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# An overall probability of winning heuristic for complex risky decisions: Choice and eye fixation evidence

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ABSTRACT

When faced with multi-outcome gambles involving possibilities of both gains and losses, people often use a simple heuristic that maximizes the overall probability of winning (Pwin). Across three different studies, using choice data as well as process data from eye tracking, we demonstrate that the Pwin heuristic is a frequently used strategy for decisions involving complex (multiple outcome) mixed gambles. Crucially, we show systematic contextual and individual differences in the use of Pwin heuristic. We discuss the implication of these findings in the context of the broader debate about single versus multiple strategies in risky choice, and the need to extend the study of risky decision making from simple to more complex gambles.



## Introduction

The study of how individuals, groups, and organizations make risky choices is perhaps the oldest area of behavioral decision research (Bernoulli, 1738; Brandstatter, Gigerenzer, & Hertwig, 2006; Lichtenstein, 1965; Payne & Braunstein, 1978; Tversky & Kahneman, 1992). Nonetheless, as noted by Luce, "the issue of a suitable descriptive decision theory for gambles with three or more consequences is still very much up in the air" (Luce, 2000). Most theories of risky choice are built on studies involving simple two-outcome gambles of the form ($x, $p$; $y, $1 - p$), where one receives $x with probability $p$ or $y with probability $1 - p$. Such gambles afford great experimental control and are ideal for studying the simple tradeoff between amount to be won and the probability of winning (Lopes, 1995; Lopes & Oden, 1999). However, many real world decisions under risk involve multiple outcomes, some of which may be perceived as gains and others as losses. Multi-outcome mixed gambles, those with at least one positive and one negative outcome, are more representative of such natural decisions. They have a number of methodological and theoretical advantages over simpler gambles (Brooks & Zank, 2005; Lichtenstein, 1965; Loomes, 2010), and offer better opportunities to explore the contingent use of heuristics and strategies in risky choice.

In this paper, we focus on one heuristic for complex mixed gambles that is based on the overall probability of winning (Pwin) aggregated across all the outcomes of a gamble (Payne, 2005). In particular, this heuristic is only meaningful when choosing between mixed gambles that involve three or more outcomes, with two outcomes of the same sign and one outcome of the opposite sign. The Pwin heuristic is consistent with the importance of achieving an aspiration level, a key idea stressed by Simon (1955) in his conception of bounded rationality in the face of a complex world, and extended in a recent model that integrates the overall probability of success and failure relative to an aspiration level into a standard utility representation (Diecidue & van de Ven, 2008). The use of a similar heuristic has been shown in other areas as well, with repeated investment decision makers being significantly averse to the overall probability of losing (Zeisberger, 2013). Specifically, investors were very sensitive to the high frequency of losses, even when these losses were relatively small and had only a limited impact on overall performance.

We pursued four main objectives in this paper. First, we sought to demonstrate that the overall probability heuristic is a frequently used strategy for risky choice involving complex gambles. Second, we utilized the temporal richness of data from eye tracking to

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characterize the processing strategies underlying the use of Pwin heuristic. Prior work demonstrating the use of Pwin heuristic has concentrated primarily on the choices made (Venkatraman, Payne, & Huettel, 2011). Though one study used fMRI to study choice preferences in a task similar to the one used here (Venkatraman, Payne, Bettman, Luce, & Huettel, 2009), much remains unknown about how and when people use the Pwin heuristic. Third, we sought to characterize the boundary conditions for the use of the Pwin heuristic. We were particularly interested in how changes in task types (e.g., expected value differences) affects the use of this heuristic and processing strategies. Finally, we sought to better understand the adaptive use of processing strategies in complex gambles by comparing the process predictions of Pwin heuristic to that of the most popular compensatory and non-compensatory models of risky choice, namely cumulative prospect theory (CPT) and priority heuristic (PH) respectively across trial types. We then relate these findings to the broader debate about the use of single versus multiple strategies in risky choice.

The rest of the paper is organized as follows: First, we introduce a modified version of the value allocation task from Payne (2005), which will be used in all studies presented in this paper. We then briefly discuss two of the most popular models of risky choice, CPT and PH, and their different predictions for the value allocation task both in terms of choice and underlying process (eye fixation) data. We will also discuss the process implications for the Pwin heuristic, and outline specific testable predictions about the effect of task context on these process measures. Next, we provide details and findings from three independent studies using the value allocation task. Finally, we discuss the implications of our findings, along with findings from previous studies using a similar paradigm, for models of risky choice and strategy selection. Specifically, we consider how our findings can address the ongoing debate about the use of single versus multiple strategies for explaining individual and task differences in risky choice.

*Value allocation task*

The *value allocation task*, first proposed by Payne (2005), is a risky choice task involving complex mixed-gambles with multiple outcomes. In the value allocation task, participants are presented with a multiple-outcome gamble ($x_1,p_1;x_2,p_2;x_3,\ldots;x_n,p_n$), where $p_i$ indicates the probability of monetary outcome $x_i$. The outcomes are rank-ordered $x_1 > x_2 > x_3 > \ldots > x_n$, where at least one outcome is a strict gain ($x_1$ > $0) and one is a strict loss ($x_n$ < $0). For example, when presented with a three-outcome gamble ($60, 1/3; −$10, 1/3; −$80, 1/3), participants can win $60 with probability 1/3, lose $10 with probability 1/3, or lose $80 with probability 1/3. Participants can then improve the gamble by adding a fixed amount ($20) to one of the outcomes. More specifically, they could choose to add the $20 to the best outcome, thereby increasing maximum possible gain to $80 (gain-maximizing or Gmax choice), or they could chose to add it to the worst outcome, reducing the worst possible loss from $80 to $60 (loss-minimizing or Lmin choice). Alternatively, they could also add the $20 to the intermediate ranked outcome, changing its valence from a loss to gain of $10. Since adding money to the intermediate alternative improves overall chances of winning (2/3 compared to 1/3 in other alternatives), choosing that alternative is referred to as the probability-of-winning (Pwin) heuristic choice. The Pwin heuristic represents a computational simplification for complex gambles that ignores payoff (value) magnitude information and focuses on the "gist" (gain versus loss) of an outcome value relative to a reference value. The value allocation task can be used to test predictions of different choice models, while still maintaining experimental control over variations in values and probabilities across gambles.

In the original study (Payne, 2005), approximately two-thirds of participants preferred the option that maximized the overall probability of winning. Individuals preferred this option even when it was associated with lower expected value, and when adding money to the intermediate outcome changed it from a loss to $0 (probability-of-not-losing). In two independent studies since, Venkatraman and colleagues replicated the preference for Pwin heuristic using both real and hypothetical payoffs (Venkatraman et al., 2009). We refer to Pwin heuristic in the current study as those that involve any change in the overall probability of winning, or not losing (i.e. changing intermediate outcome from $0 to a gain, from a loss to $0 or from a loss to a gain).

In order to systematically characterize preferences in the value allocation task, it is important to have data about ongoing processes of information acquisition and evaluation, not just the end decision. Process measures have played an important role in explaining risk preferences, and in validating models of risky choice over the past decade (Glockner & Herbold, 2011; Johnson, Schulte-Mecklenbeck, & Willemsen, 2008; Willemsen, Bockenholt, & Johnson, 2011). In this study, we focus on eye tracking to investigate decision processes (Lohse & Johnson, 1996; Rayner, 1998; Russo & Rosen, 1975). Eye-tracking data can be collected completely passively and naturally, without any impact on the processes they are designed to measure – unlike other approaches for monitoring information acquisition behavior like Mouselab (Payne, Bettman, & Johnson, 1988). Fixation durations obtained using eye tracking provide valuable insights into underlying cognitive processes (Horstmann, Ahlgrimm, & Glockner, 2009). According to the gaze cascade model, alternatives most likely to be chosen receive the greatest attention as measured by increased gaze processing (Glaholt & Reingold, 2009; Shimojo, Simion, Shimojo, & Scheier, 2003). Additionally, the richness of temporal data obtained from eye tracking allows us to study the dynamics of information processing much better than Mouselab and other process methods. In a recent study using eye tracking, Glockner and Herbold tested process predictions of various models like CPT and PH using simple gambles (Glockner & Herbold, 2011). They found that choices, response times, amount of information acquired, fixation durations and direction of information search were all consistent with the use of compensatory strategies in their study. In this study, we sought to extend these findings to more complex gambles. Specifically, we evaluated choice and process predictions of popular risky choice models in the value allocation task, and contrasted them to predictions of Pwin heuristic as described below.

*Theories of risky choice*

Compensatory models of risky choice, based on the idea that people make tradeoffs between the values of possible outcomes and their probabilities of occurrence, have a rich history starting from the early insights of Pascal and Bernoulli (Bernoulli, 1738) to recent formulations like Cumulative Prospect Theory (Tversky & Kahneman, 1992). Yet, motivated by the idea of bounded information processing capacity (Simon, 1955), it has been argued that risky choice often involves the use of simpler non-compensatory heuristics (Brandstatter et al., 2006; Lichtenstein, 1965; Payne & Braunstein, 1978). Here, we focus specifically on two theories – Cumulative Prospect Theory (CPT) and the Priority Heuristic (PH). CPT is the best known compensatory descriptive model of risky behavior while the PH is a popular non-compensatory heuristic model for mixed gambles (Brandstatter et al., 2006). For the value allocation problems, both CPT (Tversky & Kahneman, 1992) and PH make distinctly different predictions from the Pwin heuristic, and from each other. We now discuss these predictions in greater detail.