1 to 0.9) while keeping the win and loss amounts fixed. Using this design, participant decision behavior can be represented in a decision space where the probability of a participant accepting the bet is mapped as a function of the probability of winning (see Fig. 1). Here, the steepness of the psychometric (sigmoid) curve is associated with risk-taking as follows: The steeper the curve along the lower winning probabilities (left half of the distribution), the more loss-averse the individual (Tversky & Kahneman, 1992). The traditional method of studying the relationship between anxiety and risk has been to compare grouped averages for "single trial" choices. In other words, each participant is exposed to only one condition or level of risk. The present design allows us to examine how the behavior of the *same individual* changes as the associated risk of a decision increases or decreases.

The second goal of the current study was to utilize a Bayesian approach to study the relationship between anxiety and risk-taking in decisions. In contrast to a null hypothesis testing approach, this approach enables one to create multiple models, each derived from a specific hypothesis, and directly compare the relative probability of each model given the observed data.

Three different Bayesian models were created, each derived from a different hypothesis. Each of the models' predictions were then compared to the observed data and the model with the highest predictive precision was selected.

1.3 A Bayesian approach to decision processes

There are several advantages to using a Bayesian modeling approach over a traditional approach to study decision-making. Some of the reasons to prefer the former method are theoretical in nature and some are statistical. An in-depth discussion of the merits of Bayesian over traditional tests is beyond the scope of this article; however, a brief discussion of the rationale of using Bayesian modeling in the present study is apropos. Traditional tests are used to compute the probability of observing some datum given a particular hypothesis (i.e., the null hypothesis). However, it is more often the case that researchers want to know the opposite: the likelihood that our hypothesis is true given our data. The Bayesian approach sets the research question in the right direction, enabling researchers to use observed data to estimate model parameters. Bayesian data analysis converts a question into a formal model and uses logic to reach an answer in the form of probability distributions. In this way, different models can be created that make specific predictions for data, and then be directly compared. A second advantage is that models actually "learn from" data in the Bayesian approach, a process known as *Bayesian inference*. The plausibility (i.e., evidence) of a particular hypothesis fluctuates as the model learns from the data (see McElreath (2020), chapter 1 for discussion of "Bayesian updating"). This is a powerful tool that can help us recreate the most likely conditions that produced the data, which is the overall goal of Bayesian analysis.

With respect to statistical analysis, the Bayesian modeling approach is unencumbered by several testing assumptions required (and often violated) by traditional statistical tests. For instance, in many traditional tests the significance of results is dependent on a pre-specified alpha level, sample size, and effect size. In Bayesian analysis, there are no alpha levels, *p*-values (in the classical sense), or population parameters. Furthermore, since the analysis is based solely on information obtained from the observed data, results are valid for any sample size. In sum, the Bayesian approach enables us to go beyond rejection of a null model, implementing an alternative model that can be used to make clear and precise predictions for decision-making behavior.[1] In the present study, three different models were defined, each making specific predictions for the probability of an individual agreeing to a bet.

Probability Hypothesis: The probability of accepting a bet increases as the probability of winning increases (no effect of anxiety).

Anxiety Hypothesis: The probability of accepting a bet decreases as level of death-related anxiety increases.

Interaction Hypothesis: The probability of accepting a bet varies depending on the probability of winning and level of death-related anxiety.

It should be noted that these predictions are not mutually exclusive. For instance, it is possible that the second and third accounts are both correct. However, the objective of the present study is not model falsification, rather model comparison. The goal is to create three separate models, each making specific predictions for how the observed data should look and choosing the model that makes the *best* predictions. As discussed above, Bayesian models do not tell one the

[1] For a more in-depth discussion comparing and contrasting Bayesian and traditional methods, see Dienes (2011).

probability of observing data given the assumptions of the model. Instead, we are shown the likelihood of model parameters given our prior assumptions and the data we have observed. As a consequence, the present study permits us to assign relative plausibility to each of the three models in a way that we cannot using traditional statistical methods. If the first account is correct, participants should be more likely to accept the bet as the odds of winning increase, with no anxiety-related effects. If the second account is correct, more anxious individuals should be less likely to accept the bet regardless of the odds of winning (assuming anxiety is positively associated with risk-aversion). Finally, if the third hypothesis is correct, more anxious individuals should be less likely to accept the bet depending on the probability of winning. Specifically, it was expected that highly anxious individuals would be less likely to accept the bet when there was a low probability of a win (i.e., less likely to accept risky bets). With respect to the shape of the psychometric function (Figure 1), the slope along the left side of the distribution (i.e., lower winning probabilities) should be steeper for individuals with greater death anxiety, indicating greater loss-aversion.

2. Experiment 1

2.1 Methods

2.1.1 Participants

Two hundred thirty-four individuals recruited via Amazon Mechanical Turk (MTURK) participated in Experiment 1. Sample demographics were as follows: sex (108 female, 125 male, 2 undisclosed); age (*M* = 37.49, *SD* = 11.87); race/ethnicity (51 Asian or Pacific Islander, 9 Black or African American, 6 Hispanic or Latino, 3 Native American or Alaskan Native, 163

White or Caucasian, 2 undisclosed). All participants were at least 18 years of age, English speakers, and each participant received $1.00 in exchange for participation.

All MTURK account holders are required to include specific demographic information when creating an account. The present study was designed such that only accounts indicating the individual is (1) 18 years or older, and (2) an English speaker could participate. Only participants who completed the entire survey were included in analyses. However, no participants were dropped or excluded in Experiment 1.

2.1.2 Materials

Fear of death scale. To measure death-related anxiety, each participant completed an electronic version of the Collett-Lester Fear of Death Scale – Revised (Lester, 1990). The instrument is a self-report questionnaire including a total of 32 items, with four subscales: death of oneself = 8 items (α = .88); dying of oneself = 8 items (α = .85); death of a loved one = 8 items (α = .86); dying of a loved one = 8 items (α = .87). Responses are scored on a 5-point scale ranging from 1 = *not at all anxious* to 5 = *very anxious*. (Copy of complete measure can be accessed at: https://osf.io/7t2b6/).

Betting task. Participants also completed a betting task (n = 9 trials). This task required the participant to accept (or decline) a series of hypothetical bets with the experimenter. At the beginning of each trial, the participant was given the following instructions: "*In the following questions, you and I will be making a hypothetical bet. For each question, you will start with $10 and I will start with $20. If you win, you will receive my $20. If I win, I will receive your $10. If you do not accept the bet, we both keep our starting amount. Your job is to indicate whether you* *would accept the bet in the question, selecting 'Yes' if you would accept the bet, or 'No' if you would not accept the bet."*

On the first trial, the participant was informed that their probability of winning the bet is 10%. On each subsequent trial, the probability of winning increased by 10%. The starting amounts remained the same across all trials. These starting amounts were specifically chosen because they produce a symmetric range with respect to expected value (EV). Table 1 shows the expected value associated with each betting condition. This is computed by multiplying the probability of winning (column 2) and the amount one stands to win (column 3). Based on expected value, it would be logical to accept the bet when the EV is greater than the amount one would potentially lose (i.e., $10). Thus, an individual "should" accept this bet when the probability of a win is 0.6 or greater and decline the bet when the probability is 0.4 or lower. It has been well-established that individuals do not tend to make decisions based on expected value (Post, Assem, Baltussen, & Thaler, 2008; Gigerenzer, 2004; Kahneman, 2003; Denes-Raj & Epstein, 1994). However, the objective of the current study is to make relative comparisons of behavior across different levels of anxiety, not to compare participant behavior to predictions based on expected value. Nonetheless, using expected values to establish experimental conditions helps create a baseline scale by which to quantify risk. For instance, an individual who agrees to the bet with a 20% chance of winning is taking a mathematically "losing" bet (i.e., based on expected value), whereas an individual who agrees to the bet with an 80% chance of winning is taking a mathematically "winning" bet. Within this design, risk-taking is characterized as the point at which an individual agrees to the bet; specifically, what the probability of a win must be before the individual agrees to the bet. The smaller the value, the greater the risk.

2.1.3. Procedure

To avoid carryover effects, all participants completed the betting task first and the Fear of Death Scale (FDS) second. After data collection, a mean score was computed for each of the four subscales of the FDS for each participant. Participants were then ranked based on average scores (i.e., death of oneself subscale) from highest average score to lowest. Among the four subscales, it was assumed that one's own death would be a better predictor of risk and decision-making in the context of this experiment than anxiety associated with the death of a loved one (see Wray-Lake & Stone, 2005 for justification of this assumptions). Furthermore, the trend in the data suggested that individuals who scored higher on the death of oneself subscale also tended to score higher on the dying of oneself subscale, and vice versa for low-anxiety individuals (r = 0.77). Once ranked, participants were split into tertiles, separating the sample into the lowest 1/3, middle 1/3, and highest 1/3 of scores, effectively creating low (n = 90), medium (n = 76), and high (n = 67) anxiety groups based on average scores. Preliminary analyses revealed the three groups did not significantly differ with respect to age [F(2, 230) = 0.75, p = .47] or sex ratio [χ^2(2, N = 234) = 0.41, p = .81] (see Table 6 for descriptive statistics of groups). The total number of 'yes' and 'no' responses were summed for each of the nine betting conditions separately for each group, and these count data were then used to compute proportions.

2.2 Bayesian Modeling

2.2.1 Model specification.

The goal was to conduct a Bayesian logistic regression with the data. The first step in attempting to model the data is to create a prior probability distribution for each parameter. Since the present data are count data with only two possible outcomes they can be described by a binomial distribution where the observed variables Y (‘yes’ responses) and N (‘no’ responses) are given relative counts through the binomial distribution. For instance, the relative count of Y responses can be represented as:

$$Y \sim \text{Binomial}(n, p)$$

where Y is the count of ‘yes’ responses, n is the number of observations and p is the probability of a ‘yes’ response on any given trial. Given the present research question, the implied model for the *probability* hypothesis takes the mathematical form:

$$Y \sim \text{Binomial}(n, p_i)$$

$$\text{Logit}(p_i) = \alpha_{pwin[i]}$$

$$\alpha_j \sim \text{Normal}(.5, .5)$$

with 9 α parameters, one for each betting condition. This model examines the relative probability of responding ‘yes’ across the different betting conditions (denoted as *pwin*) while keeping the participant anxiety level constant. In other words, the probability of winning is the only predictor in the model. The implied model for the *anxiety* hypothesis takes the mathematical form:

$$Y \sim \text{Binomial}(n, p_i)$$

$$\text{Logit}(p_i) = \alpha_{group[i]}$$

$$\alpha_j \sim \text{Normal}(.5, .5)$$

with 3 α parameters, one for each anxiety group. This model includes only anxiety as a predictor. In this case, the model can be used to examine if one group is more likely to accept a bet relative to the other groups regardless of the odds of winning. Lastly, the implied *interaction* model takes the mathematical form:

$$Y \sim \text{Binomial}(n, p_i)$$

$$\text{Logit}(p_i) = \alpha_{condition[i]}$$

$$\alpha_j \sim \text{Normal}(.5, .5)$$

The model implies 27 α parameters, nine betting conditions for each of the three groups (collectively labeled '*condition*' in the formula). As shown above, it is assumed that the parameter is normally distributed. The crucial step is the selection of prior plausibility for the parameters. There are several methods for choosing priors. For the present research question, there is a principled way to choose a prior distribution. First, the probability of a 'yes' response cannot be less than 0, so the prior distribution should not include negative values. Second, the decision space can be represented as a psychometric function (see Figure 1), where a participant is more likely to accept a bet when the odds of winning increase and less likely to accept a bet when the odds decrease. We can use this function to inform prior plausibility. Based on the function, an overall average probability of accepting a bet should be approximately 50%. Thus, a sensible prior should reflect this. Here the priors are assumed to be normally distributed with a mean = 0.5 and standard deviation = 0.5. In addition to our intuitions, 0.5 can be considered a regularizing prior. Regularizing priors are skeptical of extreme parameter values, which "reduce the fit to sample but tend to improve predictive accuracy" (McElreath, 2020, p. 221).

Fortunately, it is not problematic if priors are inexact since the model will update the priors based on the observed data when creating the posterior distribution. In fact, if prior distributions are too restrictive it can be problematic since this can overestimate the fit between the model and the data, resulting in overconfidence in the model's predictive power (see McElreath (2020) for further discussion of priors). It is desirable that priors for parameters contain a degree of uncertainty to avoid overfitting. This has prompted some researchers to suggest that 'weakly informative' priors may be optimal for Bayesian modeling (McElreath, 2020; Lemoine, 2019). So long as the chosen priors are sensible the model can provide highly precise and useful inferences while decreasing the chances of overfitting.

3. Results

The results are separated into two parts. First, results from the analyses of the observed participant data will be presented. Next, assessments of model fit will be presented. Before proceeding with Bayesian modeling, it is useful to first assess whether there are differences in the outcome based on levels of the predictors. A binary logistic regression was conducted including participant response (i.e., "yes" = 1, "no" = 0) as the outcome variable, with anxiety (low, medium, high) and probability of winning (nine levels) as predictors. (All results significant at .05 unless stated otherwise). Results confirmed a significant main effect of probability of winning, *OR* = 1.16, *CI* = 1.14, 1.17. The probability of accepting the bet increased ~16% for every 10% increase of winning odds. As shown in Figure 2, the odds of accepting the bet increased incrementally as the probability of winning increased. A main effect of anxiety was also observed, *OR* = 1.22, *CI* = 1.16, 1.30. The relative odds of accepting the bet increased ~22% as anxiety level increased. Additionally, a probability of winning x anxiety interaction was observed, *OR* = 0.98, *CI* = 0.74, 0.82. To get a clearer picture of this interaction effect, pairwise comparisons were conducted examining the relative odds ratios across the three anxiety groups for each betting condition. As shown in Table 2, high-anxiety individuals were more likely to agree to the bet than medium- and low-anxiety individuals particularly at low winning probabilities (i.e., riskier odds). Furthermore, the medium-anxiety group was more likely to agree to the bet at lower winning probabilities than the low-anxiety group.

Results from participant data revealed a pattern consistent with the interaction account. Individuals higher in anxiety were generally more likely to accept the bet when compared to lower-anxiety groups, particularly when the odds of winning were low. While these data help illustrate the differences in proportion of ‘yes’ responses across groups and betting conditions, averaged data can miss important information contained in the entire response distribution. Thus, density plots were also created (Figure 3) to provide a closer examination of how group decision-making behavior varies across different odds of winning.

In Figure 3 the two ticks on the abscissa represent the means of each response option accompanied by the associated distributions. The spacing between the means reflects the Euclidean distance in the decision space. Notice, for instance, that the ‘yes’ and ‘no’ responses move further apart in the bottom row as the odds of winning approach 100%. Another important feature of the density plots is how the shapes of the distributions vary across groups and betting conditions. For instance, when the odds of winning the bet are 10% (top left plot), low-anxiety individuals show much more uniformity in rejecting the offer relative to the high-anxiety group, who show greater variability. However, when the odds increase to 50% (center plot), the relative distributions across groups are fairly similar.

3.1 Running the models

After specifying the priors for the α parameters, the observed data (i.e., count of ‘yes’ and ‘no’ responses) were entered into each model. The *quadratic approximation* method was used to derive the posterior distributions. This method derives the posterior distribution by approximating the logarithm of the posterior density. This method is appropriate since the distribution for the outcome variable (i.e., proportion of ‘yes’ responses) is symmetric and unimodal. These conditions are necessary since the quadratic approximation approach utilizes a Gaussian distribution to create the posterior distribution. One of the benefits of using this method is that the only values required to create the posterior distribution are the mean μ and the variance σ^2 of the posterior. For each condition, the model derived a posterior distribution for proportion of ‘yes’ responses; that is, the model computed a distribution of the two parameters (mean, standard deviation) based on the priors and observed data. Here, the mean represents the most probable value for the proportion of ‘yes’ responses in each condition.

3.2 Model comparison

After each of the three models derived posterior distributions, the models were directly compared using the WAIC (Widely Applicable Information Criterion) index. This statistic provides an indication of a particular model’s ability to predict new data. While there are other statistics, such as Bayes factor, that compare the relative fit between multiple models and observed data, WAIC is used to assess a model’s ability to make out-of-sample predictions (McElreath, 2020). Some researchers caution against using Bayes factor for model comparison given Bayes factor high sensitivity to prior distributions (Gelman, Carlin, Sterns, Dunson, Vehtari et al., 2013; Liu & Aitkin, 2008). WAIC can be considered a measure of uncertainty in a model. Specifically, it is an estimate of the average out-of-sample deviance (known as K-L Divergence). A higher value represents more uncertainty in the model. Thus, we wish to choose the model with the lowest WAIC.

The results in Table 3 display the relative WAIC for each of the three models. As can be seen, the model including an anxiety x probability of winning interaction term resulted in the lowest value. It is important to note that WAIC should not be taken as an absolute measure of model fit. The criterion can take on a large possible range of values depending on the number of observations and number of parameters. Therefore, the WAIC values shown in Table 3 should only be used to make *relative* comparisons across models. In the present case, we see that the interaction model is selected as the model that will produce the best predictions.

3.3 Assessing model fit

With the model of choice selected, we can now begin to examine the model fit directly. Once the posterior distributions were derived the model fit was assessed. This was done by extracting samples from the posterior distribution (n = 10,000) and isolating the maximum peak (i.e., mode) of the posterior distribution. Results are presented in Figure 4. This plot provides a visual depiction of the model's derived posterior for each anxiety group across all nine betting conditions. The model shows a pattern consistent with the observed data. Specifically, low-anxiety individuals show the lowest probability of accepting the bet when there is a low probability of a win, followed by medium-anxiety individuals, with high-anxiety individuals much more likely to agree to these risky odds.

We can get a clearer picture of the model fit by plotting observed proportions alongside the model-implied posterior predictions. Figure 5 illustrates both the participant data and model predictions grouped by probability of winning. The model shows predictions very close to the observed data. The model predictions are not an exact match, however, particularly at the extremes. For example, when the probability of a win is 10%, the model predicts a higher acceptance rate (~16%) among low-anxiety individuals than was observed with participants (~6%).

4. Discussion

Experiment 1 examined the effects of death-related anxiety on risk in decision-making. Participants were required to decide whether to accept or decline a bet in which the probability of a win systematically varied. Participants were then separated into low, medium, and high anxiety groups and each group's behavior was examined. Bayesian analysis was conducted, and three models were fit to the data with each model making different predictions of the data. Results from the participant data revealed an interaction between level of anxiety and probability of winning. Anxiety showed a tiered effect with high-anxiety individuals most likely to accept a bet, followed by medium-anxiety individuals, with the low-anxiety group being most risk-averse. This effect was largest at low win probabilities ($p(\text{win}) \leq 0.4$). We can quantify risk-taking by calculating the average probability at which each group chose to take the bet. As a group, high-anxiety individuals agreed to the bet when the probability of a win was 0.40 ($SD = 0.28$). The medium-anxiety group agreed to the bet, on average, at 0.49 ($SD = 0.27$), and the low-anxiety group agreed to the bet when the probability of a win was 0.57 ($SD = 0.21$). Many studies of loss aversion have conducted parametric tests on such values to detect significant group differences, but this is not appropriate given that the response options of the present study (and most studies of loss aversion) are ordinal. While these differences are informative for the purpose of observing group differences, rank order tests or nonparametric tests, such as logistic regression, are better suited for testing group differences statistically.

4.1 Behavioral results

The results of Experiment 1 are intriguing since they support an association between anxiety and risk-taking. However, the association was *positive*. When the probability of a win was low, individuals with greater anxiety were more likely to accept the bet than individuals with less anxiety. Figure 2 visually illustrates this effect. The slope along the left side of the psychometric curve is steeper for individuals lower in anxiety, indicating greater loss-aversion. This unexpected outcome contrasts with previous accounts of a negative association between anxiety and risk-taking (Maner et al., 2007; Wray-Lake & Stone, 2005). The results are also inconsistent with studies reporting no effects of anxiety on risk-taking (Gu et al., 2017; Howlett & Paulus, 2017). It is important to note that the current study specifically examined the effects of death anxiety on risk in decision-making. To the author's knowledge, this specific relationship has not been studied before. It may be inappropriate to compare results across studies assessing different types of anxiety. Different types of anxiety have been previously shown to have opposing effects on decision-making (Pajkossy et al., 2009). Thus, it is possible that death anxiety has a different effect on decision-making behavior than trait anxiety. For instance, in a study with older adults it was found that seniors with higher death anxiety showed greater preference for smaller, immediate monetary rewards than larger rewards later (Ly, Diaz-Santos, Campbell, Caldera, Kuhn et al., 2019).

One possible explanation for the present results is that death anxiety disposes one towards current gains over long-term gains. In turn, this may attenuate the psychological effect of a small potential loss. According to prospect theory (Kahneman & Tversky, 1979), for instance, decisions are influenced by the interaction of winning odds and winning amount. Most individuals reject a gamble with 50% winning odds unless the potential gain is at least twice the size of the potential loss (Tversky & Kahneman, 1992). The present results suggest this is true for low and moderately anxious individuals, but not highly anxious individuals. Roughly half of the participants in the low- and medium-anxiety groups agreed to the bet when the odds of winning were 50%. In contrast, 62% of highly anxious individuals accepted the same bet. Interestingly, half of the highly anxious participants agreed to the bet when there was a 40% chance of a win. In the interest of experimental control, the present study fixed gain/loss amounts and let probability of winning vary. However, it would have been just as plausible to fix probability and manipulate gain/loss amounts to examine if death anxiety produces the same pattern (as done in Gachter et al., 2007). Would highly anxious individuals display the same degree of risk-taking if there was a larger potential loss?

The results from Experiment 1 are clear in illustrating that one's anxiety concerning death and dying has a strong association with degree of risk-taking in decision-making behavior – at least in the context of betting. Furthermore, this was not a modest effect. Looking at Figure 2, we see that group differences are considerable. Remarkably, over 40% of the high-anxiety individuals accepted the bet when there was only a 10% chance of winning (compared to 25% in the medium-anxiety group and 6% in the low-anxiety group). However, one must also consider the within-group variability. The density plots in Figure 3 show that there is also greater variability in behavior among the high-anxiety group at low winning odds. Thus, an explanation is needed that takes this variability (i.e., uncertainty) into account. The Bayesian modeling approach used in the present experiment is perfectly suited to this end.

4.2 Modeling results

The model predictions closely approximated participant behavior (Figure 5). However, some features of the model warrant discussion. As mentioned in the results section, model predictions were less accurate at the extremes of the probability distribution; that is, when the probability of winning was 10% and 90%. This effect is likely due to the prior plausibility of a ‘yes’ response being set to 0.5. Prior to training the model on the data it was assumed that the probability of a ‘yes’ response on any given trial was 50%. This prior value likely “pulled” predictions closer to 0.5, resulting in slightly higher predictions at $p(\text{win}) = 0.1$ and slightly lower predictions at $p(\text{win}) = 0.9$. As discussed above (Section 2.2.1), regularizing priors tend to reduce model fit to the current sample but improve the accuracy of out-of-sample predictions. Indeed, when a flat prior (i.e., $M = 0$, $SD = 1.5$) was used instead, the model predictions became highly accurate across all anxiety x winning odds combinations. Specifically, no misses greater than 1% were observed. The inclusion of flat (i.e., uninformative) priors can improve model fit since the model assumes that every parameter value is equally plausible. However, this greatly increases the likelihood of model overfitting (McElreath, 2020). Simply put, the model becomes too strongly trained on the current sample, weaking the model’s ability to make predictions for new samples. As shown in the present study, there is variability in participant behavior from one group of individuals to another, and individuals in future samples will not behave exactly the same as those included in the present sample. Thus, a good predictive model should include this element of uncertainty. Since the goal of the current study is to derive a model that can be used to make predictions with new samples, the inclusion of a flat prior is not desirable. Nonetheless, the present results can be used to help determine which prior values to select when conducting similar studies and illustrates how the model behaves when including different priors.

5. Experiment 2

While Experiment 1 suggests that level of anxiety interacts with winning odds to influence decision behavior, the effects of framing were not examined. Note that choices in Experiment 1 were framed in terms of gains. Rather than informing participants they have a 10% chance of winning the bet, one could reframe the choice as a loss: you have a 90% chance of losing the bet. It is possible that individuals with high death anxiety would not display the same degree of risk-taking if choices were framed in terms of losses (Gu et al., 2017). Thus, in Experiment 2 both the instructions and the description of the participant's options were framed in terms of losses rather than gains. On each trial, the participant was informed of their probability of losing the bet rather than their probability of winning as was done in Experiment 1. For instance, "*you have a 10% chance of winning the bet*" was changed to "*you have a 90% chance of losing the bet*."

5.2 Methods

5.2.1 Participants

One hundred eighty-four individuals recruited via Amazon Mechanical Turk (MTURK) participated in Experiment 2. Sample demographics were as follows: sex (74 female, 110 male); age (*M* = 39.71, *SD* = 11.23); race/ethnicity (38 Asian or Pacific Islander, 12 Black or African American, 7 Hispanic or Latino, 1 Native American or Alaskan Native, 126 White or Caucasian). All participants were at least 18 years of age, English speakers, and each participant received \$1.00 in exchange for participation.[2] Only participants who completed the entire survey were included in analyses in Experiment 2. No participants failed to do so, thus no participants were dropped or excluded in Experiment 2.

5.2.2 Procedure

The materials and procedure were kept identical to those used in Experiment 1, except both instructions and winning odds were framed in terms of losses, rather than gains. On each trial, participants were informed of their odds of *losing* the bet. As in Experiment 1, participants were ranked and then split into tertiles, creating low- (n = 53), medium- (n = 56) and high-anxiety (n = 75) groups. Groups did not significantly differ in sex ratio [$\chi^2(2, N = 184) = 2.33$, $p = 0.31$]. However, groups did significantly differ with respect to age, [$F(2, 181) = 5.75$, $p = .004$]. The low-anxiety group (M = 43.98, SD = 11.37) was older, on average, than the medium-anxiety (M = 37.44, SD = 11.16) and high-anxiety (M = 38.40, SD = 10.49) groups. See Table 7 for full descriptive statistics of groups.[3]

6. Results

Results showed a significant main effect of winning probability, OR = 1.17, CI = 1.15, 1.18. The probability of accepting the bet increased ~17% for every 10% increase of winning odds. There was also a significant main effect of anxiety, OR = 1.42, CI = 1.34, 1.51. Lastly, there was a significant probability of winning x anxiety interaction effect, OR = 0.97, CI = 0.96, 0.97. As done in Experiment 1, pairwise comparisons were conducted to more clearly examine

[2] Experiment 2 was configured such that individuals who participated in Experiment 1 were unable to participate in Experiment 2.

[3] Between Experiments 1 and 2, low (z = 0.32, p = 0.37), medium (z = 0.67, p = .25), and high (z = 1.03, p = 0.15) anxiety groups did not significantly differ with respect to anxiety score.

the interaction between winning odds and anxiety on willingness to agree to the bet. (All results significant at $p < .05$ unless stated otherwise).

Table 4 shows the relative odds ratios separated by winning probability and anxiety levels. A similar pattern was observed in Experiment 2 as that found in Experiment 1, with groups higher in anxiety more likely to accept the bet than groups lower in anxiety. This effect was most pronounced at low winning probabilities. Unlike Experiment 1, little difference in behavior was observed between medium- and high-anxiety groups. On average, the high-anxiety group accepted the bet when the probability of a win = 0.32 (0.28). Medium-anxiety individuals accepted the bet when the probability of a win = 0.37 (0.28), and low-anxiety individuals accepted the bet when the probability of a win = 0.65 (0.28).

6.1 Model comparison

As in Experiment 1, a Bayesian model based on each of the three theoretical approaches was used to derive posterior distributions. The results were directly compared using the WAIC index. As shown in Table 5, the model including an anxiety x probability of winning interaction term resulted in the lowest value, indicating the model as the best predictor of out-of-sample decision behavior. Figure 8 illustrates the posterior distributions derived from the interaction model. The observed data and model predictions are presented in Figure 9. Once again, model predictions closely approximated the observed data.

7. General Discussion

The results of Experiment 2 replicated the findings of Experiment 1, illustrating a positive association between death-related anxiety and risk in decision-making. However, the results of the second experiment expand on the initial findings by showing that this association holds regardless of the framing of outcomes. Specifically, individuals higher in death-related anxiety display greater degrees of risk-seeking in decision-making than those lower in death-related anxiety whether outcomes are framed in terms of gains or losses. This observation is significant because it contrasts with accounts showing greater loss aversion in individuals higher in trait anxiety (Gu et al., 2017). If highly anxious individuals were more sensitive to negative framing, they should display greater loss aversion (i.e., less willing to take low probability bets) when outcomes are framed in terms of losses. This was not the case.

The present findings also have important theoretical implications. Prospect theory (Kahneman & Tversky, 1979) and the more recent cumulative prospect theory (Tversky & Kahneman, 1992) has been the highly favored model for describing decision making under uncertainty for decades. However, empirical tests of the theory have generally emphasized external factors that modulate an individual's decision behavior (e.g., reference dependence, framing, probability, gain/loss ratio) over internal traits like personality, emotion, or experience (Rakow & Newell, 2010; Newell, Lagnado, & Shanks, 2007). This discrepancy is likely due to the inherent difficulties in creating model parameters that can quantify these kinds of constructs. Such efforts are further complicated by the finding that individual risk-taking behavior (i.e., or "risk sensitivity") tends to be variable, rather than stable, across different domains (Weber, Elke, & Johnson, 2009; Weber, Blais, & Betz, 2002; Bromily & Curley, 1992). However, the present study helps illustrate the relatively large degree of variability observed in decision-making behavior even within groups. Such variability often goes unnoticed when researchers consider only group-averaged statistics used to examine risk-aversion or loss aversion. Researchers need to consider this variability in behavior.

While prospect theory has been used to successfully account for individual differences in loss aversion based on traits such as age, education level, and income level (Gachter et al., 2007) the theory is primarily *descriptive*. That is, the utility model implemented within prospect theory is well-suited for describing decision-making behavior but does not provide explanations for the psychological processes involved in decision making (Staddon, 2017) and sometimes leads to predictions that directly contrast with human behavior (Nwogugu, 2006). Describing behavior is not the same as explaining behavior. To gain a better understanding of the actual psychological mechanisms involved in the decision process, we need to consider both external and internal factors. It is not enough to illustrate that individuals have different degrees of risk-sensitivity or aversion to loss, for instance, it is necessary to isolate the psychological factors underpinning these differences.

An advantage of the present study over previous studies used to examine the relationship between risk and decision behavior is the implementation of Bayesian techniques. Traditional significance tests only enable researchers to make decisions concerning a null model. In this context, a model which assumes zero differences in participant behavior across winning odds and anxiety levels. Such a model is almost certain to be false, which makes significant findings rather unsurprising. Rather than assessing how different observed data are from a null model, Bayesian model comparisons enable one to determine how much evidence there is for the *alternative* hypotheses based on the observed data. Furthermore, Bayesian modeling takes into account the full distribution of group scores when deriving posterior distributions (i.e., predictions), not just group means. Based on the data observed in the two experiments, the most evidence was found for a model specifying that the probability of a win interacts with level of anxiety to influence decision-making behavior.

7.1 Limitations and future directions

The present study supports a positive relationship between death-related anxiety and risk-taking behavior. However, open questions remain on the dynamic nature of this relationship. Additional research is needed to assess if the present findings extend beyond the context of economic decisions. A limitation to the current study is that age-related effects were not examined. Too few older adults were included in the samples to adequately test for age-related effects. However, it is very probable that age-related differences in death anxiety (Tomer, 2000) and loss aversion (Gachter et al., 2007) exist, which may illustrate that the relationship between anxiety and risk-taking is more complex than the patterns observed here. Despite this limitation, the current study has an advantage over many studies examining the relationship between anxiety and decision-making by including a more representative sample with respect to age (18-74). Many influential and reputable findings concerning the association of anxiety and decision-making are derived from studies with samples restricted to young adults (i.e., undergraduate students). This practice places great limitations on the generalizability of findings.

An additional limitation of the present study is data reflecting trait anxiety were not obtained. Measuring participants on both death-related anxiety and trait anxiety would enable us to determine whether the patterns observed in the present study are specific to death-anxiety or observed across both trait and death-anxiety. It is also possible that additional measures of mental health may covary with death-related anxiety. Individuals higher in death anxiety may be more likely to suffer from mood or personality disorders, for instance, than those lower in death anxiety. Future research needs to account for potential covariates of death-anxiety.

In sum, the present findings expand our understanding of the relationship between anxiety and risk-taking by investigating a form of anxiety (i.e., death anxiety) that has received little attention in the context of decision-making. The present study design enables us to go beyond a verbal description of group differences, providing a more dynamic picture of how the risk associated with a choice influences decisions within individuals. By utilizing a Bayesian modeling approach, we can assign relative plausibility to competing accounts concerning how anxiety and risk relate to decision-making. In turn, we can use model predictions to inform future research.

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Table Captions

Table 1. *Expected Values (EV) for Each Trial in Betting Task*

Table 2. *Odds Ratios for 'Yes' Response Based on Probability of Winning (pwin), and Anxiety Level (low, medium, high)*

Table 3. *Widely Applicable Index Criterion (WAIC) Values for Anxiety, Probability, and Interaction Models*

Table 4. *Odds Ratios for 'Yes' Response Based on Probability of Winning (pwin), and Anxiety Level (low, medium, high*)

Table 5. *Widely Applicable Index Criterion (WAIC) Values for Anxiety, Probability, and Interaction Models*

Table 6. *Descriptive Statistics for Anxiety Groups (Experiment 1*)

Table 7. *Descriptive Statistics for Anxiety Groups (Experiment 2)*

Tables

Starting Amount	*P*(Win)	Amount	EV = *P*(Win)*Amount
10	0.1	20	2
10	0.2	20	4
10	0.3	20	6
10	0.4	20	8
10	0.5	20	10
10	0.6	20	12
10	0.7	20	14
10	0.8	20	16
10	0.9	20	18

Anxiety	*Odds Ratio*	*CI*	*p*	
High vs. Low				
pwin (0.1)	1.42	1.26, 1.62	<.001	***
pwin (0.2)	1.41	1.23, 1.60	<.001	***
pwin (0.3)	1.42	1.26, 1.62	<.001	***
pwin (0.4)	1.26	1.08, 1.46	0.003	**
pwin (0.5)	1.12	0.96, 1.31	0.145	
pwin (0.6)	1.11	0.96, 1.30	0.146	
pwin (0.7)	1.1	0.97, 1.25	0.127	
pwin (0.8)	1.1	1.01, 1.22	0.034	*
pwin (0.9)	1.05	0.99, 1.12	0.101	
Medium vs. Low				
pwin (0.1)	1.2	1.06, 1.35	0.003	**
pwin (0.2)	1.19	1.05, 1.34	0.006	**
pwin (0.3)	1.23	1.09, 1.40	0.001	**
pwin (0.4)	1.09	0.95, 1.27	0.215	
pwin (0.5)	1.03	0.89, 1.20	0.682	
pwin (0.6)	1.06	0.92, 1.22	0.406	
pwin (0.7)	1.04	0.93, 1.19	0.445	
pwin (0.8)	1.01	0.92, 1.11	0.771	
pwin (0.9)	1.04	0.98, 1.11	0.186	
High vs. Medium				
pwin (0.1)	1.18	1.04, 1.35	0.012	*
pwin (0.2)	1.18	1.04, 1.35	0.013	*
pwin (0.3)	1.15	1.01, 1.32	0.037	*
pwin (0.4)	1.14	0.98, 1.34	0.085	
pwin (0.5)	1.09	0.92, 1.28	0.307	
pwin (0.6)	1.05	0.90, 1.22	0.53	
pwin (0.7)	1.05	0.92, 1.20	0.448	
pwin (0.8)	1.09	0.99, 1.21	0.076	
pwin (0.9)	1.01	0.95, 1.07	0.724	

	WAIC	SE	dWAIC	dSE	pWAIC	weight
int_model	2127.8	36.24	0.0	NA	17.4	1
prob_model	2162.4	41.89	34.6	16.61	7.3	0
anxiety_model	2848.8	17.30	721.0	35.35	3.0	0

Anxiety	*Odds Ratio*	*CI*	*p*	
High vs. Low				
pwin (0.1)	1.75	1.51, 2.03	<.001	***
pwin (0.2)	1.74	1.49, 2.03	<.001	***
pwin (0.3)	1.79	1.54, 2.08	<.001	***
pwin (0.4)	1.81	1.57, 2.11	<.001	***
pwin (0.5)	1.42	1.21, 1.67	<.001	***
pwin (0.6)	1.28	1.11, 1.49	0.001	**
pwin (0.7)	1.23	1.07, 1.40	0.003	**
pwin (0.8)	1.14	1.03, 1.25	0.007	**
pwin (0.9)	1.08	1.01, 1.16	0.017	*
Medium vs. Low				
pwin (0.1)	1.56	1.34, 1.84	<.001	***
pwin (0.2)	1.53	1.31, 1.80	<.001	***
pwin (0.3)	1.53	1.31, 1.80	<.001	***
pwin (0.4)	1.67	1.42, 1.97	<.001	***
pwin (0.5)	1.51	1.27, 1.79	<.001	***
pwin (0.6)	1.25	1.06, 1.46	0.008	**
pwin (0.7)	1.22	1.05, 1.40	0.008	**
pwin (0.8)	1.12	1.01, 1.24	0.025	*
pwin (0.9)	1.08	1.01, 1.16	0.035	*
High vs. Medium				
pwin (0.1)	1.12	0.97, 1.30	0.128	
pwin (0.2)	1.13	0.98, 1.32	0.093	
pwin (0.3)	1.16	1.01, 1.35	0.041	*
pwin (0.4)	1.09	0.93, 1.26	0.280	
pwin (0.5)	0.94	0.80, 1.11	0.450	
pwin (0.6)	1.03	0.89, 1.20	0.718	
pwin (0.7)	1.01	0.88, 1.15	0.890	
pwin (0.8)	1.01	0.80, 1.00	0.776	
pwin (0.9)	1.00	0.94, 1.07	0.892	

	WAIC	SE	dWAIC	dSE	pWAIC	weight
int_model	1628.8	30.78	0.0	NA	15.4	1
prob_model	1810.2	32.88	181.5	20.99	7.2	0
anxiety_model	2023.3	31.05	395.0	26.70	2.9	0

Group	*M*(Age)	*N*(Males)	*N*(Females)	*M*(Fear of Death Scale)
high	36.64 (10.63)	34	33	3.97 (0.46)
medium	36.81 (11.52)	42	33	2.72 (0.36)
low	38.70 (13.01)	49	41	1.48 (0.37)

Note. Values in parentheses represent standard deviations.

Group	*M*(Age)	*N*(Males)	*N*(Females)	*M*(Fear of Death Scale)
high	38.40 (10.49)	40	35	4.09 (0.41)
medium	37.44 (11.16)	35	21	2.79 (0.34)
low	43.98 (11.37)	35	18	1.45 (0.31)

Note. Values in parentheses represent standard deviations.

Figure Captions

Figure 1. Psychometric function of betting decision (simulated data).

Figure 2. Proportion of ‘yes’ responses on betting task based on odds of winning across low, medium, and high anxiety groups. Bars represent standard deviations.

Figure 3. Density plots for betting experiment.

Figure 4. Posterior distributions derived from interaction model.

Figure 5. Observed (top) and model predicted (bottom) posterior means.

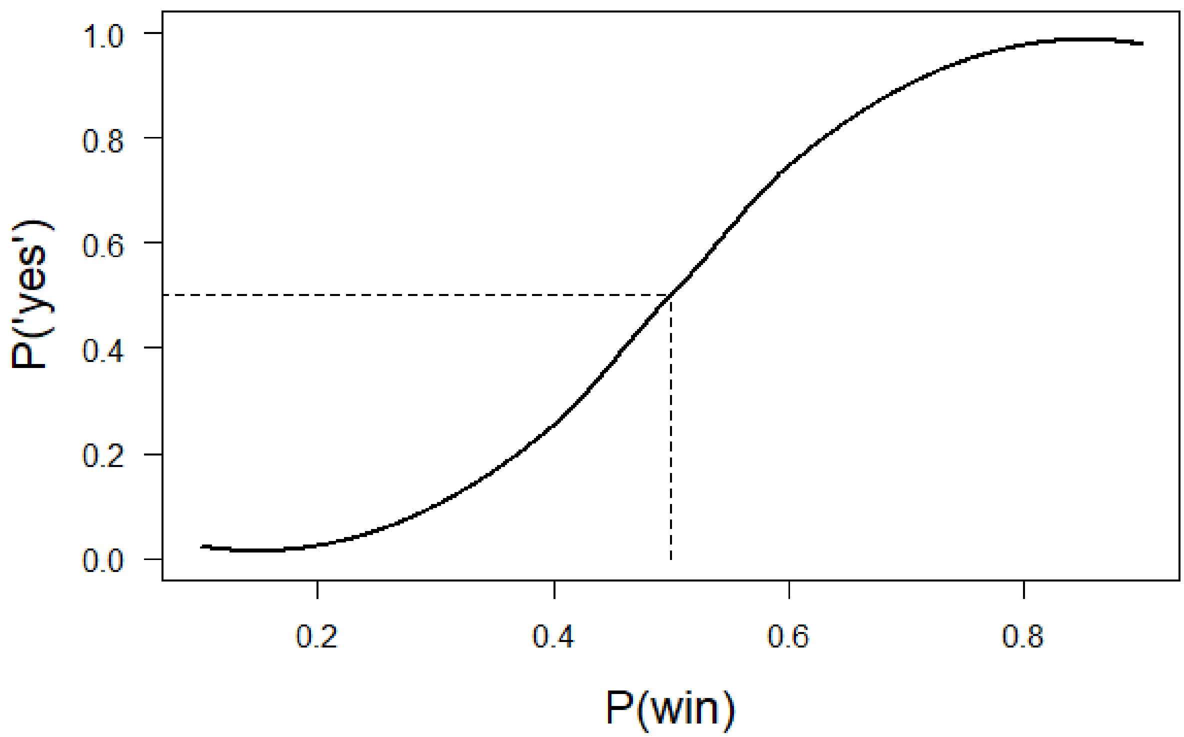
Figure 6. Proportion of ‘yes’ responses on betting task based on odds of winning across low, medium, and high anxiety groups. Bars represent standard deviations.

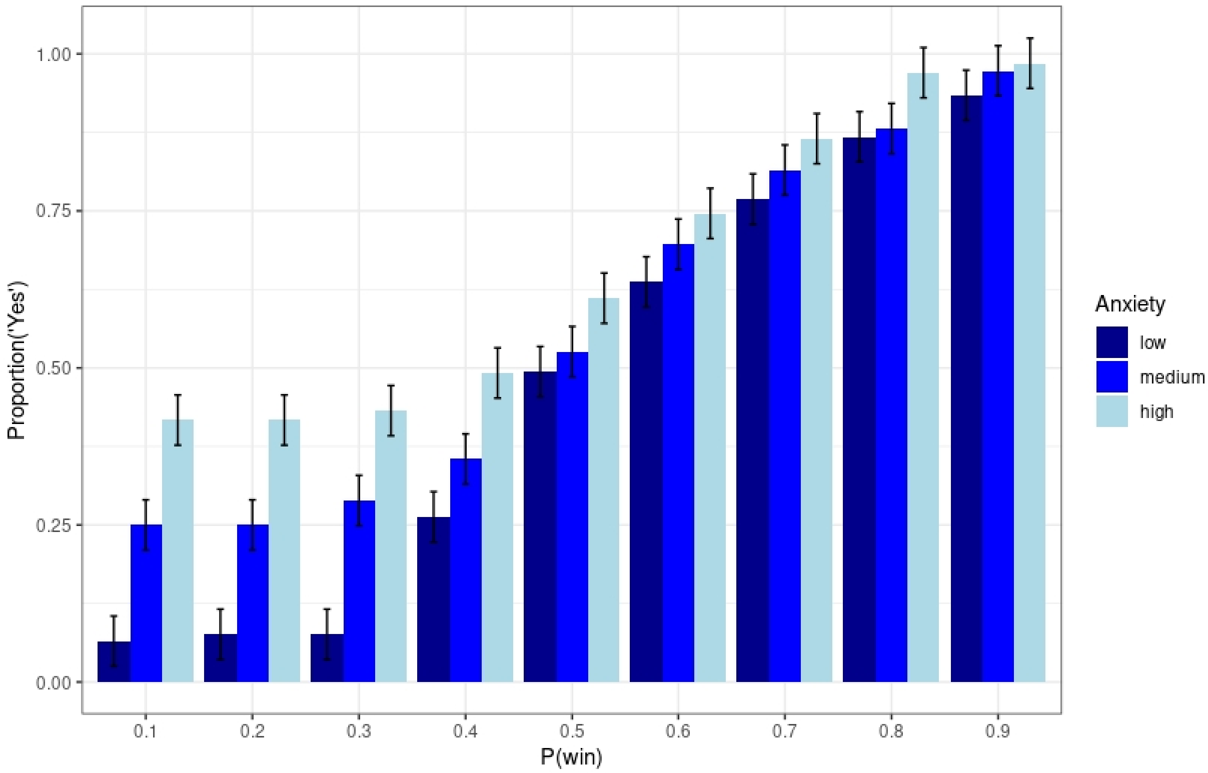
Figure 7. Density plots for Experiment 2.

Figure 8. Posterior distributions derived from interaction model (Experiment 2).

Figure 9. Observed (top) and model predicted (bottom) posterior means.

Figures

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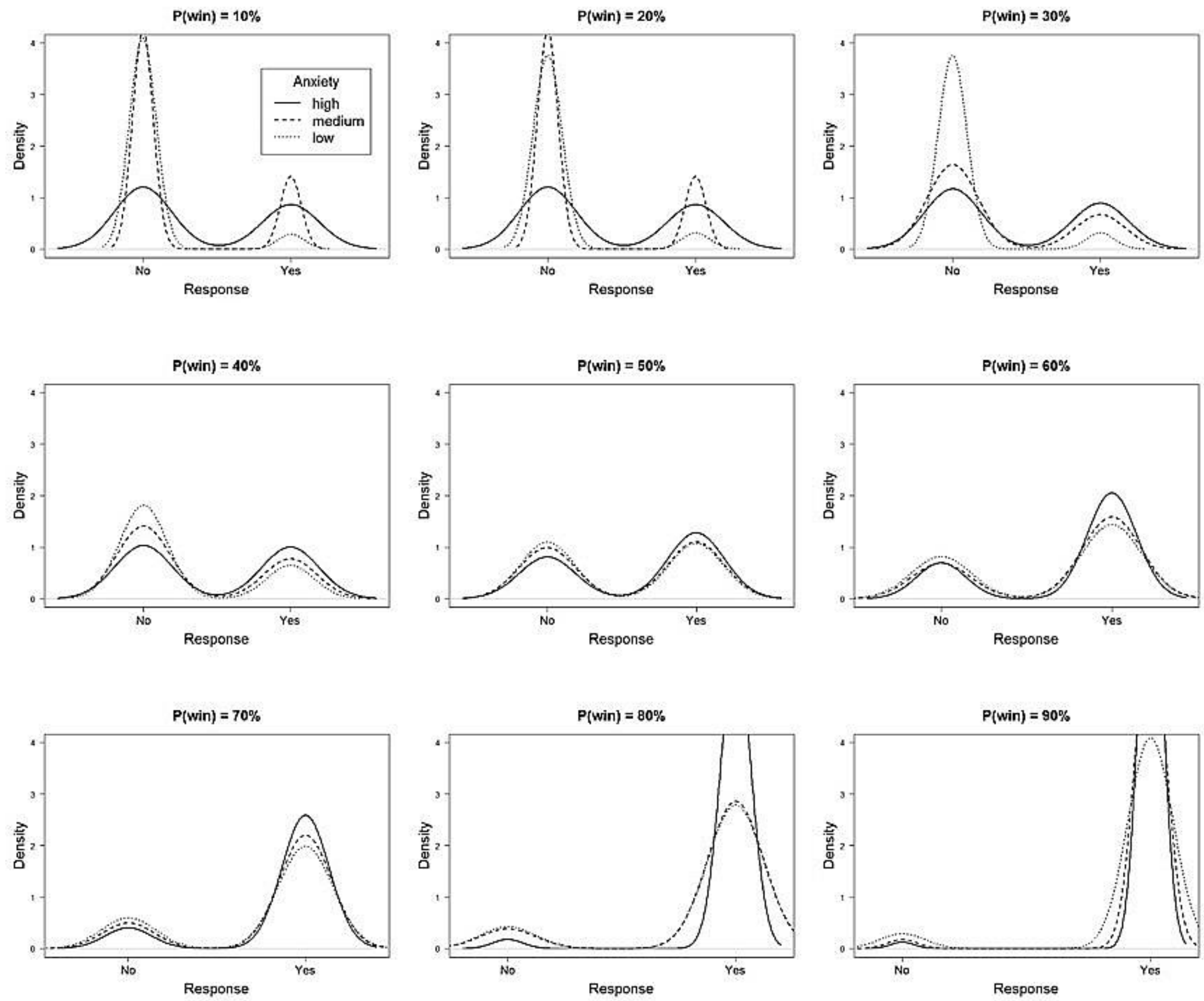
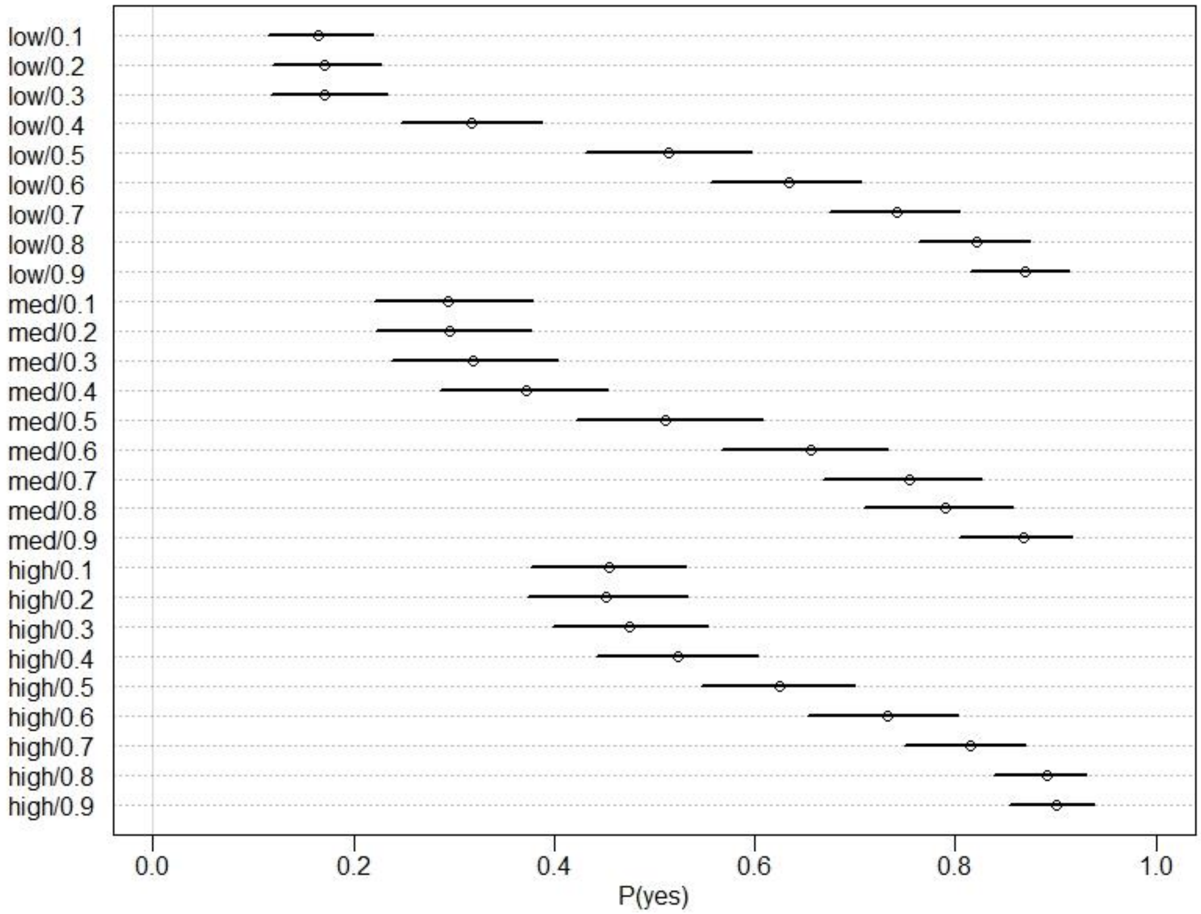
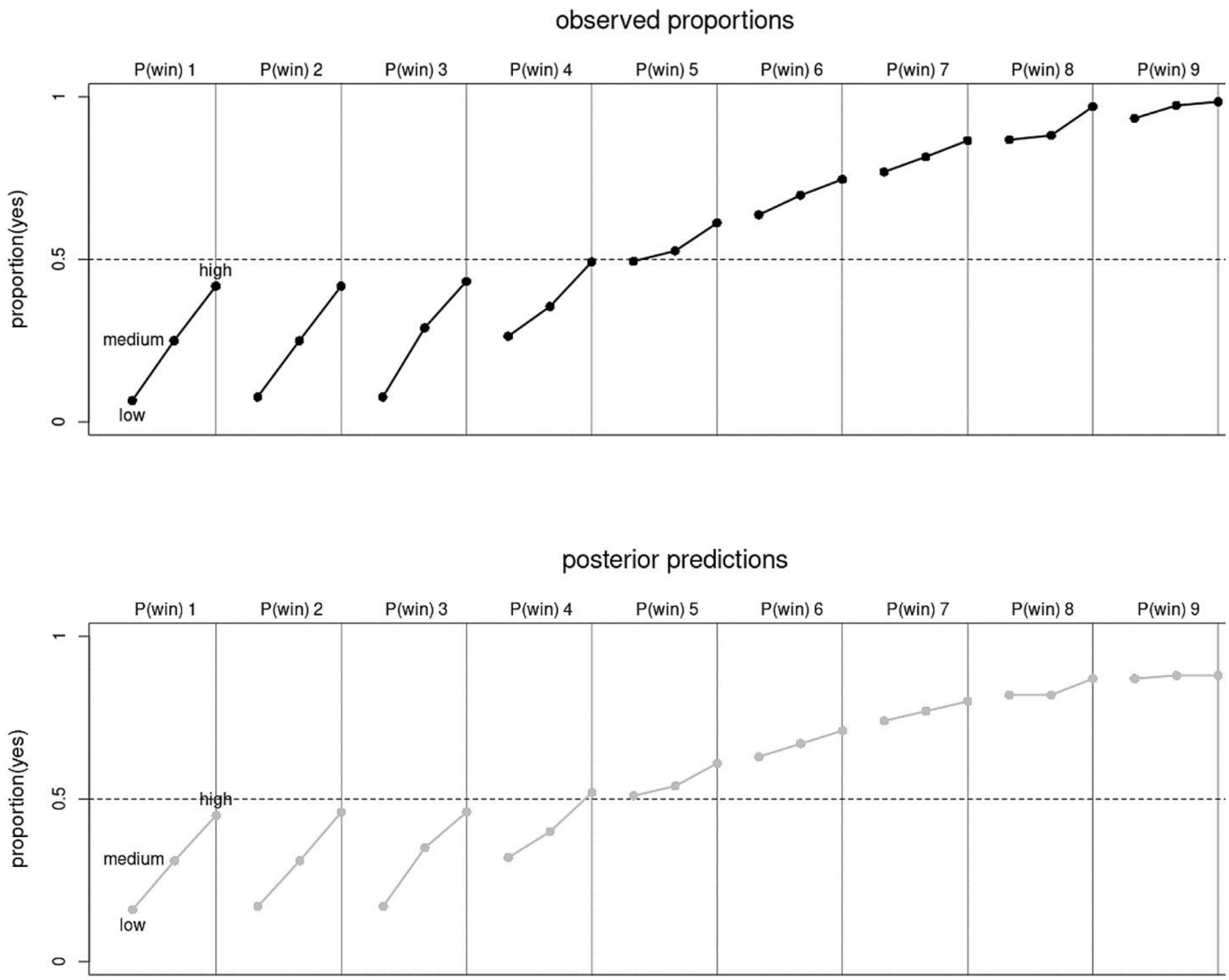
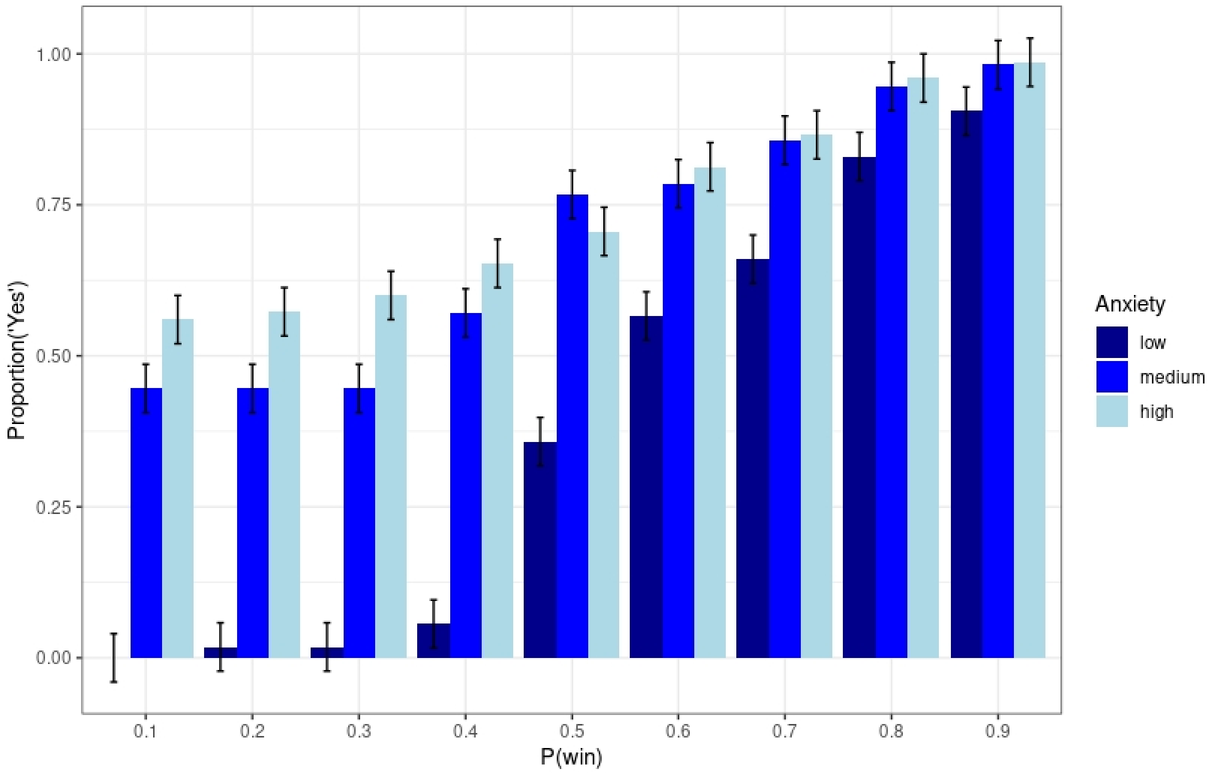
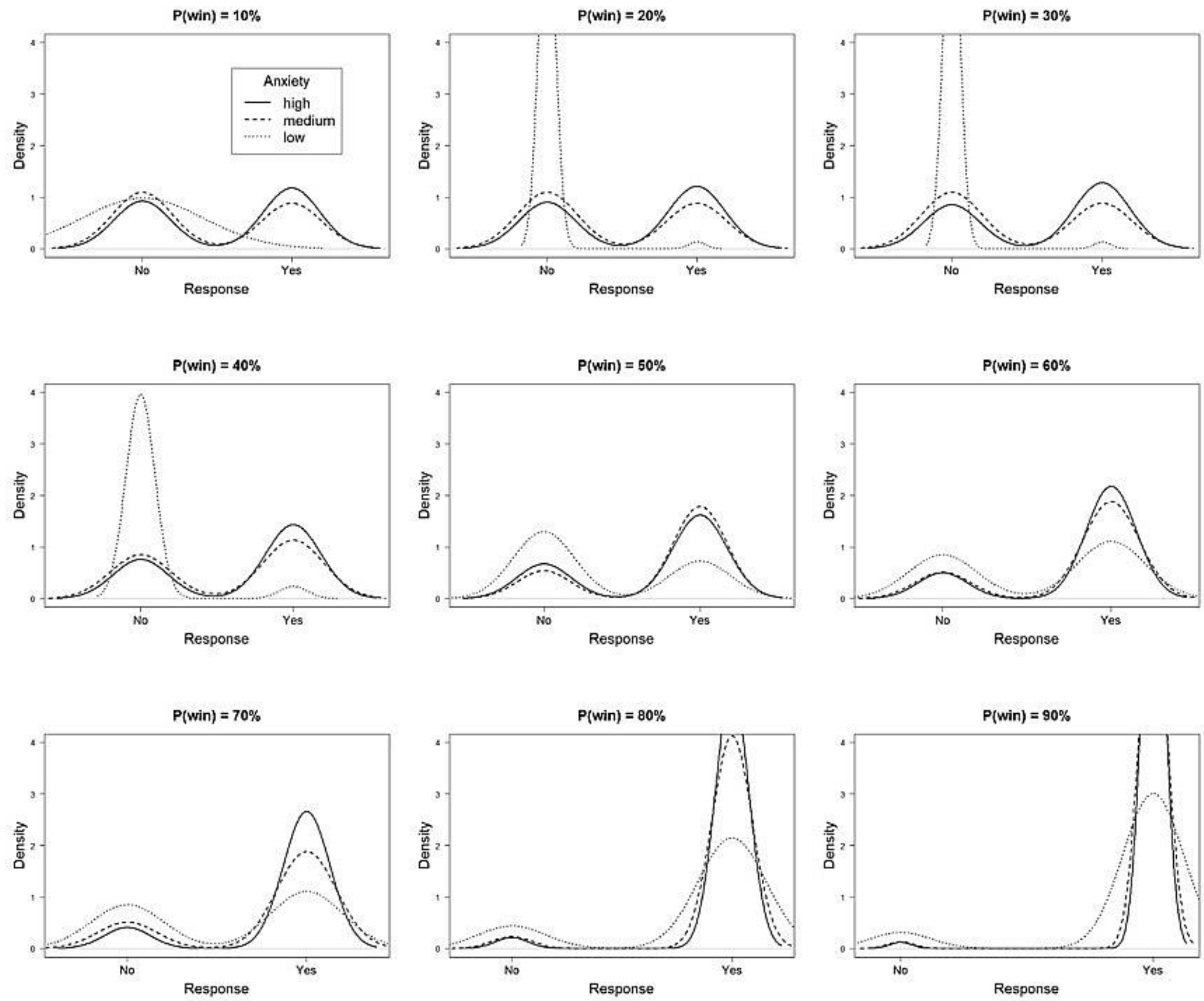
1.00
0.75
0.50
0.25
0.00
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
P(win)
Anxiety
low
medium
high


P(win) = 10%
P(win) = 20%
P(win) = 30%
P(win) = 40%
P(win) = 50%
P(win) = 60%
P(win) = 70%
P(win) = 80%
P(win) = 90%
Anxiety
high
medium
low
Density
Response
No
Yes

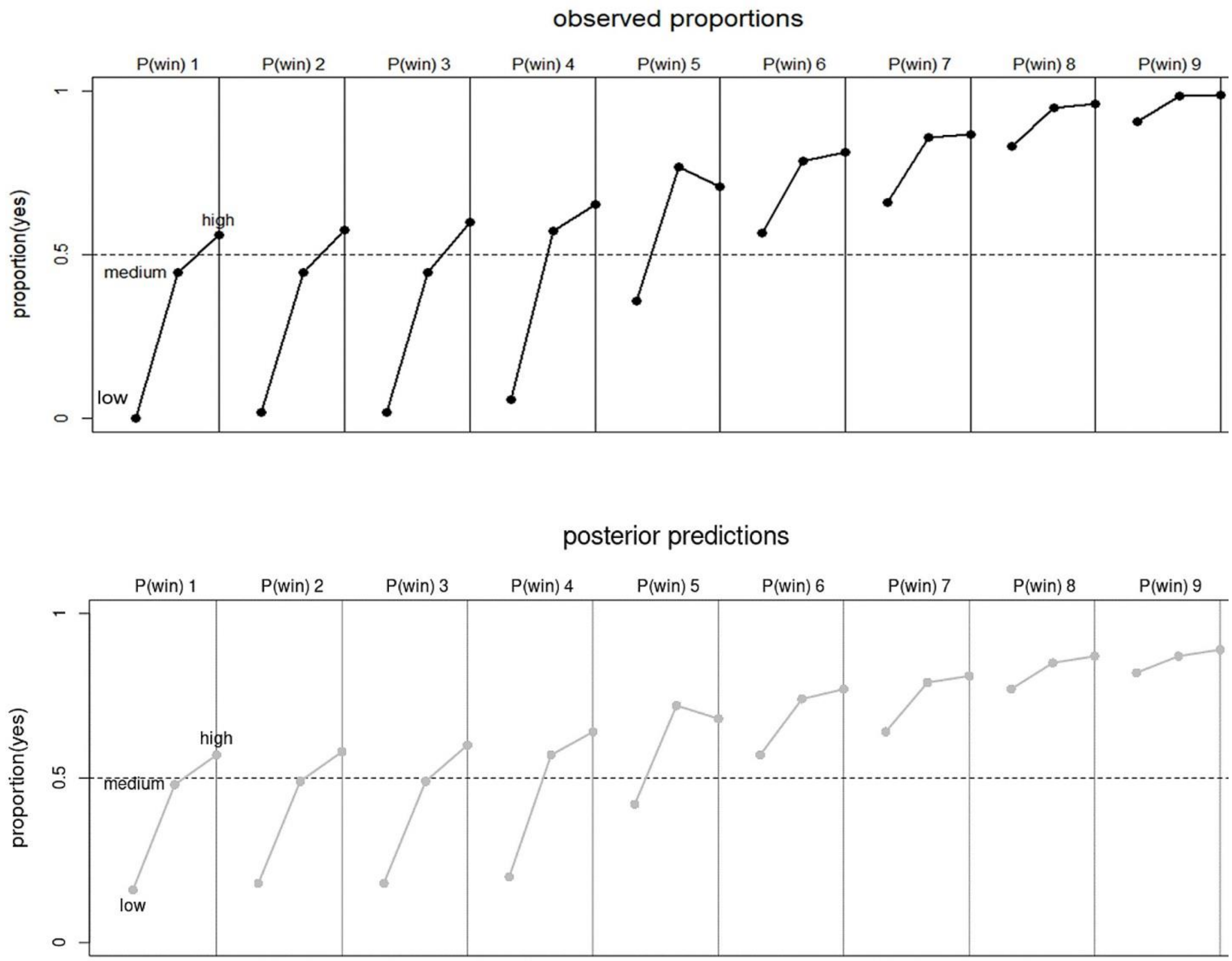

low/0.1
low/0.2
low/0.3
low/0.4
low/0.5
low/0.6
low/0.7
low/0.8
low/0.9
med/0.1
med/0.2
med/0.3
med/0.4
med/0.5
med/0.6
med/0.7
med/0.8
med/0.9
high/0.1
high/0.2
high/0.3
high/0.4
high/0.5
high/0.6
high/0.7
high/0.8
high/0.9
0.0
0.2
0.4
0.6
0.8
1.0
P(yes)


observed proportions
P(win) 1
P(win) 2
P(win) 3
P(win) 4
P(win) 5
P(win) 6
P(win) 7
P(win) 8
P(win) 9
proportion(yes)
1
0.5
0
high
medium
low
posterior predictions
P(win) 1
P(win) 2
P(win) 3
P(win) 4
P(win) 5
P(win) 6
P(win) 7
P(win) 8
P(win) 9
proportion(yes)
1
0.5
0
high
medium
low


1.00
0.75
0.50
0.25
0.00
Proportion('Yes')
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
P(win)
Anxiety
low
medium
high



P(win) = 10%
P(win) = 20%
P(win) = 30%
P(win) = 40%
P(win) = 50%
P(win) = 60%
P(win) = 70%
P(win) = 80%
P(win) = 90%
Anxiety
high
medium
low
Density
Response
No
Yes
0
1
2
3
4


observed proportions
P(win) 1
P(win) 2
P(win) 3
P(win) 4
P(win) 5
P(win) 6
P(win) 7
P(win) 8
P(win) 9
proportion(yes)
1
0.5
0
high
medium
low
posterior predictions
P(win) 1
P(win) 2
P(win) 3
P(win) 4
P(win) 5
P(win) 6
P(win) 7
P(win) 8
P(win) 9
proportion(yes)
1
0.5
0
high
medium
low