Palmer's Comments 2/18/25

Sources of Bias in Naturalistic Decision Making Under Risk from A Signal Detection Perspective

use lower case

Chao Qin, Susan Joslyn, John Palmer

University of Washington

Abstract

Severe weather events require protective actions even when the probability is low. In naturalistic decision experiments based on these situations, people were risk-seeking such that they often did not take protective actions when it is economically rational to do so. To better understand this behavior, the current study used a signal detection theory perspective. A person ~~could~~ might make risk seeking decisions because their criterion for taking protective action is too high or because their perceived likelihood of the event is too low. In two experiments the economically rational criterion and gain-loss framing were manipulated to examine their effects. According to an ~~random likelihood model~~ analysis based on signal detection theory, when the economically rational criterion was manipulated, the subjective criterion was between the economically rational criterion and the center of the range. When gain-loss framing was manipulated, the subjective criterion was higher in a loss than a gain frame. Participants also ~~showed~~ overestimated the subjective likelihood ~~that was~~ in all conditions regardless of ~~unaffected by~~ the manipulations. However, the shifted subjective criterion overcame this overestimation, resulting in risk-seeking decisions. Thus, we conclude that the shift of the subjective criterion can lead to risk-seeking decisions in naturalistic decision tasks. Potential interventions to improve the placement of the subjective criterion were discussed.

~~Introduction~~

In ~~real-world~~ risky decision making ~~situations~~ about real world events such as severe weather events, people often need to make decisions for an uncertain future. For example, when facing a possible tornado, people must decide whether to take protective actions such as taking shelter. Taking protective action costs time and resources but can protect from harm. On the other hand, not taking protective actions might expose decision-makers to potential harm but can save time and resources if a tornado does not materialize. Due to the potential serious harm of these events, people are advised to take protective actions even when the probability is low. For example, tornado warnings are ~~sometimes~~ issued by the US National Weather Service when the probability of a tornado is as low as 10% (Qin et al., 2024). Due to the low probability ~~in some areas~~, the severe weather event often fails to occur at the residents' location, making protective actions seem like a waste of time. Indeed, research on people's response to real forecasts and warnings in severe weather events, such as floods, tornadoes, and hurricanes, showed that people often failed to comply with the recommended protective actions (e.g., evacuation), a risk-seeking tendency (Baker, 1991; McKinley & Urbina, 2008; Parker et al., 2009; Smith & McCarty, 2009; Morss & Hayden, 2010; Nagele & Trainor, 2012; Gibbs & Holloway, 2013; Martin et al., 2017; Rashid et al., 2025).

One reason contributing to ~~this low uptake of~~ not taking protective action in severe weather events ~~like tornadoes may~~ might be that people do not receive probabilistic information (e.g., there is a 40% chance of tornado) of the event from the forecast which may reduce trust. Indeed, many forecasts do not provide people with an estimated probability of the event (deterministic forecasts), although such information is increasingly available with its dissemination encouraged by scholars (AMS, 2002, NRC. 2006, Morss et al., 2008; Nagele & Trainor, 2012, Gallo et al., 2016; Karstens et al., 2015). There is experimental evidence that providing such information helps people better understand the likelihood of the weather event, increases trust in the forecast, and allows people to make better decisions compared to deterministic forecasts (Ash et al., 2014; Joslyn & LeClerc, 2013; Klockow-McClain et al., 2020; Demnitz & Joslyn, 2020; Gulacsik et al., 2022; Qin et al., 2024). The only exceptions were at very low probability levels (e.g., 10%; Morss et al., 2010, Qin et al., 2024) where no advantage was observed for probabilistic forecast.

Moreover, in cases where probabilistic forecasts improved decisions, participants still showed a risk-seeking tendency (not taking protective actions when warranted). ~~The~~ This risk seeking tendency was observed despite the fact that participants' self-reported perception of the likelihood of the weather event was fairly accurate or slightly overestimated (Grounds & Joslyn, 2018; Burgeno & Joslyn, 2023; Gulacsik et al., 2022; Qin et al., 2024). This suggests that ~~receiving~~ perceiving the probability of the severe weather event is only part of the problem. Additional biases must have contributed to their risk-seeking decisions.

Naturalistic Weather Tasks Requiring Decision Making under Risk

A typical experimental approach to weather decision tasks is to provide participants with forecasts ~~(probabilistic or deterministic)~~ for a possible severe weather event over multiple trials and measure their decisions and sometimes their risk perception (Morss et al., 2010; Joslyn & LeClerc, 2013; Grounds & Joslyn, 2017; Demnitz & Joslyn, 2020; Klockow-McClain et al., 2020; Gulacsik et al., 2022; Burgeno & Joslyn, 2023; Qin et al., 2024). On each trial participants decided whether to spend points from an initial endowment to protect themselves (safe options) or lose points if they ~~did not do so~~ do not protect themselves and severe weather occurred (risky option). These tasks were usually framed as a loss such that participants ~~could~~ can only lose points, similar to real world severe

[move sentence from below]

weather situations. The participants' goal was to retain as many points as possible after a series of trials. These studies usually had two dependent measures on each trial: 1) Subjective likelihood: Participants' rating of the likelihood of the weather event, usually measured using a continuous scale from 0% to 100% (reported in Demnitz & Joslyn, 2020; Gulacsik et al., 2022; Qin et al., 2024); 2) Binary decisions: The decision between the safe and the risky option (reported in all studies).

Both measures were compared to a rational standard (Joslyn & LeClerc, 2013; Grounds & Joslyn, 2018; Demnitz & Joslyn, 2020; Klockow-McClain et al., 2020; Gulacsik et al., 2022; Burgeno & Joslyn, 2023; Qin et al., 2024). Subjective likelihood was compared to objective probabilities, which were the probabilities of the weather event on each trial that were calibrated to be roughly reliable[1]. These Objective probabilities were provided to participants on each trial, ~~in experimental~~ [redacted]. Binary decisions were compared to economically rational decisions based on expected value theory: If people want to maximize their gain or minimize their loss, they should choose the option with the best expected value (sum of the option's outcome multiplied by the probability; Tversky & Fox, 1995). The probability at which the fixed cost of the safe option and the expected value of the risky option broke even is the economically rational criterion ~~(the probability above which one should choose the safe option rather than the risky option as it has better expected value)~~. Decisions made ~~with~~ using this criterion [redacted] were considered economically rational.

The findings of these studies were twofold. First, participants' subjective likelihood was slightly overestimated compared to the objective probabilities (Demnitz & Joslyn, 2020; Gulacsik et al., 2022; Qin et al., 2024). Next, although participants' decisions were often closer

[1] Usually rounded up or down to a number divisible by 5 (e.g., 33.33% rounded to 30%).

to economically rational with probabilistic information than without, there was still a gap (Joslyn & LeClerc, 2013; Grounds & Joslyn, 2018; Demnitz & Joslyn, 2020; Gulacsik et al., 2022; Burgeno & Joslyn, 2023; Qin et al., 2024). Decisions were generally risk-seeking (failing to choose the safe option when it was warranted) despite the fact that participants' subjective likelihood of the weather event was close to or an overestimation of the objective probabilities (Demnitz & Joslyn, 2020; Gulacsik et al., 2022; Qin et al., 2024). Most tasks used a loss frame like the example above in which participants could only lose points. However, some of the tasks involved a mixed gamble in which it was possible to both gain and lose points from the options. Here, participants were overall risk-averse, a decision bias where they chose the safe option more often than economically rational (Demnitz & Joslyn, 2020).

Participants' overall risk-seeking tendency in a loss frame and risk-aversion in a mixed gamble is consistent with a gain-loss framing effect in which people tend to take more risk than economically rational for losses and less risk than rational for gains (Kahneman & Tversky, 1979). However, the result of overestimated subjective likelihood and risk-seeking decisions in a loss frame (Gulacsik et al., 2022; Qin et al., 2024) presents a curiosity if considered together. When all else is equal and unbiased, an overestimated self-reported subjective likelihood should have led to risk-averse decisions. If people thought the likelihood of the weather event was higher than it actually was, they should have taken the safe option more often than economically rational. Nonetheless, the studies reviewed here found an opposite tendency (Gulacsik et al., 2022; Qin et al., 2024).

This combination of biases was also observed in a game of chance experiment, suggesting that the phenomenon is not limited to naturalistic weather tasks (Barron & Ursino, 2013). In this loss-frame study, participants indicated subjective likelihood and chose between a safe option (sure loss) and a risky option (a gamble). Unlike the experiments reviewed above no probabilistic information was provided. Both the probability of a large loss on each trial and the economically rational criterion in the risky lottery was at 15%, similar to low probability high severity weather events in real life. Participants' decisions showed risk-seeking, but their subjective likelihood showed overestimation. Therefore, this disconnect between the subjective likelihood and decisions was not unique to naturalistic weather settings.

Solving this curiosity is important because it suggests that there is another component in the decision-making process that leads to the risk seeking bias described above. In the study reported here, we ask whether the observed risk seeking tendency could be explained by a high subjective criterion, the likelihood above which one decide to take protective actions. A signal detection theory perspective was used such that we assume that people choose the safe option whenever their subjective likelihood is above their subjective criterion, which may or may not be the same as the economically rational criterion. The study reported here tested the hypothesis that a biased subjective criterion is the primary component in the risk seeking decision-making in naturalistic weather decision tasks.

A biased subjective criterion ~~was~~ has been thought to explain biased reasoning in the motivated reasoning literature. People required more evidence to be convinced that their preferred conclusion is false compared to the nonpreferred conclusion (Kunda, 1990;Windschitl et al., 2010). This account suggests that while people's subjective likelihood was accurate, they had a lower subjective criterion to predict a desirable as compared to an undesirable outcome. A biased subjective criterion might also be a factor in risk-seeking behavior in naturalistic weather tasks. When subjective likelihood is well calibrated to objective probabilities, a higher subjective criterion could explain a decision risk-seeking bias, as people require higher subjective

[Only italize the circled words]

likelihood in order to choose the safe option. Theoretically a high enough subjective criterion ~~could~~ can counteract an overestimated subjective likelihood and lead to risk-seeking decisions. For example, if the objective probability is 30% and the economically rational criterion is 20%, one should choose the safe option. However, a person ~~could~~ might choose the risky option because their subjective criterion is 50% and subjective likelihood is 40%. In this case, despite the overestimated subjective likelihood, this person shows a decision bias towards the risky option. Therefore, a ~~[illegible]~~ biased subjective criterion can explain the disconnect between overestimated subjective likelihood and risk-seeking decisions.

Signal Detection Theory and Decision Making

Originating from perceptual experiments, signal detection theory concerns two separate psychological mechanisms: *An internal representation referred to as the signal of the stimulus* and *the subjective criterion in signal strength required by the decision maker to identify it as present* (See Figure 2; Macmillan & Creelman, 2005). Separate internal representations are generated, one by the presence of the stimulus and the other by background noise that would be present even when the stimulus is absent. Both are assumed to be noisy and follow ~~a normal~~ some typically normal distribution. Because of the noise, the same external signal ~~might be internally~~ is represented differently each time. The ability to differentiate internal representations of the stimulus present versus absent is the person's *sensitivity*. The sensitivity is jointly determined by the distance between the two internal representation distributions and ~~how noisy they are~~ their noise. The further apart or the less ~~noisy they are,~~ noise the less the two distributions overlap, ~~and in turn the~~ which results in greater ~~the~~ sensitivity.

(New Para.)

The subjective criterion is the strength of the internal representation above which the presence of the stimulus is reported. The placement of the subjective criterion indicates whether there is a decision bias towards reporting a presence or an absence of the stimulus. Under the same internal representations, a lower subjective criterion ~~(a decision bias towards reporting a presence of the stimulus~~) leads to an increase in both hits and false alarms while a high subjective criterion ~~(a decision bias towards reporting an absence~~) leads to a decrease in both these outcomes. In short, a change in subjective criterion can lead to a behavioral change even if the internal representation distributions stay the same.

Assuming stochastic internal representations such as those of signal detection theory is not new to decision theory (Busemeyer & Townsend, 1993; Thurstone 1994; Wallin et al 2018). For stochastic representations, one does not necessarily make the same decision based on the same external information ~~every time~~. This means that, in the context of weather decision tasks, one does not take protective action every time the objective probability is above the economically rational criterion. Signal detection theory with variable internal representations can be integrated with behavioral economics theories such as prospect theory that consider the uncertainty in the outcomes to better understand decision-making processes (Lynn et al., 2015).

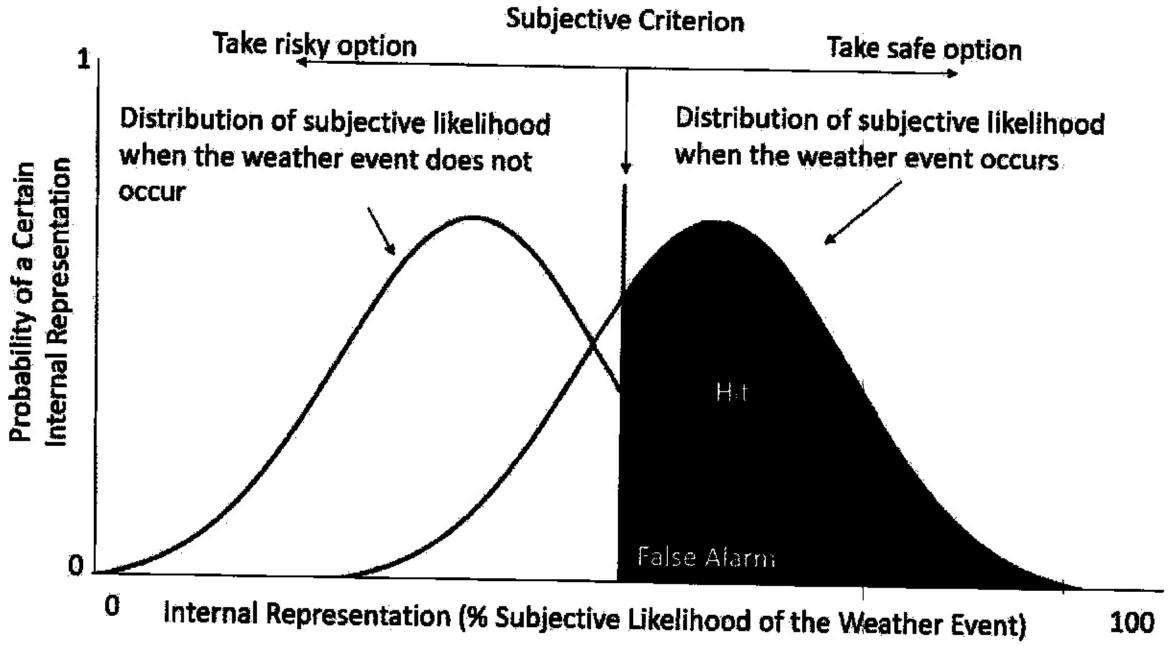

Figure 2

Random Likelihood Model Example Based on Signal Detection Theory

Note. The random likelihood model ~~does not~~ need not assume the shape of the internal representation distribution. Normal distributions are used in the graph as an example.

Figure 2 needs to be described.

Signal detection theory has been applied to the study of diagnostic decisions in real life decision making under risk (Swets et al., 2000). For example, a physician needs to diagnose whether a patient has cancer based on an X-ray. The physician's ability to interpret the X-ray is a combination of their sensitivity and the amount of evidence they need in order to diagnose cancer (subjective criterion). As with many diagnostic decisions, the utility of a miss is not the same as the utility of a false alarm. In this example, perhaps not diagnosing cancer when the patient actually has cancer is less acceptable than incorrectly diagnosing cancer when the patient does not have cancer. Therefore, the physician should have a lower, more liberal criterion (require less evidence) to increase hits at the expense of higher false alarms. Signal detection theory has been applied in these situations is to identify the (economically) rational criterion to increase decision utility in domains like medical/psychiatric diagnoses, violent risk assessment, weather forecasting, and school admissions (Swets et al., 2000). In previous work ~~In other words~~, some ~~previous~~ studies, ~~employing this approach,~~ aimed to provide a prescriptive rational criterion for decision makers. Others have aimed to distinguish effects on "sensitivity" and "bias". ~~a descriptive goal~~ like the research reported here. For instance, signal detection theory was applied in weather forecasting to distinguish forecast accuracy (sensitivity) from forecasters' decision criteria (bias) (Harvey et al., 2012). ~~Unlike the study reported here however, it did not compare the forecasters' decision criteria with a rational standard to examine bias which is the focus of the study reported here.~~

Stimulus-Response Table		
	Stimulus Present	Stimulus Absence
Reporting a presence	Hit	False Alarm
Reporting an absence	Miss	Correct Rejection
Weather Tasks		
	Severe Weather Present	Severe Weather Absence
Taking protective actions	Hit	False Alarm
Not taking actions	Miss	Correct Rejection

Table 1

Stimulus-Response Table Used in Signal Detection Theory And Adaptation in Weather Tasks

Random Likelihood Model

Signal detection theory is applied in this project by assuming a random likelihood model. It is analogous to a ~~analogous to the~~ random utility model ~~where~~ in which a given value is translated to a noisy utility (Bockenholt, 2006). As illustrated in Table 1, the four outcomes in the naturalistic weather decision tasks align with the four outcomes in signal detection theory (hit, false alarm, miss, correct rejection), allowing the application of the theory to participants' behavior in these tasks (Ferrell & McGoey, 1980, Harvey et al., 2012). Subjective likelihood is considered the internal representation of whether or not the weather event will occur, using a similar method to a previous application of signal detection theory (Ferrell & McGoey, 1980). We assume that the subjective likelihood of the weather event has variability while the subjective criterion has no variability.

This model assumes that the subjective likelihood varies over the trials even when given the same forecast information. This assumption is ~~also~~ consistent with previous studies with naturalistic decision-making tasks where the subjective likelihood differed in the same participant in different trials with the same objective probability (Demnitz & Joslyn, 2020; Gulacsik et al., 2022; Qin et al., 2024). The model does not assume a specific shape of distribution for this variability. This is possible because ~~in this study~~ subjective likelihood ratings were elicited directly as an estimate of the distribution. ~~This assumed variability is consistent with signal detection theory where the internal representation is noisy (Macmillan & Creelman, 2005).~~ In this project, this random variability of subjective likelihood is considered the result of an amalgamation of many factors. For example, experience with weather events in preceding trials has been ~~was~~ found to affect the behavior in the subsequent trials, perhaps due to the availability heuristic, where an event is deemed more likely if an event of the same type is experienced more recently and therefore, more likely to come to mind (Kahneman, 2003; Demnitz & Joslyn, 2020).

The random likelihood model assumes that the subjective criterion has no variability, consistent with the typical application of signal detection theory (Macmillan & Creelman, 2005). I[illegible] People might change their subjective criterion between decisions depending on the outcome of previous trials (Demnitz & Joslyn, 2020). However, we chose a fixed subjective criterion as a simplifying assumption f[illegible].

This model allows [illegible] for [illegible] bias in the subjective likelihood or the subjective criterion. [illegible] Biases in either [illegible] can shift one's decision away from the economically rational decision in three separate ways. 1) A higher subjective criterion can lead to risk-seeking bias while a lower subjective criterion can lead to a risk-averse bias. 2) A bias in the subjective likelihood ([illegible]). Higher subjective likelihood shifts the internal representations further above the subjective criterion [illegible], [illegible]ly leading to a decision bias towards the safe option. Lower subjective likelihood shifts the internal representations down toward the subjective criterion [illegible], leading to a bias towards the risky option. This bias is assumed to not affect the sensitivity as both internal representation distributions are moved equally. 3) A greater sensitivity either resulting from increased distance between the distributions or reduced variability can lead to more hits and fewer false alarms regardless of the decision bias.

The study reported here used the random likelihood model to examine two possible explanations for the tendency toward risk seeking decisions: A sy[illegible] bias in the subjective criterion [illegible] versus a [illegible] bias in the subjective likelihood distribution.

Possible Sources of Bias

[cast these as co–
2 hypotheses?]

Two possible explanations for a shift in the subjective criterion away from the economically rational criterion are investigated in the study reported here: The centering effect and the gain-loss framing effect. People judging a quantity tend to bias their judgement towards the center of the quantity's range (also called central tendency bias; Poulton, 1979; Olkkonen et al., 2014). This effect ~~traced~~ has its roots in perceptual experiments ~~and~~ but has been observed in many ~~different~~ settings, including noise volume, distance, color perception, and estimation of opposing bidders' bid in an auction (Poulton, 1979; Radvansky et al., 1995; Olkkonen et al., 2014). It is possible that a similar effect is ~~also~~ present in the subjective criterion and subjective likelihood ~~in~~ of decision-making tasks. For instance, an economically rational criterion at 20% might result in the subjective criterion to between 20% and the midpoint of 50%, while an economically rational criterion at 80% might lead to a subjective criterion between 50% and 80%. Similarly, subjective likelihood might be placed between the objective probability and 50%.

[Add ref. for prospect theory]

A second source of decision bias is the gain-loss framing effect, as explained by prospect theory. In the current analysis, this manifests ~~manifesting~~ as a biased subjective criteria. Risk-aversion in the gain frame might be due ~~correspond~~ to a subjective criterion lower than what is economically rational, while a risk-seeking tendency in the loss frame might be due ~~correspond~~ to a higher subjective criterion. These two sources of bias are not mutually exclusive and might both contribute to a biased subjective criterion.

Overview of Analyses and Experiments

~~First the study reported here reanalyzed~~ To begin, two previously published experiments from Qin et al., 2024 were reanalyzed using the random likelihood model to determine the subjective likelihood, subjective criterion, and the sensitivity. The analysis further considered whether the results ~~in existing~~

[redacted] were consistent with the centering effect or the gain-loss framing effect. Then [redacted] two new naturalistic weather decision experiments were conducted to examine the biased criterion hypothesis and the biased likelihood hypothesis[2] [redacted]

Reanalysis of Previous Experiments

Method of Tornado Experiments

In the two previously published experiments (Qin et al., 2024), participants made decisions based on a tornado warning about whether to take shelter from possible tornadoes (safe option) or not (risky option). The tornados warning were presented either with or without the probability of a tornado, manipulated between groups. The reanalysis presented here included only the probabilistic conditions. In these conditions, participants were given reliable objective probabilities of the tornado (e.g., 30% chance of tornado) either in the form of a color-coded visualization (red format) or a numeric percentage (tabular format). As the differences between these conditions was not the concern of the study reported here, they were combined. There were 83 participants from experiment 1 and 85 from experiment 2 in the reanalyses.

The procedure of the two experiments was identical. There were 68 trials in total. On each trial, participants saw a tornado warning, rated how likely they thought the tornado would be (likelihood ratings), and decided between the safe option and the risky option (binary decision). At the end of each trial, they were told whether the tornado occurred. As mentioned above, there was a point cost to shelter and a larger point penalty if participant failed to shelter and a tornado hit their location. Therefore only losses were possible. Participants' goal was to lose as few points as possible by the end of the experiment.

[2] Two pilot experiments, not reported here, examined the gain-loss framing effect. One yielded a significant effect and the other yielded a trend in the expected direction but failed to reach significance due to low power.

[I would cut this or move it to the Methods.]