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Is Making a Risky Choice Based on a Weighting and Adding Process? An Eye-Tracking Investigation

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The debate about whether making a risky choice is based on a weighting and adding process has a long history and is still unresolved. To address this long-standing controversy, we developed a comparative paradigm. Participants' eye movements in 2 risky choice tasks that required participants to choose between risky options in single-play and multiple-play conditions were separately compared with those in a baseline task in which participants naturally performed a deliberate calculation following a weighting and adding process. The results showed that, when participants performed the multiple-play risky choice task, their eye movements were similar to those in the baseline task, suggesting that participants may use a weighting and adding process to make risky choices in multiple-play conditions. In contrast, participants' eye movements were different in the single-play risky choice task versus the baseline task, suggesting that participants were not likely to use a weighting and adding process to make risky choices in single-play conditions and were more likely to use a heuristic process. We concluded that an expectation-based index for predicting risk preferences is applicable in multiple-play conditions but not in single-play conditions, implying the need to improve current theories that postulate the use of a heuristic process.

Keywords: risky choice, weighting and adding process, eye movements, single-play versus multiple-play, probability-proportion task paradigm

Living in the information age is both exhilarating and mind-boggling. Vast numbers of goods and services are currently available, and the range increases every day. With the advent of the "goods explosion," many daily decisions, such as whether to buy insurance or eat genetically modified foods, must be made at certain risks. These decisions can be interpreted as choices between options with different outcomes, which are realized with specific probabilities. Risky choices are commonly made in everyday life, and the following two fundamental questions naturally arise as a result: How do people behave when facing risky choices, and what mechanism underlies decision making under conditions of risk?

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The Family of Compensatory Models

A common prediction that can be deduced from mainstream theories of risky choices is that people integrate outcomes and probabilities in a compensatory weighting and adding process. In other words, individuals weight each outcome by its probability, sum all of the possible outcomes to assign an overall value (expectation) to each option (given by $\sum \pi(p_i) \cdot \nu(x_i)$, where ν denotes the subjective transformation of an outcome and π is the subjective transformation of a probability), and then select the option that offers the highest expectation (Basili & Chateauneuf, 2011; Edwards, 1954; Kahneman & Tversky, 1979; Savage, 1954; Tversky & Kahneman, 1992; von Neumann & Morgenstern, 1947).

The original member of the family of compensatory models is *expected value theory,* which defines an expectation in terms of the objective probabilities p_i (i.e., $\pi(p_i) = p_i$) and the objective values of outcomes x_i (i.e., $\nu(x_i) = x_i$) (Pascal, 1670). Therefore, judging the attractiveness of each option is based on its expected value, which is calculated with the formula $\sum p_i \cdot x_i$. However, several robust phenomena in people's responses to risky choices clearly violate expected value theory. For example, few people are likely to pay even $25 to play the St. Petersburg game with an infinite expected value (Hacking, 1980).[1] Therefore, proponents of the

[1] A casino offers a game of chance for a single player in which a fair coin is tossed at each stage. The pot starts at 1 dollar and is doubled every time a head appears. The first time a tail appears, the game ends and the player wins whatever is in the pot. Thus, the player wins 1 dollar if a tail appears on the first toss, 2 dollars if a head appears on the first toss and a tail appears on the second, 4 dollars if a head appears on the first two tosses and a tail appears on the third, 8 dollars if a head appears on the first three tosses and a tail appears on the fourth, and so on. In short, the player wins 2^{k-1} dollars if the coin is tossed k times until the first tail appears.

original expected value theory have transformed it into many other forms. For example, *expected utility theory* (von Neumann & Morgenstern, 1947) defines an expectation in terms of objective probabilities and nonlinear utilities of outcomes (e.g., $v(x_i) = \log(x_i)$), and *subjectively expected value theory* (Edwards, 1954) involves nonlinear subjective probabilities and objective values of outcomes. *Cumulative prospect theory* (Tversky & Kahneman, 1992), on the other hand, involves both nonlinear subjective probabilities (i.e., $\pi(p_i) = p_i^{\gamma}/[p_i^{\gamma} + (1 - p_i)^{\gamma}]^{1/\gamma}$) and nonlinear utilities of outcomes (i.e., $v(x_i) = x_i^{\alpha}$). Other examples of modified theories include the *rank-dependent utility model* (Quiggin, 1982) and the *sign-dependent utility model* (Einhorn & Hogarth, 1986). These theories differ in their assumptions about whether the utilities of outcomes and the subjective probabilities are linear or nonlinear with respect to the objective values. However, the theories converge on the prediction that the attractiveness of a risky option is given by its expectation, which is obtained with a two-step, weighting and adding algorithmic computation. Therefore, according to the family of compensatory models, making choices between risky options seems quite simple and straightforward, as decision makers are required only to (a) calculate the mathematical expectation of each option separately following a weighting and adding process with respect to the functions π and v and (b) select the option that maximizes the expectation.

The Family of Noncompensatory Models

The family of compensatory models, however, has been increasingly doubted. Some challenging evidence has indicated that some compensatory models, such as expected value and expected utility theories, perform poorly when predicting the choices that will be made between risky options in single-play conditions, although they seem to perform adequately in multiple-play conditions (Keren, 1991; Klos, Weber, & Weber, 2005; Langer & Weber, 2001; S. Li, 2003; Montgomery & Adelbratt, 1982; Redelmeier & Tversky, 1992; Wedell & Böckenholt, 1994). Because the computational capacity of human decision makers is limited, researchers have developed another family of decision-making models called noncompensatory models. Guided by a distinctly different theoretical orientation, these models suggest that a heuristic process is involved in decision making. By following a heuristic process, people do not need to integrate information from all dimensions to arrive at a decision; rather, they rely on only one (or a few) key dimension(s). For instance, the *minimax heuristic* (Brandstätter, Gigerenzer, & Hertwig, 2006) predicts that people rely on only the minimum payoff dimension and choose the option with the highest minimum payoff. The *priority heuristic* (Brandstätter et al., 2006) predicts that people sequentially make comparisons between options according to their minimum gains, the probabilities of attaining their minimum gains, and their maximum gains (for details, see Table 1). The *equate-to-differentiate* approach (S. Li, 2004) models risky decision making as a process in which people seek to "equate" the less significant differences between options in either the best or worst possible payoff dimensions, leaving the greater one-dimensional difference to be differentiated as the determinant of the final choice.

The main distinctions between a weighting and adding process and a heuristic process appear in three aspects of information search and processing: direction, depth, and complexity level. Using a weighting and adding process generally requires an alternative-based (option-based) information search pattern, integration of all the information about the options, and complex computations (e.g., multiplication and integration). In contrast, using a heuristic process requires a dimension-based information search pattern, selective use of information about the options, and simple and ordinal comparisons. Hogarth (1987) and Payne (1976) stated that the dimension-based heuristic processes can be psychologically simpler to use and implement than the alternative-based weighting and adding processes. Researchers have also argued that individual risky choices in single-play conditions can sometimes be better predicted by noncompensatory models (e.g., the priority heuristic, the equate-to-differentiate, and the least-likely heuristic) than by compensatory models (Brandstätter et al., 2006; Brandstätter, Gigerenzer, & Hertwig, 2008a, 2008b; S. Li, 2004; Pachur & Galesic, 2012; Rubinstein, 1988). These findings challenge mainstream theories by suggesting that the attractiveness of risky options in single-play conditions may actually not be judged on the basis of their respective expectations.

Table 1
Decision Rules of Six Models Tested in Predicting Choice Data

Model	Decision rule
Expected value theory	Calculate the sum of all weighted possible outcomes using the formula $\Sigma\, p_i \cdot x_i$. Choose the gamble with the highest weighted sum.
Expected utility theory	Calculate the sum of all weighted outcomes using the following formula: $\Sigma\, p_i \cdot v(x_i)$. Choose the gamble with the highest weighted sum. We assume the utility function $v(x_i) = \log(x_i)$ in this study.
Cumulative prospect theory	Calculate the sum of all weighted outcomes using the following formula: $\Sigma\, \pi(p_i) \cdot v(x_i)$, $\pi(p_i) = p_i^{\gamma}/[p_i^{\gamma} + (1 - p_i)^{\gamma}]^{1/\gamma}$, $v(x_i) = x_i^{\alpha}$. Choose the gamble with the highest weighted sum. We assume $\alpha = .88$, $\gamma = 0.61$ in the present study, as suggested by Tversky and Kahneman (1992).
The priority heuristic	Go through reasons in the following order: minimum gain, probability of minimum gain, maximum gain. Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probabilities scale. Choose the gamble with the more attractive gain (probability).
The equate-to-differentiate model	Choose the gamble with more attractive gain on the dimension (best or worst payoff) with the greatest intradimensional utility difference. We assume the utility function $v(x_i) = \log(x_i)$ in the present study.
The minimax heuristic	Choose the gamble with the highest minimum payoff.

Paradigm Developed in the Present Study

The debate about whether making a risky choice is based on a weighting and adding process has a long history and has still not been resolved. This study sought to address this long-standing controversy by using, to the best of our knowledge, a novel comparative paradigm. We compared participants' processes of information search and processing in a risky choice task with those used in a baseline task in which participants consciously made calculations using a weighting and adding process. Visually identical materials were used in both the risky choice and baseline tasks. We termed this baseline task the "proportion" task because the mathematical symbol *x*% that followed a payoff value denoted "you will get an *x*% proportion of this payoff" in this task. The same symbol meant "you will have an *x*% probability of getting this payoff" in the risky choice task. Participants were thus required to choose between riskless options, each involving several partially available payoffs, in the proportion task, whereas they were required to choose between risky options, each involving several probabilistic payoffs, in the risky choice task. It is worth noting that, in the proportion task, participants had to deliberately calculate weighted sums to obtain a maximized total payoff prior to making a choice. Such a natural mental arithmetic process is consistent with the weighting and adding processes predicted by the family of compensatory models: Payoffs in each option were first weighted by their respective proportions and then added together to obtain a total payoff to determine a final choice. The proportion task thus served as a baseline of comparison to test whether a weighting and adding process was also used in the risky choice task. We made the following two predictions:

1. If people followed a weighting and adding process when making risky choices, their processes of information search and processing in the risky choice task should be similar to those in the proportion task. If, however, participants' processes of information search and processing differed between the two tasks, the weighting and adding processes should be absent when people made risky choices.

2. If people followed a weighting and adding process when making risky choices, factors affecting the total payoff computation in the proportion task, such as computational difficulty, should affect participants' information processing in the risky choice task as well. Otherwise, the weighting and adding processes should be absent when people made risky choices.

Previous Studies on the Mechanisms Underlying Risky Choices

Most previous studies have investigated the mechanisms underlying risky choices by comparing the choices of individuals with the predictions of given models (e.g., Ayal & Hochman, 2009; Birnbaum, 2008a, 2008b). However, using choice data cannot validate or invalidate all the members of the family of compensatory models. Once a given form of expectation has been shown to be a poor predictor of individuals' risky choices, revamped forms would subsequently be proposed to accommodate the choice data.

Since the 1970s, a large body of studies has used a seemingly more efficient way to address this issue. These studies examined whether individuals' processes of information search and processing in making risky choices were consistent with the predictions deduced from weighting and adding or heuristic processes. Along this way, studies from the 1970s through the 1990s claimed to have found consistent evidence for the use of heuristic processes (Mann & Ball, 1994; Payne & Braunstein, 1978; Rosen & Rosenkoetter, 1976; Russo & Dosher, 1983). For instance, researchers suggested that people examine information about risky options using a dimension-based strategy, which is consistent with the predictions deduced from heuristic processes (Payne & Braunstein, 1978; Russo & Dosher, 1983). In contrast, more recent studies have provided evidence for the weighting and adding processes by testing whether individuals' processes of information search and processing were consistent with the predictions deduced from weighting and adding processes (Glöckner & Betsch, 2008; Glöckner & Herbold, 2011; Johnson, Schulte-Mecklenbeck, & Willemsen, 2008b). For example, Johnson et al. (2008b) found that although the probability-payoff transitions predicted by weighting and adding processes are common in information search and processing, the dimension-based comparisons that are predicted by heuristic processes are rare.

However, we argue that at least some of these previous studies should be considered with caution due to three potentially problematic aspects of their experimental designs. (a) Previous researchers left out some processes, such as perception, motor action, fatigue, and intentions, when they deduced hypotheses about the process data, such as reaction time and eye movements, from the decision models. Marewski and colleagues suggested that these processes would give rise to the process data (Marewski & Mehlhorn, 2011; Marewski & Schooler, 2011). Therefore, without considering the interplay among various cognitive processes, the hypotheses about the process data deduced from the decision models could be incomplete. (b) In some studies, the fact that the options were either placed in extra boxes (e.g., Johnson et al., 2008b) or separated by lines (e.g., Glöckner & Betsch, 2008; Glöckner & Herbold, 2011) may have fostered alternative-based searches and may have blocked dimension-based comparisons (Brandstätter & Gussmack, 2013). (c) Participants were required to respond as quickly as possible in some studies (e.g., Glöckner & Herbold, 2011). As suggested by Ben Zur and Breznitz (1981), time pressure influences information acquisition under certain conditions. The current study was designed to overcome these limitations of previous researches and to formulate increasingly sound arguments about the underlying mechanisms of making risky choices.

Conditional Hypotheses on the Process Test

We applied the above mentioned comparative paradigm to the present eye-tracking study. We compared people's eye movements in a risky choice task with those in the proportion task to examine whether the calculation of the weighted sums required in the proportion task was also applicable in making risky choices. As mentioned previously, the main distinctions between a weighting and adding process and a heuristic process concern three aspects of information search and processing: direction, depth, and complexity level. Using a weighting and adding process generally requires an alternative-based information search pattern, integration of all the information available about the options, and complex computations. In contrast, using a heuristic process requires a dimension-based information search pattern, selective use of information about the options, and simple and ordinal comparisons. Three pairs of competing hypotheses concerning the main distinctions between the processes were thus derived.

Hypotheses Concerning the Direction of the Information Search

Hypothesis 1a (H_{1a}): If making a risky choice is based on a weighting and adding process, the distribution of alternative-based and dimension-based saccades across the information presented in the risky choice task will be similar to that observed in the proportion task.

Hypothesis 1b (H_{1b}): If making a risky choice is based on a heuristic process, dimension-based saccades should be more dominant in the risky choice task than in the proportion task.

Hypotheses Concerning the Depth of Information Acquisition

Hypothesis 2a (H_{2a}): If making a risky choice is based on a weighting and adding process, the amount of information that is fixated on before reaching a decision in the risky choice task will be similar to that fixated in the proportion task.

Hypothesis 2b (H_{2b}): If making a risky choice is based on a heuristic process, less information should be fixated on before reaching a decision in the risky choice task than in the proportion task, due to the selective use of information in the heuristic processes.

Hypotheses Concerning the Complexity Level of Information Processing

Hypothesis 3a (H_{3a}): If making a risky choice is based on a weighting and adding process, then the mean fixation duration in the risky choice task, which is expected to increase with increasing complexity level of information processing in the risky choice task, will be similar to that in the proportion task.

Hypothesis 3b (H_{3b}): If making a risky choice is based on a heuristic process, the mean fixation duration should be shorter in the risky choice task than in the proportion task because the complexity level of information processing is comparatively lower when using a heuristic process.

Furthermore, we manipulated the difficulty of the total payoff computation (in the proportion task). The difficulty levels were determined by whether both the payoff amounts and the proportions/probabilities of the options were two-digit or one-digit numbers multiplied by 10^n, where n is a non-zero integer (for details, see Materials and Procedure). Because computation difficulty affects the total payoff computation in the proportion task due to the complexity of the mental arithmetic and because a weighting and adding mental arithmetic is absent in the heuristic processes, a fourth pair of hypotheses concerning the impact of computational difficulty was tested in this study:

Hypothesis 4a (H_{4a}): If making a risky choice is based on a weighting and adding process, then the impact of computational difficulty on the decision time and the eye movement patterns in the risky choice task will be similar to those in the proportion task.

Hypothesis 4b (H_{4b}): If making a risky choice is based on a heuristic process, no impacts of computational difficulty on either decision times or eye movement patterns should be observed.

In the current study, participants performed two types of risky choice tasks in which they were required to choose between risky options in single-play and multiple-play conditions. We examined the mechanisms of making risky choices in these two conditions and determined whether a qualitative change (a change in the mechanism) or merely a quantitative change (a change in the number of replications) exists between multiple-play and single-play risky choices.

Method

Participants

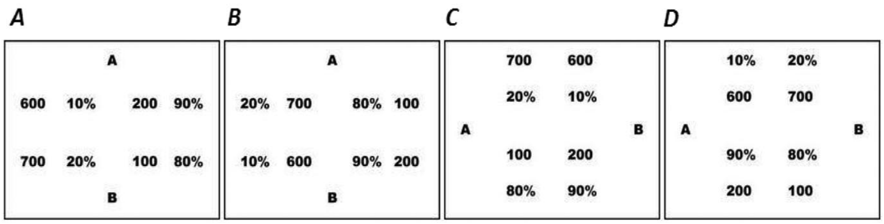
A total of 50 college students (23 males, mean age = 21.53 years) participated in this experiment. All of them had normal or corrected-to-normal vision and provided oral consent prior to the experiment. Each participant was paid 60 yuan (RMB; approximately $10) in cash for participation plus an additional amount (0–45 yuan) that was determined by his or her performance during the experiment. The mean payment was 87.67 yuan (*SD* = 16.92 yuan). One participant was excluded from the analyses due to incomplete tracking data.

Apparatus

The participants' eye movements were monitored with an EyeLink II tracker (SR Research, Canada), with the eye position sampled at 250 Hz. Participants viewed stimuli with both eyes, but eye movement data were collected from only one eye. The eye tracker automatically recorded the eye that performed better during calibration. The stimuli were presented on a 19-in. CRT monitor controlled by a Dell PC with a display resolution of 1,024 × 768 pixels. Although the eye-tracking system compensated for head movements, a chin rest located 60 cm away from the monitor was used to minimize head movements. Viewed from this distance, the screen subtended a visual angle of 28° horizontally and 21° vertically. The participants responded during the experiment by pressing a button on a Microsoft SideWinder gamepad.

Materials and Procedure

There were three tasks in the present study: a proportion task and two risky choice tasks (i.e., a single-play probability task and a multiple-play probability task). Each participant performed all three tasks. Participants performed only one task on a given day, with an interval of exactly 7 days between any two subsequent tasks. The order of the tasks was counterbalanced across participants. Visually identical experimental materials were used in all three tasks (see Figure 1 for examples). As mentioned in the previous section, the mathematical symbols *x%* that followed a payoff value meant "you will have an *x%* probability of getting this payoff" in the two risky choice tasks. Participants were re-



Panel A & Panel D

In the single-play and multiple-play probability tasks

(Making decisions between risky options in a single-play/multiple-play condition, each involving two probabilistic payoffs)

Option A ***You will have a 10% probability of getting 600 Yuan and a 90% probability of getting 200 Yuan.***

Option B ***You will have a 20% probability of getting 700 Yuan and a 80% probability of getting 100 Yuan.***

In the proportion task

(Making decisions between riskless offers, each involving two partially available payoffs)

Option A ***You will get a 10% proportion of 600 Yuan and a 90% proportion of 200 Yuan.***

Option B ***You will get a 20% proportion of 700 Yuan and a 80% proportion of 100 Yuan.***

Panel B & Panel C

In the single-play and multiple-play probability tasks

(Making decisions between risky options in a single-play/multiple-play condition, each involving two probabilistic payoffs)

Option A ***You will have a 20% probability of getting 700 Yuan and a 80% probability of getting 100 Yuan.***

Option B ***You will have a 10% probability of getting 600 Yuan and a 90% probability of getting 200 Yuan.***

In the proportion task

(Making decisions between riskless offers, each involving two partially available payoffs)

Option A ***You will get a 20% proportion of 700 Yuan and a 80% proportion of 100 Yuan.***

Option B ***You will get a 10% proportion of 600 Yuan and a 90% proportion of 200 Yuan.***

Figure 1. The same stimuli were used in all tasks, with the only exception being that the mathematical symbol *x%* represented "you will get an x% proportion of this payoff" in the proportion task but represented "you will have an x% probability of getting this payoff" in the single-play and multiple-play probability tasks. Participants were asked to make decisions between riskless offers in the proportion task, each involving two partially available payoffs, and to separately make decisions between risky options in single-play and multiple-play conditions in the single-play and multiple-play probability tasks, each involving two probabilistic outcomes.

quired to choose between risky options in single-play (single-play probability task) and multiple-play (multiple-play probability task) conditions. They were instructed as follows: "After you have made your decision, the option you selected will be played *one time/one hundred times* by the background program [as in Yechiam, Barron, & Erev, 2005]. The actual outcome of each selected gamble will automatically be added to your virtual 'winning' account. The greater the total amount in your account, the more you will be paid for this task."

In the proportion task, the mathematical symbols *x%* that followed a payoff value meant "you will get an *x%* proportion of this payoff." Participants were required to choose between riskless options. They were instructed as follows: "After you have made your decision, the total payoff of each selected option will be automatically added to your virtual 'winning' account. The greater the total amount in your account, the more you will be paid for this task." Before the experiment began, the participants were informed that they would be shown all of the actual outcomes for the selected options and paid based on the amount in the virtual account for each task after the entire three-task experiment was completed.

We constructed 32 pairs of two-payoff monetary options (see Appendix). All of the options involved gains only. The 32 pairs of options were divided into two equal groups according to the difficulty level of the total payoff computation in the proportion task (high vs. low). For the low level of computational difficulty, both the amounts of the payoffs and the probabilities/proportions were single-digit numbers multiplied by 10^n, where n was a non-zero integer (e.g., 800 and 90%, respectively). For the high level of computational difficulty, the amounts of the payoffs and the probabilities/proportions were both two-digit numbers multiplied by 10^n, where n was a non-zero integer (e.g., 750 and 85%, respectively).

Each task consisted of four 32-trial blocks, and the presentation mode was counterbalanced across the blocks—that is, 2 presentation patterns of the options (vertically, horizontally) × 2 positions of the payoffs relative to their respective probabilities/proportions (outcome first vs. probability/proportion first)—to avoid any potential influence of presentation mode on participants' information search patterns (see Figures 1 and 2). Therefore, each participant provided a total of 128 responses for each task. The order of the blocks was counterbalanced across participants with a Latin square design. In addition, any two of the eight numbers in a single stimulus lay in the periphery (out of the central 5° of vision) to ensure that participants could not perceive or identify more than one number at a time without making an eye movement (Rayner, 1998, 2009).

In each block, after the initial calibration, five practice trials (using the same pattern but different materials from those used in the testing session) were first presented to familiarize the partici-

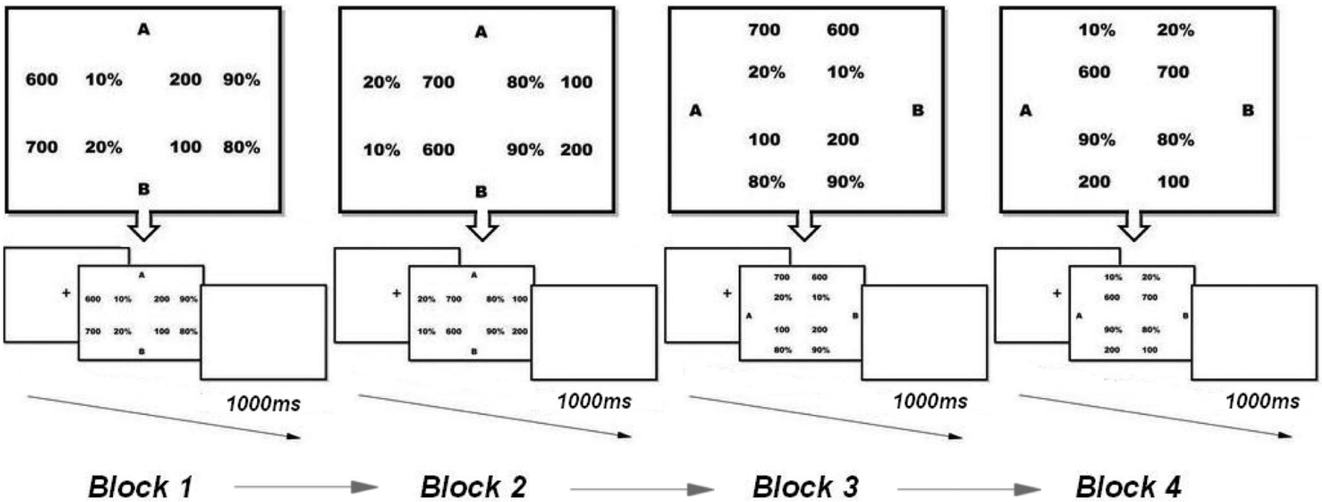


Figure 2. Each task consisted of four 32-trial blocks, with the presentation pattern of stimuli counterbalanced across blocks. The block order was counterbalanced across participants using a Latin-square design. Each trial began with a fixation cross in the middle of the screen. After each response, a 1,000-ms intertrial interval with a blank screen was presented before the next trial began.

pants with the presentation pattern for the stimuli in the block. The participants were instructed to read the options contained in each trial aloud and to orally report their choices to demonstrate their full understanding of the task. During the testing session, the participants were asked to perform the tasks without time constraints. At the beginning of each trial, the participants fixated on a cross at the center of the screen. After the participants responded, a 1,000-ms interval (with a blank screen) followed before the next trial began (for details, see Figure 2). The order of the trials in each block was randomized. No feedback concerning the outcome of the selected option was provided until the entire experiment was completed.

Data Analysis

The eye movement data were analyzed with the Eyelink DataViewer software (SR Research, Canada). Saccades were defined as eye movements with velocities faster than 30°/s and with accelerations greater than $8{,}000°/s^2$. Fixations were defined as periods of relatively stable gazes between two saccades. However, fixations shorter than 50 ms were excluded from the analyses. Eight nonoverlapping, identically sized (218 × 156 pixels) rectangular regions of interest (ROIs) were defined: Four regions covered the payoffs of both options, and four regions covered the probabilities (or proportions). We analyzed the number of fixations on each ROI, the number of saccades between ROIs, and the mean fixation duration.

Results and Discussion

Overall, 211 of the 6,272 trials (approximately 3.3%) were excluded from the analyses. Of these, 74 trials (approximately 1.2%) were discarded because of eye-tracking failures. Trials with decision times shorter than 200 ms were considered to be anticipations and were not included in the analyses (87 trials, approximately 1.4%). In each task, trials with decision times longer than 3 standard deviations from the mean (for that task) were also excluded from the analyses (50 trials, approximately 0.8%). The mean fixation duration was 224.38 ms, and the standard deviation was 35.93 ms.

Choices

We separately calculated the percentages of choices that were correctly predicted by three compensatory models: expected value theory, expected utility theory, and cumulative prospect theory. Our goal was to examine whether the participants' responses in the single-play and multiple-play probability tasks were consistent with the predictions of these three representative members of the family of compensatory models. We also separately calculated the percentages of choices that were correctly predicted according to three noncompensatory models: the priority heuristic, the equate-to-differentiate model, and the minimax heuristic. We aimed to examine how well these noncompensatory models accounted for the participants' choices. The decision rules for these six models are summarized in Table 1.

The results of the participants' choices are shown in Figure 3. A 2 (task: single-play probability task, multiple-play probability task) × 6 (model: expected value theory, expected utility theory, cumulative prospect theory, the priority heuristic, the equate-to-differentiate model, the minimax heuristic) repeated-measures analysis of variance (ANOVA) of the percentage of choices that were correctly predicted revealed a significant main effect of task, $F(1, 48) = 7.48$, $p = .009$, $\eta^2 = .14$; a significant main effect of model, $F(5, 240) = 50.56$, $p < .001$, $\eta^2 = .51$; and a significant interaction effect, $F(5, 240) = 74.21$, $p < .001$, $\eta^2 = .61$. For the single-play probability task, pairwise comparisons (least significant difference; LSD) revealed that the percentages of choices that were correctly predicted by the priority heuristic (57.0%), the equate-to-differentiate model (55.7%), cumulative prospect theory (55.1%), expected value theory (54.9%), and the minimax heuristic (54.2%) did not differ significantly from each other. However, all of these models correctly predicted significantly more choices than expected utility theory (48.4%; $ps < .01$). For the

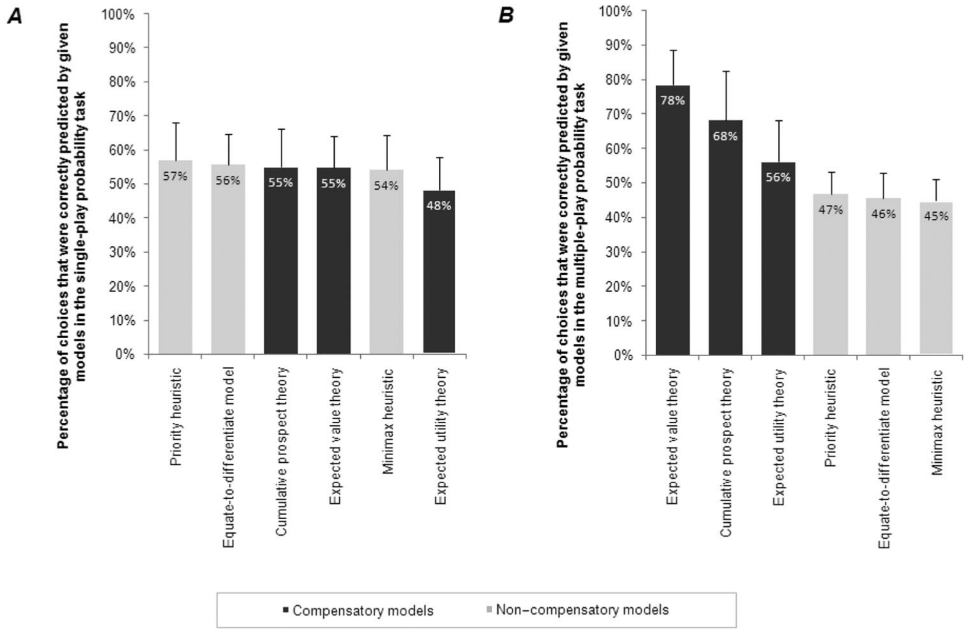


Figure 3. Panel A: Neither the compensatory models nor the non-compensatory models necessarily outperformed the others in accounting for choices made between risky options in the single-play probability task. Panel B: More choices in the multiple-play probability task were accurately predicted by the compensatory models, especially by expected value theory, than by the non-compensatory models. The error bars in Panels A and B represent standard errors of mean percentages of choices that were correctly predicted by the given decision-making models.

multiple-play probability task, the compensatory models performed significantly better than the noncompensatory models in predicting individual choices (ps $<$ .01). Expected value theory, cumulative prospect theory, and expected utility theory correctly predicted 78.4%, 68.3%, and 56.2% of individual choices, respectively. In contrast, the noncompensatory models made correct predictions at rates that were below chance (the priority heuristic = 46.9%; the equate-to-differentiate model = 45.7%; and the minimax heuristic = 44.9%).

These findings reveal that neither the compensatory models nor the noncompensatory models outperformed one another in predicting choices in the single-play probability task. The compensatory models, however, especially expected value theory, more accurately predicted choices than the noncompensatory models did in the multiple-play probability task. It is worth noting that the original version of expectation theory, expected value theory, does not perform worse (in the single-play probability task) or even perform better (in the multiple-play probability task) than the modified versions (e.g., cumulative prospect theory and expected utility theory). This implies that extensions and modifications of expected value theory appear to be unnecessary, especially in multiple-play conditions.

Decision Time

We analyzed decision time to test our hypotheses concerning the impact of computational difficulty (H_{4a} and H_{4b}). We further predicted that if making a risky choice was based on a weighting and adding process, decision time in the risky choice task should be similar to that in the proportion task. In contrast, if making a risky choice was based on a heuristic process, less time should be required to achieved a decision in the risky choice task than in the proportion task due to the lack of complex computations and the smaller amount of information to be processed (Pachur & Hertwig, 2006; Rao et al., 2011; Wang & Li, 2012).

Decision times were analyzed with a 3 (task: single-play probability task, multiple-play probability task, proportion task) × 2 (computational difficulty: high, low) repeated-measures ANOVA. The results revealed a significant effect of task, $F(2, 96) = 96.05$, $p < .001$, $\eta^2 = .67$, on decision time.[2] The participants spent, on average, the most time on the proportion task (14,862 ms) and the least time on the single-play probability task (6,585 ms), whereas the average decision time in the multiple-play probability task (11,352 ms) fell between these two extremes. Pairwise comparison tests (LSD) yielded significant between-task differences in decision times (ps $< .001$). The results also demonstrated a significant main effect of computational difficulty, $F(1, 48) = 176.75$, $p < .001$, $\eta^2 = .79$, and a significant interaction, $F(2, 96) = 77.61$, $p < .001$, $\eta^2 = .62$. A simple effects analysis of the interaction revealed a significant effect of computational difficulty in both the proportion task, $F(1, 48) = 178.00$, $p < .001$, $\eta^2 = .79$, and the multiple-play probability task, $F(1, 48) = 59.20$, $p < .001$, $\eta^2 =$

[2] In current analyses of decision time, SM value, and mean fixation duration, the means were computed by averaging decision times, SM values, and mean fixation durations across trials for each participant. All of the results were also upheld when the analyses were run based on means that were computed by using the medians across trials for each participant.

.55, but this effect was absent in the single-play probability task, $F(1, 48) = 2.06$, $p = .16$. In particular, a significant increase in decision time occurred in both the multiple-play probability task (from 8,339.70 ms to 14,364.87 ms), $F(1, 48) = 59.20$, $p < .001$, $\eta^2 = .55$, and the proportion task (from 9,428.07 ms to 20,294.99 ms), $F(1, 48) = 178.00$, $p < .001$, $\eta^2 = .79$, when the level of computational difficulty was higher. In contrast, the participants spent equal amounts of time making each decision in the single-play probability task, regardless of whether the level of computational difficulty was low (6,504.85 ms) or high (6,665.15 ms), $F(1, 48) = 2.06$, $p = .16$.

These results revealed a task-specific effect: The increase in computational difficulty, which was expected to impact the weighting and adding computation processes, affected decision time only in the multiple-play probability task. The hypothesis of the weighting and adding processes concerning the impact of computational difficulty on decision time (H_{4a}) was supported by the data obtained in the multiple-play probability task but rejected in the single-play probability task. The results also revealed a significant difference in decision time between the proportion task and the single-play probability task. We suggest that individuals were more likely to make risky choices following a weighting and adding process in multiple-play conditions and that they used a simpler heuristic in single-play conditions.

The Direction of Information Search

An index that quantifies the degree to which the direction of search is alternative based or dimension based is the *alternative-based versus dimension-based search measure* (SM) (Böckenholt & Hynan, 1994a).[3] SM is a function of the difference between the observed alternative-based and dimension-based saccades (for a critical view, see Böckenholt & Hynan, 1994a, 1994b), which is calculated as follows:

$$\mathrm{SM} = \frac{\sqrt{N}[(AD/N)(r_a - r_d) - (D - A)]}{\sqrt{A^2(D-1) + D^2(A-1)}} \tag{1}$$

where A and D denote the number of alternatives (options) and the number of dimensions, respectively (i.e., in the present study, $A = 2$, $D = 4$); r_a and r_d denote the number of alternative-based saccades and dimension-based saccades, respectively; and N denotes the number of total saccades (i.e., r_a, r_d, and N were recorded by the eye tracker). The predominance of alternative-based saccades increases with an increasing value of SM. We used this index to test our hypotheses concerning the direction of information search; that is, whether the distribution of alternative-based and dimension-based saccades in the risky choice task was similar to that in the proportion task (H_{1a}), as indicated by similar values of SM, or whether dimension-based saccades were more dominant in the risky choice task than in the proportion task (H_{1b}), as indicated by a smaller value of SM. We also used this index to test our hypotheses concerning the impact of computational difficulty (H_{4a} and H_{4b}). We reasoned that when people use a weighting and adding process that includes alternative-based computational processes, the increase in computational difficulty will lead to a more marked predominance of alternative-based saccades, which will be reflected by an increase in the value of SM.

The data were analyzed with a 3 (task: single-play probability task, multiple-play probability task, proportion task) × 2 (computational difficulty: high, low) repeated-measures ANOVA. We found a significant effect of task, $F(2, 96) = 168.09$, $p < .001$, $\eta^2 = .78$, and a significant interaction effect of task and the computational difficulty, $F(2, 96) = 16.88$, $p < .001$, $\eta^2 = .26$, on the value of SM. As shown in Figure 4 (Panel A), pairwise comparison tests (LSD) revealed a significant difference in the values of SM in the multiple-play probability task ($M = 2.02$) and the proportion task ($M = 2.55$; $p = .003$), both of which were positive and higher than the value of SM in the single-play probability task ($M = -0.25$; ps $< .001$). A simple effects analysis revealed a marginally significant increase in the value of SM in the multiple-play probability task (from 1.91 to 2.13), $F(1, 48) = 3.63$, $p = .06$, $\eta^2 = .07$, and a highly significant increase in the proportion task (from 2.27 to 2.82), $F(1, 48) = 19.18$, $p < .001$, $\eta^2 = .29$, when computational difficulty increased. The results of the simple effects analysis also revealed a significant decrease in the value of SM in the single-play probability task (from $-.15$ to $-.34$), $F(1, 48) = 22.18$, $p < .001$, $\eta^2 = .32$, when computational difficulty increased.

The above results revealed a similarity in the values of SM in the multiple-play probability task and the proportion task: The mean values of SM in these two tasks were both positive, indicating that information acquisition in these two tasks were generally in the form of alternative-based saccades, which is more consistent with the "traditional" prediction of the weighting and adding process. The results also revealed noticeable differences in the values of SM between the single-play probability task and the proportion task. The mean value of SM in the single-play probability task was negative, indicating that behaviors were generally in the form of dimension-based saccades, which is more consistent with the "traditional" prediction deduced from heuristic processes. The hypothesis of the weighting and adding processes concerning the direction of information search (H_{1a}) was rejected in light of the data in the single-play probability task, but the hypothesis of the heuristic processes (H_{1b}) was supported. Moreover, computational difficulty positively influenced the value of SM in the multiple-play probability task and the proportion task: The predominance of alternative-based saccades increased with increasingly difficulty levels of computation. The data obtained in the multiple-play probability task supported the hypothesis of the weighting and adding process concerning the impact of computational difficulty (H_{4a}). Accordingly, we suggest that the alternative-based computation process, which is one of the most important characteristics of the weighting and adding processes, emerges in making risky choices in multiple-play conditions but is likely to be absent in single-play conditions.

The Depth of Information Acquisition

The second variable of interest concerning eye movements is the percentage of total available information that was fixated on in each task. We used this variable to test our hypotheses concerning the depth of information acquisition (Payne & Braunstein, 1978); that is, whether the amount of information that was fixated on

[3] We thank an anonymous reviewer for suggesting this method of analysis.

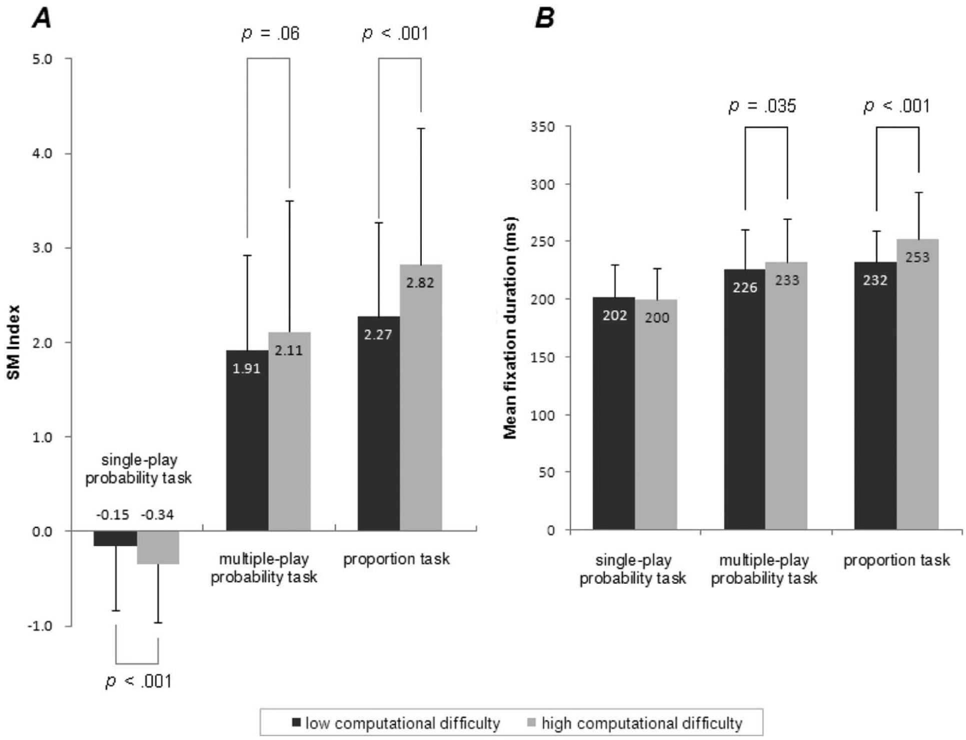


Figure 4. Panel A: The values of SM in the multiple-play probability and the proportion tasks, in both, were positive and higher than the value in the single-play probability task. Computational difficulty positively influenced the value of SM in the multiple-play probability task and the proportion task but negatively influenced the value of SM in the single-play probability task. Panel B: The mean fixation duration was shortest in the single-play probability task and was longest in the proportion task. In the multiple-play probability and proportion tasks, the mean fixation duration was longer when the computational difficulty was greater. The impact of computational difficulty on the mean fixation duration was absent in the single-play probability task. The error bars in Panels A and B, respectively, represent the standard errors of the mean SM and those of the mean fixation durations. SM indicates alternative-based versus dimension-based search measure.

before reaching a decision in the risky choice task was similar to (H_{2a}) or less than (H_{2b}) that observed in the proportion task.

The data were analyzed with a one-way repeated-measures ANOVA, with the percentage of total information searched as an dependent variable and the task as a within-subject factor. The results revealed a significant main effect of task, $F(2, 47) = 23.54$, $p < .001$, $\eta^2 = .50$. Pairwise comparisons (LSD) revealed that the percentage of total information searched in the single-play probability task (88.5%) was significantly lower than that in the multiple-play probability task (95.0%) and the proportion task (95.8%; ps $< .001$). No difference in this variable was observed between the multiple-play probability task and the proportion task ($p = .07$).

Similar to our findings on the SM value, the above results revealed a clear similarity in the percentage of total available information that was fixated on prior to response in the multiple-play probability task and the proportion task, both of which approximated 100%. The data obtained in the multiple-play probability task supported the hypotheses of the weighting and adding process concerning the depth of information acquisition (H_{2a}). The above results also revealed a significantly smaller percentage of total information that was searched in the single-play probability task compared with that in the proportion task, which supported the hypotheses of the heuristic processes (H_{2b}). Therefore, these findings suggest that people indeed ignored some of the information about the options when making risky choices in single-play conditions rather than integrating all of the information. Such integration processes, which are regarded as necessary and indispensable to the weighting and adding processes, were more likely to emerge only in the multiple-play probability task.

The Complexity Level of Information Processing

The third variable that we analyzed in this study was mean fixation duration. Velichkovsky and colleagues suggested that the duration of single fixations increases with increasingly complexity levels of information processing (Velichkovsky, 1999; Velichkovsky, Rothert, Kopf, Dornhöfer, & Joos, 2002). On the basis of this theory, we reasoned that the weighting and adding processes, which were assumed to comprise more complex computations in the integration of information (e.g., multiplication and integration), should be characterized by a longer mean fixation duration than the heuristic processes, which were assumed to comprise only simple and ordinal comparisons. We thus used this variable to test our hypotheses concerning the complexity level of information processing (H_{3a} and H_{3b}). Moreover, the mean fixation duration should increase with an increasing level of computational difficulty only when a weighing and adding process is used, because the change in the difficulty of the total payoff (or expectation) computation does not influence the complexity level of the dimension-based comparison. Therefore, we also used this variable to test our hypotheses concerning the impact of computation difficulty (H_{4a} and H_{4b}).

We performed a 3 (task: single-play probability task, multiple-play probability task, proportion task) × 2 (computational difficulty: high, low) repeated-measures ANOVA and found significant main effects of task, $F(2, 96) = 58.49$, $p < .001$, $\eta^2 = .55$, and computational difficulty, $F(1, 48) = 23.95$, $p < .001$, $\eta^2 = .33$, and a significant interaction effect between these two factors on the mean fixation duration, $F(2, 96) = 22.64$, $p < .001$, $\eta^2 = .32$. Pairwise comparison tests (LSD) revealed that the mean fixation duration was shortest in the single-play probability task (201.08 ms; $ps < .001$) and was longest in the proportion task (242.61 ms; $ps < .01$).

A simple effects analysis of the interaction showed that computational difficulty affected the mean fixation durations in the multiple-play probability task, $F(1, 48) = 4.70$, $p = .035$, $\eta^2 = .09$, and the proportion task, $F(1, 48) = 39.16$, $p < .001$, $\eta^2 = .45$, but not in the single-play probability task, $F(1, 48) = 2.87$, $p = .10$. In particular, as shown in Figure 4 (Panel B), the mean fixation durations in the proportion task increased with increasing levels of computational difficulty (from 232.34 to 252.87 ms). Similar results were found in the multiple-play probability task. In contrast, no significant differences in mean fixation durations were found in the single-play probability task, regardless of whether the computational difficulty was high or low.

The mean fixation duration results revealed more complex processing prior to decision making in the proportion task than in the single-play and multiple-play probability tasks. The hypothesis of weighting and adding processes concerning the complexity level of information processing (H_{3a}) was rejected by the data obtained in the single-play and multiple-play probability tasks. However, when computational difficulty, which was expected to impact computation-based strategies, was manipulated to be set at a higher level, more elaborate information processing was found in the multiple-play probability task but was absent in the single-play probability task. The hypothesis of weighting and adding processes concerning the impact of computational difficulty (H_{4a}) was rejected by the data obtained in the single-play probability task but supported by those obtained in the multiple-play task. The above results add to the wealth of evidence supporting the idea that people are more likely to use a weighting and adding process only when making a choice between risky options in multiple-play conditions. Making a risky choice in single-play conditions is more consistent with the heuristic processes deduced from the noncompensatory models.

Fixation Position Distribution

In addition, we calculated the percentage of total fixations on each element (i.e., the larger payoffs, the smaller payoffs, the larger probabilities/proportions, and the smaller probabilities/proportions) for the options in each task. We used this variable to identify how the participants distributed their fixations between the four elements. We predicted that if a weighting and adding process was used, the distribution of the fixations on each element of the options in the risky choice task would be similar to that in the proportion task. In contrast, if people used a heuristic process, the fixations that fall on certain dimensions would be more dominant in the risky choice task than in the proportion task, due to selective use of the information offered about the options.

The results are summarized in Figure 5. A 3 (task: single-play probability task, multiple-play probability task, proportion task) × 4 (element: larger payoffs, smaller payoffs, larger probabilities/proportions, smaller probabilities/proportions) repeated-measures ANOVA revealed a significant interaction effect between tasks and elements, $F(6, 288) = 45.02$, $p < .001$, $\eta^2 = .48$. A simple effects analysis demonstrated a highly significant effect of element on the percentage of fixations in the single-play probability task, $F(3, 46) = 73.15$, $p < .001$, $\eta^2 = .83$, and a marginally significant effect of element in the multiple-play probability task, $F(3, 46) = 2.51$, $p = .07$, $\eta^2 = .14$. In contrast, no significant effect of element was observed in the proportion task, $F(3, 46) = 0.76$, $p = .53$. Pairwise comparisons (LSD) of the percentage of fixations on each element of the options revealed that they differed from each other in the single-play probability task ($ps < .05$). Larger probabilities received the greatest percentage of fixations (28.3%) across all elements and were followed, in descending order according to the number of fixations, by larger payoffs (27.2%), smaller probabilities (22.9%), and smaller payoffs (21.5%). These differences, however, mostly disappeared in the multiple-play probability task, and only the percentage of fixations on smaller probabilities (25.5%) was statistically greater than that on smaller payoffs (24.6%; $ps < .05$). These differences disappeared in the proportion task, suggesting that participants uniformly distributed their fixations over all of the elements.

The results revealed a similarity in the fixation position distributions of the multiple-play probability task and the proportion task, which was consistent with our prediction of the weighting and adding processes. Therefore, a weighting and adding process was more likely to be used in the multiple-play probability task. On the other hand, participants made significantly more fixations on the probability dimension, especially on the larger probabilities, than on the payoff dimension in the single-play probability task. The data obtained in the single-play probability task were consistent with our prediction of the heuristic process concerning fixation position distribution. Therefore, we suggest that choices between risky options in single-play conditions are likely guided by a heuristic process.

General Discussion

The debate about whether making a risky choice is based on a weighting and adding process or a heuristic process has a long history. A large body of literature has indicated that choices between risky options in single-play conditions cannot be predicted by expectation models (e.g., Dawes, 1979; L.-B. Li, He, Li, Xu, & Rao, 2009; Nwogugu, 2006; Payne, Bettman, & Johnson, 1993). Brandstätter et al. (2006, 2008a, 2008b) contended that the priority heuristic is more descriptively accurate than compensatory models. In contrast, other researchers have used choice data to support compensatory models (e.g., Birnbaum, 2008a, 2008b; Johnson, Schulte-Mecklenbeck, & Willemsen, 2008a; Johnson et al., 2008b; Rieger & Wang, 2008). Using choice data clearly has

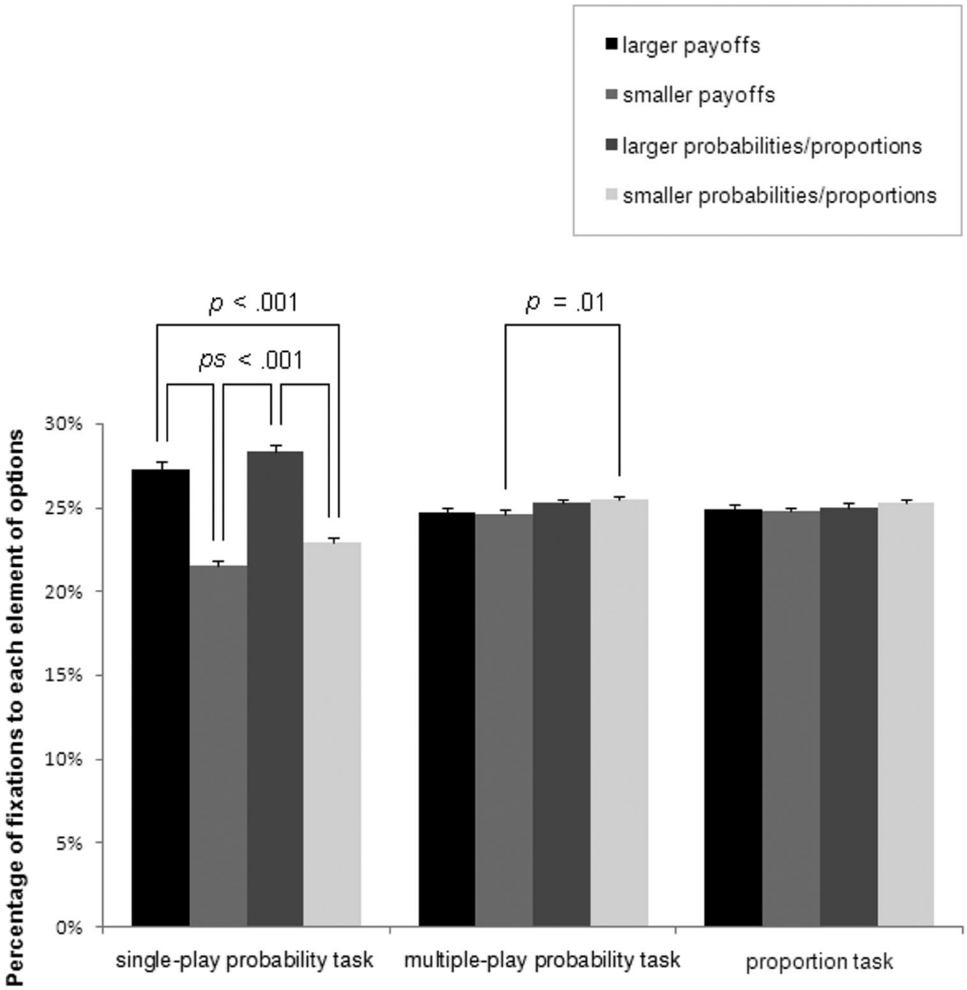


Figure 5. There was a highly significant effect of element on the percentage of fixations in the single-play probability task and a marginally significant element effect in the multiple-play probability task. Participants' fixations were uniformly distributed over elements in the proportion task. The error bars represent standard errors of mean percentages of fixations to each option element.

not resolved this controversy. Alternatively, since the 1970s, researchers have also directly tested the mechanisms underlying risky choices. Process tests of risky choices between the 1970s and the 1990s have found strong and consistent evidence for the use of heuristic processes in risky choices (Mann & Ball, 1994; Payne & Braunstein, 1978; Rosen & Rosenkoetter, 1976; Russo & Dosher, 1983). More recent studies that have investigated processes have argued for a weighting and adding process (Glöckner & Betsch, 2008; Glöckner & Herbold, 2011; Johnson et al., 2008b). This study extended previous process tests by using a novel paradigm and a more rigorous experimental design to overcome the potential problems of previous studies.

Summary of the Present Study

The current study tested a total of four pairs of competing hypotheses that were deduced from the weighting and adding processes and heuristic processes. An overview of the results of the decision time and eye movement analyses is provided in Figure 6.

These results revealed some similarities in the SM values, the percentages of total information that was fixated, the mean fixation durations, and the fixation position distributions that were measured in the multiple-play probability task and the proportion task. The hypotheses of the weighting and adding processes concerning the depth of information acquisition (H_{2a}) and the impacts of computational difficulty on decision times and eye movements (H_{4a}) were supported by the data obtained in the multiple-play probability task. Therefore, we conclude that making choices between risky options in multiple-play conditions is likely to be guided by a weighting and adding process. The analysis of choice data in the multiple-play probability task also revealed that choices can be more accurately predicted by the compensatory models than by the noncompensatory ones. These results provide evidence in favor of the family of compensatory models for making risky choices in the multiple-play condition. The current study, which jointly conducted a choice test and process tests, corroborated the observations of existing studies suggesting that people's choices

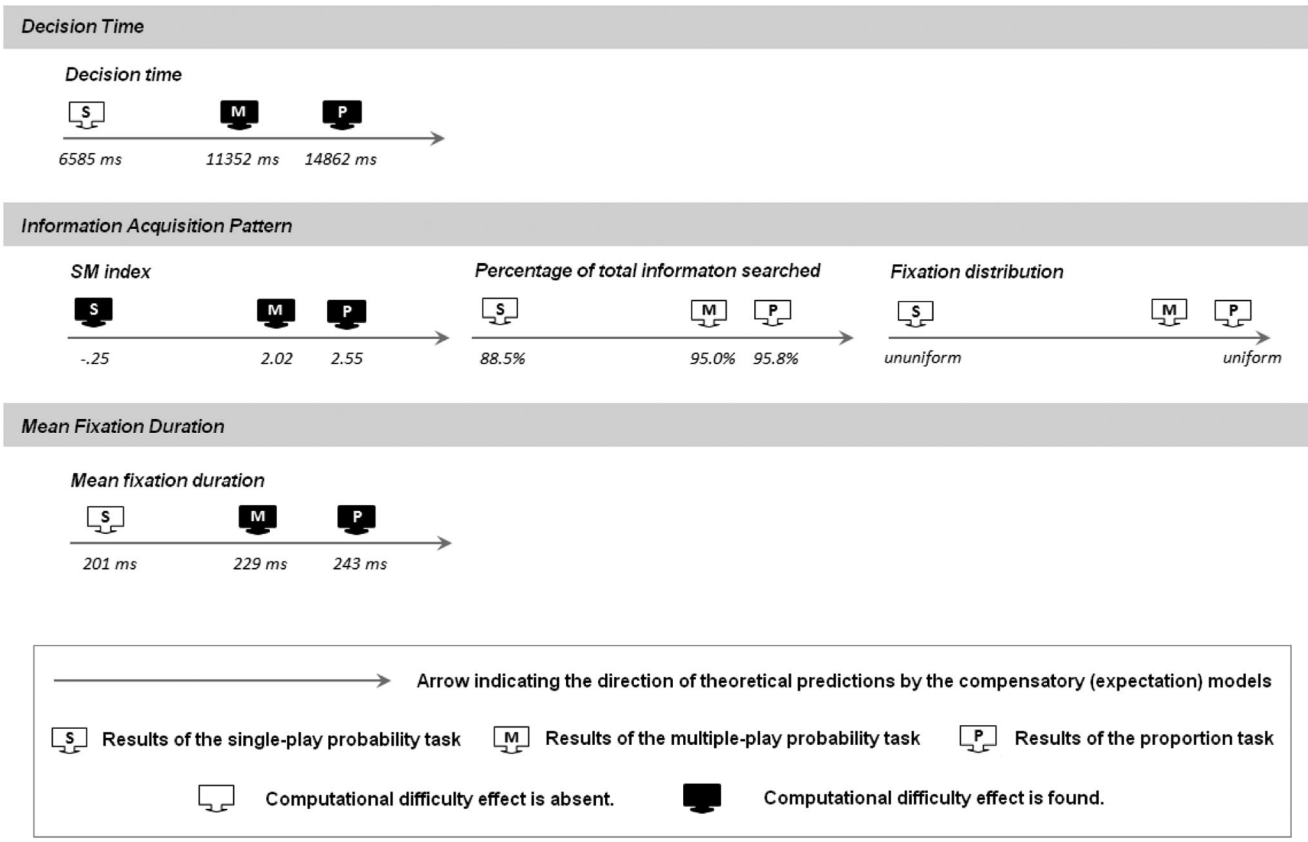


Figure 6. An overview of the results concerning decision time and eye movements. SM indicates alternative-based versus dimension-based search measure.

and pricing behaviors are consistent with the predictions of compensatory models in multiple-play conditions (Colbert, Murray, & Nieschwietz, 2009; Keren, 1991; Klos et al., 2005; Langer & Weber, 2001; S. Li, 2003; Montgomery & Adelbratt, 1982; Redelmeier & Tversky, 1992; Wedell & Böckenholt, 1994).

More important, the results of the present study revealed significant differences in both decision times and eye movement patterns (including the SM value, the percentage of total information that was fixated, the mean fixation duration, and the fixation position distribution) between the single-play probability task and the proportion task. The hypotheses of the weighting and adding processes (H_{1a}, H_{2a}, H_{3a}, and H_{4a}) were all rejected based on the data in the single-play probability task. In contrast, the data obtained in the single-play probability task significantly supported the hypotheses of the heuristic process (H_{1b}, H_{2b}, H_{3b}, and H_{4b}). Therefore, we conclude that making a risky choice in single-play conditions is not guided by a weighting and adding process and instead is more likely to be guided by a heuristic process. These results provide evidence in favor of the family of noncompensatory models for making a risky choice in the single-play conditions. The findings converge with those of previous process tests that were claimed to have provided clear evidence for the use of heuristic processes in making risky choices using information boards (Mann & Ball, 1994; Payne & Braunstein, 1978), eye tracking (Rosen & Rosenkoetter, 1976; Russo & Dosher, 1983), verbal protocols (Cokely & Kelley, 2009), and predict-aloud protocols (Brandstätter & Gussmack, 2013). However, the noncompensatory models tested in the present study (i.e., the priority heuristic, the equate-to-differentiate model, and the minimax heuristic) did not significantly outperform the compensatory models (i.e., expected value theory, expected utility theory, and cumulative prospect theory) in accounting for choices made between risky options in single-play conditions, although the results of the process tests provided clear evidence for the use of heuristic processes.

Given both of these findings, it can be concluded that people are likely to use different strategies in single-play and multiple-play conditions. The current findings align with several perspectives (DeKay, Hershey, Spranca, Ubel, & Asch, 2006; Lopes, 1981) on why expectation theories can account for choices made between risky options in multiple-play conditions but not for choices made in single-play conditions. We suggest that the change from multiple-play to single-play risky options is qualitative (a change in mechanism and strategy) rather than merely quantitative (a change in the number of replications) and should be regarded from a different perspective. Because the concept of expectation is based on an analysis of aggregated (long-term) outcomes (Wedell, 2011), we suggest that weighting and adding strategies should not be blindly transplanted to the short-term domain. Efforts to revamp the form of "expectation" to accommodate choice data may be futile, as the common prediction that can be deduced from expectation theories, the use of a weighting and adding process, is absent in single-play conditions. It is also worth noting that although much process evidence provides support for the notion that making a risky choice in single-play conditions is based on a heuristic processes, recent data also indicate that existing models of heuristics (e.g., the priority heuristic) are limited in their ability to predict people's choices (e.g., Glöckner & Pachur, 2012). Progress in future studies could be made either by modifying the existing noncompensatory models or by developing new models that predict a heuristic process to account for risky choices in single-play conditions.

Comparisons With Related Studies

The current study extends previous process tests in several ways. We provided a new paradigm for examining the weighting and adding processes. We directly compared the information search and processing in risky decision making with those in a baseline task in which people naturally perform a deliberate calculation of the weighted sums. The new comparative paradigm developed in this study provides more straightforward and objective evidence on whether making a risky choice is based on a weighting and adding process. By simultaneously performing between-task comparisons and prediction tests, we overcame, at least to some extent, the limitation on deducing hypotheses about the process data from the decision models that did not take the relevant processes into consideration (Marewski & Mehlhorn, 2011; Marewski & Schooler, 2011).

The current findings seems to contradict those obtained in recent process test studies using Mouselab (Glöckner & Betsch, 2008; Johnson et al., 2008b) and eye tracking (Glöckner & Herbold, 2011), both of which upheld the compensatory models. We argue that the data obtained in the present study are more likely to reflect the actual process underlying risky decision making because we overcame the last three potential problems of methodology and experimental design. First, compared to the information board methods, such as Mouselab, used by Glöckner and Betsch (2008) and Johnson et al. (2008b), the eye-tracking methodology used in the present study decreases the likelihood that the method itself will influence information search and processing. Second, the options were presented in a more neutral way in this study than in those conducted by Johnson et al. (2008b) and Glöckner and Herbold (2011). That is, the options were presented without any unnecessary structures that may have introduced bias, such as lines between the options (Johnson et al., 2008b) or boxes around each possible payoff and respective probability (Glöckner & Herbold, 2011). Third, there was no time pressure in the present study, which has been shown to influence the information acquisition process under certain conditions (Ben Zur & Breznitz, 1981), such as fixation distribution. Considering these four aspects, the data obtained in the present study might provide a more accurate view of information search and processing.

Implications for Future Studies

First, nearly all models that have been tested are actually underspecified with respect to reaction time (RT) and process data. Making complete and objective RT and process data predictions requires models of how the decision processes assumed by a model interplay with perceptual, memory, motor and other relevant processes (Marewski & Mehlhorn, 2011; Marewski & Schooler, 2011); that is, the models must be implemented within a cognitive architecture (for an introduction, see, e.g., Gluck, 2010). Steps have been taken in this direction. For instance, Marewski and Mehlhorn (2011) used the ACT-R architecture (for details, see, e.g., Anderson et al., 2004) to implement predictions of 39 compensatory and noncompensatory quantitative process models. In future studies that test decision-making models of human risky choice behavior, predictions should be corroborated by similarly implementing the models and testing them in a detailed cognitive architecture, spelling out not only the decision processes but also how these processes interplay with other cognitive and motor processes.

Second, the findings of the present study imply that strategy selection in risky decision making depends on the nature of the task at hand. Notably, the focus of recent studies testing cognitive processes has progressively shifted from the question of whether people use a given strategy in all conditions to the question of how people select from these strategies to solve given tasks (Bröder, 2011; Marewski & Schooler, 2011; Marewski, Schooler, & Gigerenzer, 2010). The strategy selection problem has posed a major challenge to theories in decision-making science (Gigerenzer, Hoffrage, & Goldstein, 2008; Glöckner & Betsch, 2008; Marewski, 2010; Marewski et al., 2010; Rieskamp & Otto, 2006). Theories of strategy selection that predict the strategies that are relied upon in various conditions are thus urgently needed. In related fields such as probabilistic inference, detailed computational theories of strategy selection have been developed, such as the strategy selection learning theory (Rieskamp & Otto, 2006) and the cognitive niches model (Marewski & Schooler, 2011). Along these lines, the ultimate goals of future comparative tests of process models of risky decisions may be to develop precise and detailed computational models and to predict how selection emerges through the interplay among strategies, basic cognitive capacities, and the structure of the environment.

Finally, only the processes underlying human risky choices in the gain domain were examined in this study, whereas investigation of the processes employed in the loss domain was absent. However, exploring the cognitive processes involved in human risky decision making in the loss domain is also important. First, viewed from the perspective of evolution, losses have greater impacts on human survival than gains do (Coombs & Lehner, 1984; Frederick, Loewenstein, & O'Donoghue, 2002). Studies have also found that people often place more emphasis on losses than on gains of equivalent value in risky choices (Abdellaoui, Bleichrodt, & Paraschiv, 2007; Tom, Fox, Trepel, & Poldrack, 2007). Second, mounting evidence shows that people treat gains differently from losses (Kahneman & Tversky, 1979; Levin & Hart, 2003; S. Li, Wang, Rao, & Li, 2010; Xu, Liang, Wang, Li, & Jiang, 2009). Considering both of the above aspects, we suggest that future studies use the paradigm applied in the current study to examine domain-specific effects on the cognitive processes underlying human risky choices.

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(*Appendix follows*)

Appendix

Thirty-Two Pairs of Two-Payoff Monetary Options

Option	Outcome 1 *n*	Outcome 1 %	Outcome 2 *n*	Outcome 2 %	Option	Outcome 1 *n*	Outcome 1 %	Outcome 2 *n*	Outcome 2 %
Low computational difficulty									
Option A	600	10%	200	90%	Option A	200	90%	900	10%
Option B	700	20%	100	80%	Option B	100	80%	800	20%
Option A	700	30%	300	70%	Option A	200	80%	800	20%
Option B	900	20%	100	80%	Option B	400	70%	600	30%
Option A	900	70%	100	30%	Option A	300	10%	600	90%
Option B	800	80%	200	20%	Option B	200	20%	700	80%
Option A	900	70%	200	30%	Option A	300	20%	700	80%
Option B	700	90%	400	10%	Option B	100	40%	900	60%
Option A	600	20%	100	80%	Option A	100	80%	900	20%
Option B	900	10%	100	90%	Option B	100	70%	700	30%
Option A	900	40%	100	60%	Option A	200	60%	800	40%
Option B	900	30%	200	70%	Option B	100	50%	800	50%
Option A	900	60%	100	40%	Option A	100	20%	700	80%
Option B	800	70%	100	30%	Option B	100	40%	800	60%
Option A	900	80%	400	20%	Option A	200	10%	800	90%
Option B	900	90%	100	10%	Option B	400	20%	800	80%
High computational difficulty									
Option A	600	15%	200	85%	Option A	250	90%	950	10%
Option B	700	25%	100	75%	Option B	150	80%	850	20%
Option A	650	10%	250	90%	Option A	200	75%	800	25%
Option B	750	20%	150	80%	Option B	400	65%	600	35%
Option A	850	70%	150	30%	Option A	350	10%	650	90%
Option B	650	90%	350	10%	Option B	250	20%	750	80%
Option A	800	65%	200	35%	Option A	300	15%	700	85%
Option B	600	85%	400	15%	Option B	100	25%	900	75%
Option A	650	30%	150	70%	Option A	100	85%	800	15%
Option B	850	20%	150	80%	Option B	100	75%	600	25%
Option A	900	45%	200	55%	Option A	250	70%	950	30%
Option B	900	35%	300	65%	Option B	150	60%	950	40%
Option A	900	55%	100	45%	Option A	150	30%	850	70%
Option B	800	65%	100	35%	Option B	150	40%	950	60%
Option A	950	80%	450	20%	Option A	100	15%	800	85%
Option B	950	90%	150	10%	Option B	200	25%	800	75%

Note: *n* indicates the value of the corresponding outcome, while the % indicates the probability/proportion of the corresponding outcome.

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