Journal of Behavioral Decision Making, *J. Behav. Dec. Making*, **29**: 169–182 (2016)
Published online 5 February 2016 in Wiley Online Library (wileyonlinelibrary.com) **DOI:** 10.1002/bdm.1943

A Scanpath Analysis of the Risky Decision-Making Process

LEI ZHOU[1,2], YANG-YANG ZHANG[1,2], ZUO-JUN WANG[3], LI-LIN RAO[1], WEI WANG[4], SHU LI[1], XINGSHAN LI[1]* and ZHU-YUAN LIANG[1]*

[1]*Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China*

[2]*University of Chinese Academy of Sciences, Beijing, China*

[3]*Department of Psychology, Ningbo University, Ningbo, China*

[4]*Department of Medicine, Brigham and Women's Hospital, Harvard Medical School, MA, USA*

ABSTRACT

In the field of eye tracking, scanpath analysis can reflect the sequential and temporal properties of the cognitive process. However, the advantages of scanpath analysis have not yet been utilized in the study of risky decision making. We explored the methodological applicability of scanpath analysis to test models of risky decision making by analyzing published data from the eye-tracking studies of Su et al. (2013); Wang and Li (2012), and Sun, Rao, Zhou, and Li (2014). These studies used a proportion task, an outcome-matched presentation condition, and a multiple-play condition as the baseline for comparison with information search and processing in the risky decision-making condition. We found that (i) the similarity scores of the intra-conditions were significantly higher than those of the inter-condition; (ii) the scanpaths of the two conditions were separable; and (iii) based on an inspection of typical trials, the patterns of the scanpaths differed between the two conditions. These findings suggest that scanpath analysis is reliable and valid for examining the process of risky decision making. In line with the findings of the three original studies, our results indicate that risky decision making is unlikely to be based on a weighting and summing process, as hypothesized by the family of expectation models. The findings highlight a new methodological direction for research on decision making. Copyright © 2016 John Wiley & Sons, Ltd.

Additional supporting information may be found in the online version of this article at the publisher's web-site.

KEY WORDS risky choice; scanpath analysis; similarity score; typical trial; eye tracking; process testing

INTRODUCTION

Decision making under risk is vital to human survival and development. How people make risky choices is a compelling question facing scientists today. To solve this puzzle, in recent years, new techniques have been used to study the complex cognitive activity involved in decision making. Among these techniques, eye tracking has been shown to be successful (Glöckner & Herbold, 2011; Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Shi, Wedel, & Pieters, 2013; Su et al., 2013). Given that eye movements provide abundant information about underlying cognitive processes, this technology is particularly useful for studying complex cognitive activities that require real-time visual perception, such as decision making. Moreover, because eye tracking is a passive observation technology, researchers can study cognitive processes without interfering with subjects' behavior (Hayhoe & Ballard, 2005). Most previous studies using eye tracking to study decision making analyzed data on local details (e.g., fixation and saccade), neglecting to some extent the sequential and temporal properties of the cognitive processes underlying decision making (Day, 2010; Glöckner & Herbold, 2011; Su et al., 2013; Sun et al., 2014; Wang & Li, 2012). Analyzing the sequential and temporal properties of eye movements, which can be represented by the scanpath, can lead to a better understanding of the decision-making process (Harte, Westenberg, & van Someren, 1994). In the present study, we attempted to assess the applicability of scanpath analysis to examining the processes of risky decision-making models.

Risky decision-making models

In the study of decision making, characteristics of choice are determined by general rules (Stevenson et al., 1990) that classify various decision models. Stevenson et al. (1990) organized a variety of preferential choice rules by crossing the following three factors: (i) *Compensatory/non-compensatory rule*. The compensatory rule involves the processing of all relevant information about the available alternatives and the explicit consideration of the tradeoffs among values. The non-compensatory rule uses information in a more limited and often highly selective fashion and avoids tradeoffs (Payne & Bettman, 2004); (ii) *Holistic/dimensional rule*. The holistic rule means that primary information processing is *alternative based*; that is, multiple attributes of a single option are processed before another option is considered. The dimensional rule, which is also referred to as *attribute based*, means that the values of several options for a single attribute are examined before information on another attribute is considered (Payne & Bettman, 2004); (iii) *Deterministic/stochastic rule*. The deterministic rule postulates a binary preference relationship that is either true or false for any pair of actions, whereas the stochastic rule postulates a probability function that maps each pair of actions into a closed interval (Busemeyer & Townsend, 1993).

A majority of existing risky decision-making models can be unambiguously classified by the aforementioned factors. Historically, mainstream theories of decision making under risk

*Correspondence to: Zhu-Yuan Liang and Xingshan Li, Institute of Psychology, Chinese Academy of Sciences, Beijing 100101, China. E-mail: liangzy@psych.ac.cn, lixs@psych.ac.cn.

have followed a compensatory, holistic, and deterministic rule. Based on the hypothesis of these theories, when making a risky choice, people weigh each outcome by its probability and then sum all the risky outcomes to assign an overall value (expectation) to each option. Finally, they select the option that offers the highest overall expectation (Glöckner & Herbold, 2011; Kahneman & Tversky, 1979, 1990; Tversky & Kahneman, 1992). The representative models are expected value theory (EV; Pascal, 1670), expected utility theory (EU; von Neumann & Morgenstern, 1947), subjective expected utility theory (SEU; Edwards, 1954), prospect theory (PT; Kahneman & Tversky, 1979), and cumulative prospect theory (CPT; Tversky & Kahneman, 1992). We therefore identify the "compensatory, holistic, and deterministic" decision-making process that these models assumed as a *weighting and summing process* and use this definition throughout the remainder of this paper. Not all compensatory models contain assumptions about deliberate computation process. For example, parallel constraint satisfaction models (PCS; Glöckner & Betsch, 2008; Holyoak & Simon, 1999) predict an approximately weighted integration of probabilities and subjective utilities without assuming that individuals calculate weighted sums. Some recent models, such as decision field theory (DFT; Busemeyer & Townsend, 1993) and the drift diffusion model (DDM; Ratcliff & Rouder, 1998; Krajbich & Rangel, 2011), follow the compensatory and stochastic rule. These compensatory models do not incorporate the assumption of a deliberate computation process. For example, the DDM hypothesizes that decisions are made by accumulating stochastic information over time until the net evidence in favor of one option exceeds a pre-specified threshold (Krajbich & Rangel, 2011). There are also models that follow the non-compensatory rule and assume that people rely on only one (or a few) key dimension(s) rather than integrating information from all dimensions of an option to make a decision (Brandstätter, Gigerenzer, & Hertwig, 2006; S. Li, 2004; Thorngate, 1980). For example, the equate-to-differentiate model suggests that when making risky choices, 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 (Li, 2004; Li & Xie, 2006). According to the priority heuristic model (Brandstätter et al., 2006), a decision maker will sequentially compare the minimum outcomes, the probabilities of the minimum outcomes, and the maximum outcomes of the two options to make a decision. However, the priority heuristic was reported in some studies to be unsuitable as a general model of risky choice (e.g., Birnbaum & LaCroix, 2008; Glöckner & Betsch, 2008; Hilbig, 2008; Koop & Johnson, 2013).

Behavioral experiments and process-tracing methods have been applied to examine risky-decision models (Brandstätter & Gussmack, 2012; Glöckner & Herbold, 2011; Su et al., 2013). Behavioral experiments use outcome-based techniques, manipulate input variables, and build statistical models to draw inferences about the final decision (Schulte-Mecklenbeck, Kühberger, & Ranyard, 2011a). Behavioral experiments have provided ample evidence for risky-decision-model examination. However, different models may predict the same outcome or preference despite potential differences in the underlying cognitive processes (Johnson, Schulte-Mecklenbeck, & Willemsen, 2008). Thus, a good-model-fit result does not exclude the possibility that the large majority of participants (e.g., in the decision tasks of two gambles, Glöckner & Herbold, 2011; or in affect-poor problems, Suter, Pachur, & Hertwig, 2015) who are well captured by CPT relied on non-expectation-based calculus rather than expectation-based calculus. It is difficult to justify decision models without examining the underlying process, even when the outcome data are correctly predicted. In contrast to behavioral experiments, tracing methods directly examine the processes underlying risky choice and provide process data (in addition to outcome data) for testing risky-decision models (Payne, Bettman, & Johnson, 1993; Payne & Venkatraman, 2010; Schulte-Mecklenbeck et al., 2011a). The process-tracing methods allow for the concurrent mapping of explicit and implicit processes and can overcome the limits of behavioral experiments in motivation, awareness, and opportunity by tapping implicit processes (Schulte-Mecklenbeck, Kühberger, & Ranyard, 2011b). As a result, the process data are richer than the outcome data and can therefore provide empirically valuable source evidence of the explanatory psychological mechanisms of decision processes (Payne & Venkatraman, 2010; Payne et al., 1993; Schulte-Mecklenbeck et al., 2011b; Schulte-Mecklenbeck et al., 2011a).

Eye-tracking methods and risky decision making

Currently, tracing technologies are used in many innovative ways, including functional magnetic resonance imaging (fMRI), event-related potential (ERP), mouse tracking, and eye tracking, to study people's information processing during decision making (Dshemuchadse, Scherbaum, & Goschke, 2013; Glöckner & Herbold, 2011; Krajbich et al., 2010; Pachur, Hertwig, Gigerenzer, & Brandstätter, 2013; Rao, Li, Jiang, & Zhou, 2012; Rao et al., 2011, 2013; Scarpa, Zanoli, Bruschi, & Naspetti, 2013; Su et al., 2013). Among these technologies, eye tracking has been shown to be useful and reliable for decision-making research (Day, 2010; Glöckner & Herbold, 2011; Krajbich & Rangel, 2011; Krajbich et al., 2010; Orquin & Mueller Loose, 2013; Su et al., 2013; Sun et al., 2014; Wang & Li, 2012). During decision-making, we usually move our eyes to acquire necessary visual information. Because there is a close relationship between information acquisition (through the eyes) and information processing (by the brain), eye movements provide a large amount of information about the underlying cognitive processes (Just & Carpenter, 1976; Day, 2010; Orquin & Mueller Loose, 2013). The fixation durations reflect the processing duration, the fixation positions reflect which part of the visual world is needed for decision making, and the order of inspection reflects the order of processing (Rayner, 2009). Indeed, eye tracking has been successfully used in many decision-making studies, such as value-based choice (binary choice, Krajbich & Rangel, 2011; ternary choice, Krajbich et al., 2010), multi-attribute decision making (Day, 2010), and online consumer decision making (Shi et al., 2013).

In particular, a series of eye-tracking studies in risky decision making has examined and compared the three aforementioned classifications of decision models. In these studies,

DOI: 10.1002/bdm

models were examined by testing the extent to which they could correctly predict people's choice behaviors and the characteristics of their eye movements, such as the fixation duration and position (Glöckner & Herbold, 2011; Su et al., 2013; Sun et al., 2014; Wang & Li, 2012). For example, Glöckner and colleagues (Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011) tested the predictions of typical compensatory models (i.e., CPT, DFT, and PCS) and a non-compensatory model (i.e., PH). Their results showed that only PCS could account for risky decision making on both an outcome level and a processing level. Su et al. (2013) compared eye movements when participants performed a risky-choice task and when they performed a task that required weighting and summing processes (the proportion task) to test whether the participants used a weighting and summing process during risky decision making. Their findings indicated that the eye-movement patterns were different for these two tasks, suggesting that participants were not likely to use a weighting and summing process to make risky choices. Similarly, Wang and Li (2012) showed that eye movements differed when participants made choices according to their own rules or according to the imposed EV rule. Given that decision makers behave more in accordance with the predictions of EV theory in multiple-play situations (Colbert, Murray, & Nieschwietz, 2009; DeKay, Hershey, Spranca, Ubel, & Asch, 2006; Keren, 1991; Klos, Weber, & Weber, 2005; Langer & Weber, 2001; S. Li, 2003; Redelmeier & Tversky, 1992; Wedell & Böckenholt, 1994), Sun et al. (2014) compared single-play and multiple-play risky choices using an eye-tracking method and suggested that eye-movement patterns are distinctly different between these two types of risky-choice tasks.

It should be noted that the aforementioned studies usually use local eye-movement information, such as fixation position and duration. However, eye-tracking analyses that depend on the frequency or duration of fixations or saccades neglect the fact that saccades and fixations are fundamentally sequential (one fixation/saccade is followed by another; Cristino, Mathôt, Theeuwes, & Gilchrist, 2010). This neglect is not justified because most risky decision-making models assume a sequential and dynamic process of information searching and evaluating (Brandstätter et al., 2006; Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Moreover, analyzing only local eye movement measures would prevent us from directly inspecting and obtaining a complete picture of the decision-making processes.

Scanpath analysis of eye movements

To overcome the aforementioned limits, scanpath analysis can be used to capture the dynamic and sequential nature of eye movements during risky choices. During cognition-phase viewing, individuals generate a relatively fixed "path". This path, which is characteristic of a given participant viewing a given pattern, is called a "scanpath" (Noton & Stark, 1971a). Scanpaths are an important tool for studying the sequential properties of eye movements, which can reflect the temporal and spatial dynamics of the underlying cognitive processing (Noton & Stark, 1971a).

The classical "scanpath theory" was proposed by Noton and Stark to explain the representative nature of eye-movement patterns (Noton & Stark, 1971b). The hypothesis is that an internalized cognitive model drives scanpaths, which operate in a top-down fashion and are stable across multiple exposures. Scanpaths generally reflect the order in which visual stimuli are processed in the brain (Altmann & Kamide, 2009; Foulsham & Underwood, 2009; Henderson & Hollingworth, 1999; Loftus & Mackworth, 1978; Watson, Brennan, Kingstone, & Enns, 2010). Scanpath is regulated by tasks. When participants viewed the same picture, scanpaths were different when participants were asked to do different tasks (Yarbus, 1967; Zangemeister, Sherman, & Stark, 1995). Although scanpaths are different for different tasks, they are relatively stable across multiple exposures for the same task. The research on consumers' visual attention to repeated print advertisements by Pieters, Rosbergen, and Wedel (1999) was the first to statistically demonstrate the stability of scanpaths across repeated exposures, which is likely due to their storage in memory (Underwood, Foulsham, & Humphrey, 2009) or a result of bottom–up factors that remain the same across repeated exposures (Foulsham & Kingstone, 2013). Therefore, when people perform two different tasks, comparing the similarities between scanpaths can indicate the similarity of the underlying processes in these tasks.

Scanpath theory has been used successfully in studying complex cognitive tasks, such as mathematical problem solving (Holmqvist et al., 2011a), natural scene viewing (Bradley, Houbova, Miccoli, Costa, & Lang, 2011), affective picture viewing (Ni et al., 2011), reading (Engbert & Kliegl, 2001; X. Li, Logan, & Zbrodoff, 2010), the viewing of advertisements (Pieters et al., 1999), and multi-attribute decision making (Day, 2010). In particular, scanpath data, which inherently contain sequential information, can better reflect the dynamic decision-making process and have been previously used in decision research (Day, 2010). Day (2010) attempted to use scanpath analysis to study the strategies of multi-attribute decision-making. He trained participants to use different strategies for decision making and compared the scanpath patterns corresponding to these strategies. He found that the scanpaths for the same strategy had the closest resemblance and demonstrated that scanpaths can be used to identify the underlying strategies of multi-attribute decision making.

To the best of our knowledge, no previous studies have used scanpath analysis to examine risky decision-making models when participants make a spontaneous decision.

Current research

In this paper, we attempt to assess the methodological applicability of scanpath analysis to examining risky decision-making models. Given that the *weighting and summing process* hypothesized by the family of expectation models (such as EV, EU, SEU, and PT) provides a definite and explicit prediction regarding the process and outcome of decision making, the present research focuses on these "testable" decision models. We analyzed scanpaths in the data from three published eye-tracking studies by Su et al. (2013); Wang and Li (2012), and

DOI: 10.1002/bdm

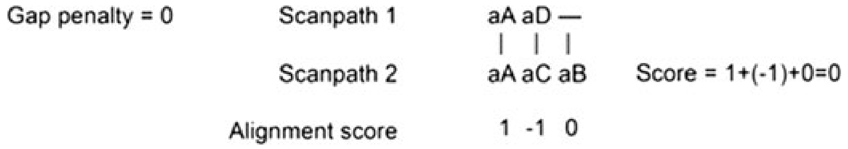

Figure 1. An example for demonstrating the effect of the gap penalty in comparing two scanpaths

Sun et al. (2014). In these studies, a proportion task, an outcome-matched presentation condition, and a multiple-play condition served as the baseline for comparison with a probability task, an outcome-crossed presentation condition, and a single-play condition, respectively. Hereafter, we refer to the two tasks/conditions in each dataset as "Condition A" (the baseline, i.e., a proportion task, an outcome-matched presentation condition, and a multiple-play condition) and "Condition B" (i.e., a probability task, an outcome-crossed presentation condition, and a single-play condition)).

In addition, we aimed to develop an objective and quantitative method to identify a typical scanpath pattern to visualize the decision-making process. We hope that the typical scanpath pattern can represent the crux of a decision-making process without trivial and redundant information and allow us to determine directly and rapidly whether two decision-making processes differ.

METHOD

Similarity of Scanpaths

To compare the scanpath patterns for different conditions, we first computed the similarity score of these scanpaths. We used ScanMatch toolbox (Cristino et al., 2010), which is based on the Needleman–Wunsch (N–W) algorithm (Needleman & Wunsch, 1970), to measure the similarities between scanpaths. The N-W algorithm is suitable for decision-making research because it allows researchers to specify the optimal scoring parameters for a given situation with a flexible scoring scheme (Day, 2010). Compared with traditional string-editing algorithms, the N–W algorithm can take the fixation length and fixation duration into account and can edit the setup of the stimulus regions of interest (ROIs) being compared.

The main steps for computing and comparing similarity scores are as follows:

Step 1. Pre-process the fixation data

The fixation data were used to create scanpaths. Fixation durations that were shorter than 50 ms (Nuthmann & Kliegl, 2009) and outside the ROIs defined by the previous studies were removed. Trial decision durations shorter than 200 ms were considered anticipation (Su et al., 2013) and were not included in the analysis.

Step 2. Create scanpaths for all conditions

For each participant, the scanpaths were created by letter sequences of ROIs. We first defined a series of non-overlapping rectangular ROIs to represent different areas in the display. Each ROI covered an area that displayed an attribute of options (i.e., outcome and probability; see Figure 3 for an example of these ROIs). Each ROI was given a unique label (e.g., aA), and the fixation in the ROI was assigned the same label. Finally, a letter string was constructed for each trial of all tasks/conditions so that the order of labels in the string represented the order in which the ROI were fixated when participants completed the trial (e.g., aFaFaHaG).

Step 3. Compute the alignment score of scanpath pairs for intra-conditions/inter-conditions

The alignment scores are for aligning two labels or the label and a gap in the sequences of the scanpaths. Using the N–W algorithm to ensure that the alignment provided the highest score (Cristino et al., 2010), the pairs of scanpaths of all intra-conditions/inter-conditions, that is, within Condition A (i.e., intra-condition A), within Condition B (i.e., intra-condition B), and between conditions (i.e., the inter-condition), were aligned. Two main parameters must be set in this algorithm: the alignment score of labels and the gap penalty. We used three principles to calculate the three types of alignment scores between two sequences in each intra-condition/inter- condition:

> When two labels at the same position of two strings were matchedthe alignment score at that position was 1.When two labels (i.e., ROIs) at the same position of two strings were different, the alignment score at that position was -1.The gap penalty represented the score for aligning any element in a sequence with a gap. To minimize the variance of the scanpath length from the similarity score, we set the gap penalty as 0.

On the principle of parsimony, we used the aforementioned parameter combination.[1] Other parameter combinations were also examined (Supplementary Material D). With these principles in mind, the alignment scores could reflect the relationship between the attributes of options in the risky-choice paradigm used in our study. That is, the alignment score for two labels belonging to the same attributes and the same option is 1. Meanwhile, the alignment score for two labels belonging to different attributes or different options is -1. Figure 1 illustrates an example of calculating the alignment score between two scanpaths (Scanpath 1 = aAaD, Scanpath 2 = aAaCaB). In these two scanpaths, the alignment score of aA with aA is 1, that of aD with aC is -1, and that of aB with a gap (space between two labels) is 0.

[1]To take fixation duration into account, the ScanMatch algorithm also introduced temporal binning into the scanpath sequence. During pre-testing, we found the temporal binning had less effect on the similarity score; thus, we omitted this parameter.

DOI: 10.1002/bdm

Step 4. Compute and compare the average similarity score for intra-conditions/inter-conditions
The similarity score of two scanpaths was obtained by normalizing the aforementioned alignment scores using the method of Cristino et al. (2010). As the similarity score increased, the two scanpaths became more similar. Then, we could compute the average similarity score of all intra-conditions/inter-conditions. We applied a multi-level model (MLM) to compare the scores on a group level. If a different cognitive process is used in different conditions, the inter-condition similarity scores should be lower than the intra-condition scores (Mathôt, Cristino, Gilchrist, & Theeuwes, 2012). Finally, to cross-validate the findings from MLM analyses, we applied a standard hierarchical clustering technique called complete linkage to further analyze scanpath sequences. Clustering refers to a broad set of techniques for clustering clusters, or finding subgroups, in a dataset (James, Witten, Hastie, & Tibshirani, 2013). The complete linkage algorithm was selected considering that this method tends to produce tight clusters of similar cases and minimizes the possible disturbing effect of outliers while clustering (Feldt, Waddell, Hetrick, Berke, & Żochowski, 2009). As hypothesized, in each dataset, the scanpath sequences of two different intra-conditions should be partitioned into two distinct groups. We then cut the clustering tree by specifying two clusters and reported the percentage of misclassification of scanpaths for each condition.

Typical trial

To optimally represent and visualize eye-movement patterns when performing a task, we identified the trial with the most typical scanpath in each condition, which we refer to as a "typical trial". A typical scanpath pattern is analogous to a prototype in the object-recognition research field, which is a typical representation of a category of objects in which the classification is performed by calculating the distance between the patterns and the prototype pattern (Jain, Duin, & Mao, 2000). The typical scanpath pattern is similar to the concept of an "average scanpath" in the field of eye-tracking studies (Holmqvist et al., 2011b). Average scanpaths were built to represent the behavior of the entire group and to enable a comparison of scanpaths for different conditions by visual inspection (Holmqvist et al., 2011b). Josephson and Holmes (2002) defined the average scanpath as the scanpath with the greatest similarity to all the other scanpaths. We followed this definition to build the typical trials. We built the typical trials following the steps later:

Step 1. For each condition, compute the similarity scores between the scanpaths of one trial and each other trials in the same condition.
Step 2. Calculate the mean similarity scores for each trial to represent the degree of similarity between this trial and the other trials.
Step 3. Select the trial with the highest mean similarity score as the typical trial, and define it as the typical trial in this condition.

DATASET 1

Dataset 1 is part of Su et al.'s (2013) eye-tracking study. In their study, a novel comparative paradigm (the probability-proportion task paradigm) was developed, in which the same sign, "%", denoted probability or proportion (Liang, Xu, Rao, Jiang, & Li, 2012) to test whether risky choices are based on a weighting and summing process. The published data for this probability-proportion task paradigm were chosen and analyzed in the present study. Su et al. (2013) hypothesized that the proportion task is a baseline task in which participants consciously make calculations using a weighting and summing process. Su et al. (2013) speculated that if people follow a weighting and summing process when making risky choices, their information perception sequence in the probability task should be similar to that in the proportion task, which requires participants to integrate probability and payoff information. However, if people do not follow a weighting and summing process when making risky choices, their information perception sequence in the probability task should be different from that in the proportion task.

Fifty college students (27 females, $M_{age} = 21.53$) participated in Su et al.'s (2013) experiment. One participant was excluded from the analyses because of incomplete tracking data. Eye movements were monitored with an EyeLink II tracker (SR Research, Canada), with the eye position sampled at 250 Hz. Participants performed two tasks with an interval of exactly 7 days, and the task order was counterbalanced. In the proportion task, they were asked to choose between riskless options, each involving several partially available payoffs. In the probability task, they were required to choose between risky options, each involving several probabilistic payoffs. The materials were visually identical to the symbol "x%", which indicated "You will get x% proportion of this payoff" in the baseline task and "You will have an x% probability of getting this payoff" in the probability task. Participants were provided 32 pairs of two-payoff monetary options for each task (Su et al., 2013, Appendix), and each time, they chose one option. The presentation mode contained two presentation patterns of the options (vertical and horizontal) and two positions of the payoffs relative to their respective probabilities/proportions (outcome first vs probability/proportion first; Su et al., 2013). To simplify the data analysis, we selected the data in only one condition (i.e., horizontal presentation, low level of computational difficulty, and outcome presented first; see Supplementary Material A) to conduct a scanpath analysis.

In accordance with Su et al.'s (2013) study, eight non-overlapping, identically sized (218×156 pixels) rectangular ROIs were defined. Four regions covered the payoffs of both options, and four regions covered the probabilities or proportions (Figure 3).

Results and discussion

Overall, 1187 of 108 661 fixations (approximately 1.09%) with durations of less than 50 ms, and one trial (approximately 0.64%) of 1568 trials with a decision time of shorter than 200 ms were excluded from the analysis.

DOI: 10.1002/bdm

Furthermore, 23 of 1568 trials (approximately 1.47%) were discarded because of eye-tracking failures. We calculated the intra-condition and inter-condition similarity scores separately for each participant. The descriptive statistics for intra-condition A (proportion task), the inter-condition, and intra-condition B (probability task) are shown in Figure 2.

To test whether participants used different cognitive processes when performing different tasks, we applied a multilevel model using the SAS program on the similarity score with the intra-conditions/inter-conditions as the fixed factor and the participant ID as the random factor. Unlike the traditional RM-ANOVA, the MLM takes the difference between participants (level-1) and conditions (level-2) into account and avoids overestimating the effect (Quené & Van den Bergh, 2004). There was a significant difference between the intra-conditions and inter-conditions ($F(2, 96) = 39.68$; $p < .001$). The correlation structure model was unstructured. The Bonferroni adjustment was used for post-hoc pairwise comparisons. Post-hoc analysis showed that the similarity score for intra-condition A ($M = .42$, $SE = .008$) was significantly higher than that for the inter-condition ($M = .35$, $SE = .008$) ($t(96) = 8.89$; adjusted $p < .001$). Moreover, the similarity score for intra-condition B ($M = .39$, $SE = .006$) was significantly higher than that for the inter-condition ($t(96) = 4.98$; adjusted $p < .001$). These results suggested that the scanpath patterns differed between the proportion and probability tasks. The results also showed that the similarity score for intra-condition A was significantly different from that for intra-condition B ($t(96) = 3.90$; adjusted $p < .001$), indicating that the internal consistency of the scanpath pattern in the proportion task was higher than that in the probability task.

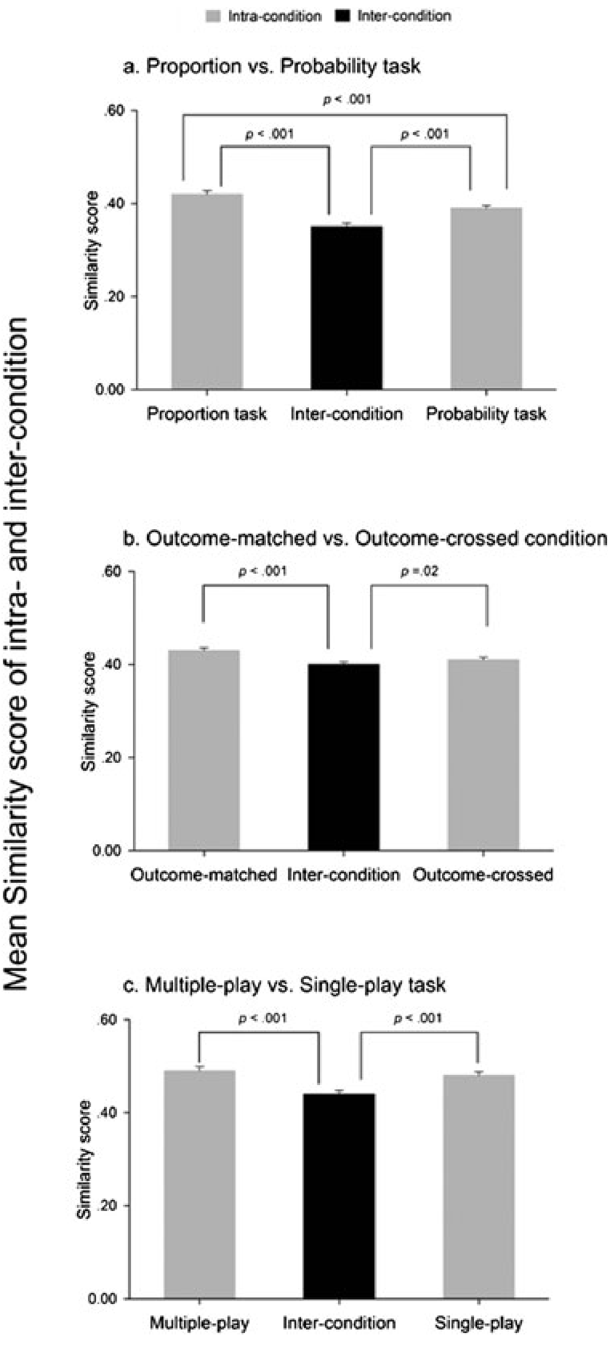

Figure 2. Similarity scores of intra- and inter-conditions in the proportion and probability task (a); outcome-matched and outcome-crossed presentation conditions (b); single-play and multiple-play conditions (c). The error bars represent standard errors of the mean scores

To cross-validate the MLM results, the sequences of the scanpaths of Conditions A and B for each participant were clustered by complete linkage agglomerative hierarchical clustering using the N–W algorithm to calculate the distance (Fred, 2002). The average percentage of incorrect classifications of scanpaths for Condition A was 26.83% ($SD = .17$, ranging between 0% and 48.39%), and that for Condition B was 27.20% ($SD = .19$, ranging between 0% and 50.00%). Consistent with the MLM results, this result indicated that the scanpaths in the two conditions were separable, thus suggesting that the scanpath patterns differed between the proportion and probability tasks.

Figure 3 illustrates the scanpaths of the typical trial we built for Conditions A and B. Along with the typical trial (the one with the highest mean similarity score), the other two trials with the second and third highest mean similarity score for Conditions A and B were also built and are depicted in Supplementary Material E to let readers judge whether the representativeness of the typical trial can be secured. The scanpaths of the typical trials showed that in the proportion task, participants first scanned between the “payoff” and “x%” within one option (option-based scanpath) and then scanned within another option, after which the scanpath pattern was repeated in the previous option. Upon inspecting the features of the typical trial, the information-processing sequence in the proportion task appears to be more consistent with a weighting and summing process. However, in the probability task, the scanpath did not diagnostically show a pattern similar to that of the proportion task.

Taken together, the results of the similarity score showed that the scanpath pattern in the proportion pattern was different from the probability task. Given that the participants must employ a weighting and summing process to perform the proportion task, our findings suggest that participants are unlikely to employ a weighting and summing process to make a decision in the probability task.

DOI: 10.1002/bdm

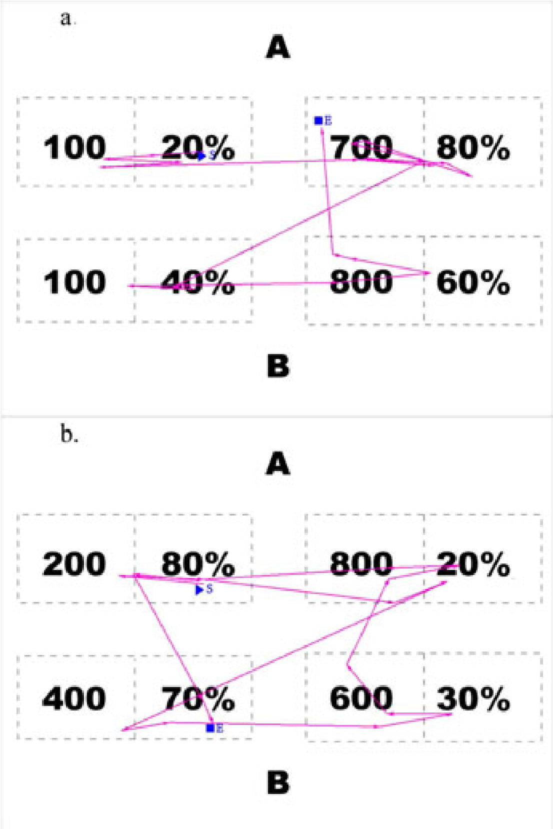

Figure 3. Typical trials formed in the proportion (a) and probability (b) tasks for Data Set 1. The arrows indicate the scanpath formed by fixations; "▶ *S*" and "■ *E*" represent the start and end of the scanpth, respectively; the dotted boxes are the ROIs defined by us

DATASET 2

Dataset 2 is part of Wang and Li's (2012) eye-tracking study. In their study, an interesting paradigm contrasting two stimuli presentations, outcome-matched versus outcome-crossed presentations, was developed to test whether risky choices are ruled by an integrative model or a priority heuristic model. In Wang and Li's study, participants were provided pairs of options, each containing two outcomes, that is, best or worst. The position of the best/worst outcomes in both options was presented as either parallel (outcome-matched) or crossed (outcome-crossed; Supplementary Material B). In the present study, the scanpath analysis was directed to analyze the published data obtained from this paradigm. Wang and Li (2012) proposed the following hypothesis: If risky choices are based on an expectation (compensatory and holistic) strategy, horizontal saccades (i.e., option-based scanpaths) should remain unchanged regardless of whether the stimuli presentation is outcome matched or outcome crossed. However, if risky choices are based on a non-expectation (non-compensatory and dimensional) strategy, for example, the priority heuristic (Brandstätter et al., 2006) or the equate-to-differentiate approach (S. Li, 2004), the attribute-based scanpath between best/worst possible outcomes (maximum/minimum outcomes) should occur in *parallel* when the stimuli presentation is outcome matched but *crossed* when the stimuli presentation is outcome crossed (Supplementary Material B).

Fifty-two college students (26 females, $M_{age} = 21.81$) participated in the study. Eye movements were monitored with an EyeLink II tracker (SR Research, Canada), with the eye position sampled at 250 Hz. Participants completed both the outcome-matched and outcome-crossed condition for choosing between two risky options. The order of tasks was counterbalanced. The original study provided eight pairs of two-payoff monetary options for each task, and the presentation mode included two levels, in which the probability and outcome of one option was presented horizontally or vertically (Wang & Li, 2012). For simplicity, we selected data for only the horizontal presentation condition to perform a scanpath analysis (Supplementary Material B).

In accordance with Wang and Li's study, eight non-overlapping, identically sized (187 × 129 pixels) rectangular ROIs were defined. Four regions covered the outcomes, and four regions covered the probabilities (Figure 4).

Results and discussion

Overall, 956 of 46 957 fixations (approximately 2.00%) with durations less than 50 ms were excluded from the analysis. The descriptive statistics for intra-condition A (outcome-matched condition), the inter-condition and intra-condition B (outcome-crossed condition) are shown in Figure 2.

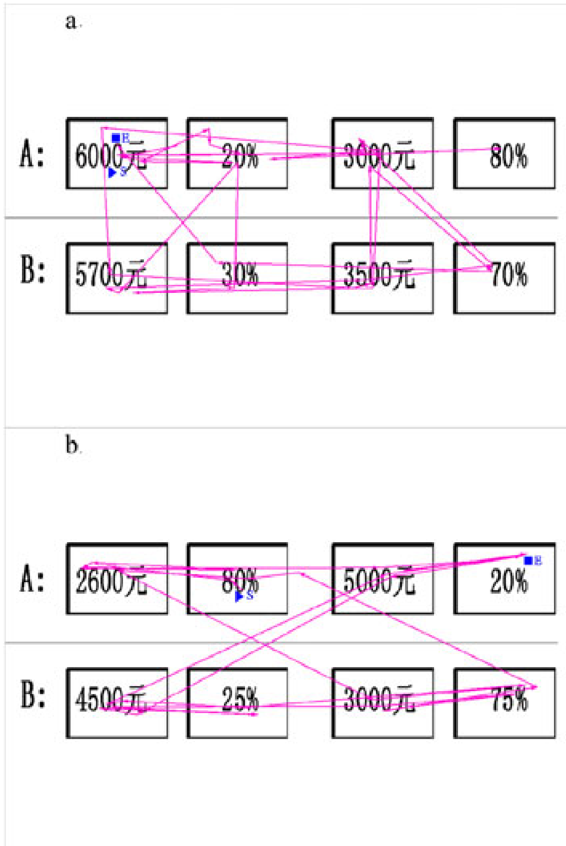

Figure 4. Typical trials formed in the outcome-matched (a) and outcome-crossed (b) presentation conditions for Data Set 2. The arrows indicate the scanpath formed by fixations; "▶ *S*" and "■ *E*"represent the start and end of the scanpth, respectively; the boxes are the ROIs defined by us

DOI: 10.1002/bdm

The MLM results showed a significant difference in the similarity scores between the intra-conditions and inter-conditions ($F(2, 102) = 9.39$, $p < .001$). The correlation structure model was unstructured. The Bonferroni adjustment was used for post-hoc pairwise comparisons. Post-hoc analysis showed that the similarity score of intra-condition A ($M = .43$, $SE = .006$) was significantly higher than the similarity score of the inter-condition ($M = .40$, $SE = .008$) ($t(102) = 4.28$; adjusted $p < .001$). The similarity score of intra-condition B ($M = .42$, $SE = .006$) was significantly higher than the similarity score of the inter-condition ($t(102) = 2.72$; adjusted $p = .02$). The results suggested that the scanpath patterns differed significantly between the outcome-matched and outcome-crossed presentation conditions.

The results of the clustering analysis indicated that the scanpaths of Conditions A and B were separable. The average percentage of incorrect classifications of scanpaths was 35.44% ($SD = .15$, ranging between 0% and 53.85%) for Condition A and 34.23% ($SD = .17$, ranging between 0 and 66.67%) for Condition B. Consistent with the MLM results, the result suggested that the scanpath patterns differed between the outcome-matched and outcome-crossed presentation conditions.

The scanpaths of typical trials of each condition are displayed in Figure 4. As in Dataset 1, trials with the first-highest, second-highest, and third-highest mean similarity score for Conditions A and B were also built and are depicted in Supplementary Material E. The scanpaths of the typical trials showed different patterns between the two conditions. Notably, as predicted by the equate-to-differentiate approach (Li & Xie, 2006), the scanpath between the best possible outcome (¥ 6000) of Option A and the best possible outcome (¥ 5700) of Option B and the scanpath between the worst possible outcome (¥ 3000) of Option A and the worst possible outcome (¥ 3500) of Option B were detected in both outcome-matched (attribute-based scanpaths occur in *parallel*) or outcome-crossed (attribute-based scanpaths occur in *crossed*) conditions.

The results suggested that the scanpath patterns differed between the outcome-matched and outcome-crossed presentation conditions. The scanpath patterns observed in the typical trials were perfectly consistent with the prediction of the equate-to-differentiate approach (S. Li, 2004; Li & Xie, 2006). An inspection of the scanpath patterns quickly leads to the diagnostic conclusion that risky decision making is unlikely to be based on the weighting and summing process.

DATASET 3

Dataset 3 is derived from Sun et al.'s (2014) eye-tracking study. In their study, the classic Asian Disease Problem (Tversky & Kahneman, 1981) was modified and tested in a single-play condition and a multiple-play condition. The eye-movement patterns in the multiple-play condition and the single-play condition were contrasted to test which pattern was more consistent with the predictions deduced from the expectation computation. Sun et al.'s (2014) eye-tracking study reasoned that the expectation-maximization rule works better in the multiple-play condition (S. Li, 2003; DeKay et al., 2006; Lopes, 1981). If distinctly different eye-movement patterns are detected in the single-play condition and the multiple-play condition, then the risky choice in the single-play condition is unlikely to be ruled by the expectation-maximization rule.

Forty-one college students (24 females, $M_{age} = 22.25$) participated in the study. One participant was excluded from the analyses because of incomplete tracking data. Eye movements were recorded using an SR EyeLink 2000 tracker (SR Research, Canada), with the eye position sampled at 2000 Hz. After being presented with the scenario, participants were asked to choose between a certain option and a higher-EV risky option in the multiple-play condition (in which the selected plan would be applied 100 times) or in the single-play condition (in which the selected plan would be applied only once). The order of tasks was counterbalanced. The choice stimuli were exactly the same between the two conditions, consisting of 14 pairs of emergency plans (Supplementary Material C).

In accordance with Sun et al.'s study, six non-overlapping, identically sized (230 × 202 pixels) rectangular ROIs were defined. Three regions covered the outcomes, and three regions covered the probabilities (Figure 5).

Results and discussion

Overall, 1223 of 33 299 fixations (approximately 3.67%) with durations of less than 50 ms were excluded from the

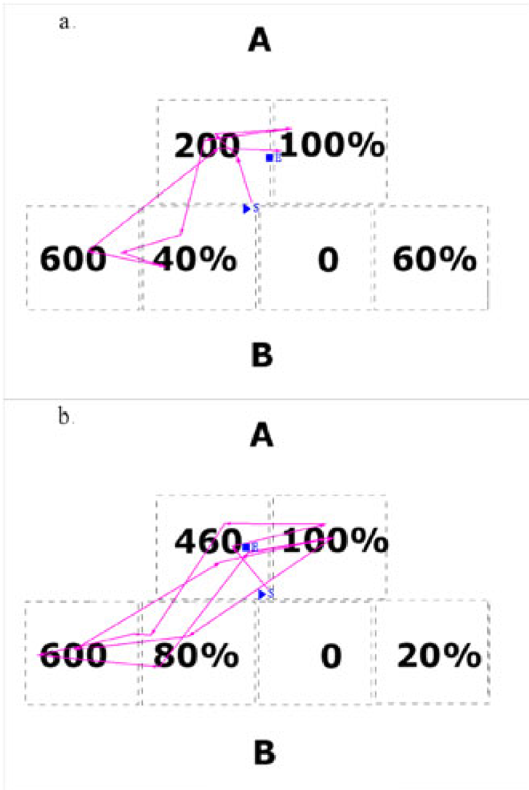

Figure 5. Typical trials formed in the multiple-play (a) and single-play (b) conditions for Data Set 3. The arrows indicate the scanpath formed by fixations; "▶ *S*" and "■ *E*" and represent the start and end of the scanpth, respectively; the dotted boxes are the ROIs defined by us

DOI: 10.1002/bdm

analysis. Seven of 1120 trials (approximately 0.54%) were discarded because of eye-tracking failures. The descriptive statistics for intra-condition A (multiple-play condition), the inter-condition, and intra-condition B (single-play condition) are shown in Figure 2.

The results showed that there was a significant difference between the similarity score of the intra-conditions and inter-conditions ($F(2,78) = 19.25$; $p < .001$). The correlation structure model was unstructured. A Bonferroni adjustment was used for post-hoc pairwise comparisons. Post-hoc analysis showed that the similarity score of intra-condition A ($M = .49$, $SE = .009$) was significantly higher than the similarity score of the inter-condition ($M = .44$, $SE = .009$) ($t(78) = 5.84$; adjusted $p < .001$). The similarity score of intra-condition B ($M = .48$, $SE = .008$) was significantly higher than the similarity score of the inter-condition ($t(78) = 4.74$; adjusted $p < .001$). These results suggested that the scanpath patterns differed between the multiple-play and single-play conditions.

The results of the clustering analysis indicated that the scanpaths of Conditions A and B were separable. The average percentage of incorrect classifications of the scanpaths was 31.74% ($SD = .16$, ranging between 0% and 50.00%) for Condition A and 33.00% ($SD = .16$, ranging between 0% and 50.00%) for Condition B. The result indicated that the scanpaths in the two conditions were separable, thus suggesting that the scanpath patterns differed between the multiple-play and single-play conditions.

The scanpaths of the typical trials of the two conditions are displayed in Figure 5. Trials with the first-highest, second-highest, and third-highest mean similarity score for Conditions A and B were also built and are depicted in Supplementary Material E. The scanpaths of the typical trials in the single-play condition were different from those in the multiple-play condition. In the multiple-play condition, participants first scanned within the sure option and then scanned within the risky option (option-based scanpath). The scanpath pattern in the multiple-play condition was similar to that in the proportion task in Dataset 1. However, in the single task, the scanpath did not diagnostically show a pattern similar to the multiple-task pattern.

The results revealed different scanpath patterns between the single-play and multiple-play conditions, suggesting that single-play risky choices are unlikely to be based on the weighting and summing process. The conclusion of Sun et al.'s (2014) study can be reached alternatively by simply assessing a single index (either the typical scanpath pattern or the similarity score).

GENERAL DISCUSSION

The present study successfully used scanpath analysis to examine risky decision-making models. Using scanpath analysis, we re-examined the data in the eye-tracking studies of Su et al. (2013), Wang and Li (2012), and Sun et al. (2014), in which a proportion task, an outcome-matched presentation condition, and multiple-play condition served as the baseline for comparison with a probability task, an outcome-crossed presentation condition, and single-play condition, respectively. The results of the three datasets consistently revealed that the similarity score within each condition was significantly higher than that between the conditions. The current research suggested that scanpath analysis has the potential to be applied for testing risky decision-making models. The results cross-validate earlier findings using a new method for analyzing scanpaths. Given that scanpath analysis provides a global view for analyzing the decision-making process, it is relatively safe to conclude that the weighting and summing hypothesis does not appear to be able to account for the processes of human risky preference.

Reliability and innovation of scanpath analysis in judgment and decision making

The results of the current research suggest that scanpath analysis is a reliable tool for examining risky-decision models. Process testing is vital for model examination (Schulte-Mecklenbeck et al., 2011a). Scanpath analysis focuses on the dynamical and holistic process and is therefore superior to other methods that integrate the sequential and global information of the decision-making process. The logic of scanpath analysis is that the difference between two tasks can be measured by investigating whether the average similarity score of the scanpaths for the intra-conditions is higher than that for the inter-conditions (Mathôt et al., 2012). In the three datasets we chose, we consistently found significant differences in the similarity scores between the inter-conditions and intra-conditions, which revealed different cognitive processes for each pair of tasks. Furthermore, we performed robustness checks by varying the parameters for the N–W algorithm to examine how they influenced the similarity score (Supplementary Material D). We found that the use of a different parameter would influence the absolute value of the similarity score but not the relationship between the intra-conditions and inter-conditions. Finally, the results of the clustering analyses for the sequences also revealed the reliability of scanpath analysis; the sequences of scanpaths in Conditions A and B could be correctly clustered into different categories.

Scanpath analysis focuses on the sequence property of eye movements and provides spatiotemporal data on the spatial distribution of attention across a visual stimulus (Gbadamosi & Zangemeister, 2001; Noton & Stark, 1971a, 1971b; Underwood, Humphrey, & Foulsham, 2008). These features of scanpath analysis indicate that the analysis is not merely a summary of more specific measures routinely used in judgment and decisionmaking (JDM); rather, it provides additional and unique information. Suppose that when participants perform two search tasks with the same stimuli, for instance, searching from digits 1 to 9 and from digits 9 to 1, they have different sequential cognitive processes. The traditional indexes, such as the total number of fixations and the distribution of fixations across different ROIs, might be the same for each task and would thus fail to detect this difference. However, scanpaths can accurately capture these different underlying cognitive processes. Compared with traditional indexes, the scanpath is likely more sensitive to the differences between decision tasks.

DOI: 10.1002/bdm

Decision-making models have assumed a sequential information seeking and evaluation process. The three previous studies (Su et al., 2013; Sun et al., 2014; Wang & Li, 2012) found differences only in the direction, depth, and complexity level of information processing between the conditions. Compared with previous research, the present findings are novel and important for better understanding the underlying cognitive process.

The present study identified a typical trial and provided a visualization of the decision-making process. To our knowledge, no attempt has previously been made to visualize the "prototype" of a decision-making process. The typical trial developed in the present study may serve as a promising candidate for such a role. Using typical trials, researchers can directly inspect decision-making processes across different conditions. Based on the inspection of typical trials in three datasets, we can directly observe that the option-based scanpath, which is predicted by the expectation-maximization rule, frequently occurs when participants make decisions in the proportion task and the multiple-play condition. In contrast, the attribute-based scanpath frequently occurs when participants make decisions during single-play preferential choices. Moreover, different segments of the scanpath might reflect different processes during decision making. A closer observation revealed that the option-based and attribute-based scanpaths seem to occur in the "evaluation" process defined by Russo and Leclerc (1994), which is characterized by the scanpath comprising re-fixation between two ROIs. Considering that a majority of the decision "work" occurs during the evaluation process (Glaholt & Reingold, 2011; Russo & Leclerc, 1994), the different scanpaths observed in the evaluation process are more likely to reflect the key divergence in the decision-making process.

In the present study, we contribute several innovations to the application of scanpath analysis in JDM research. First, we developed and validated a simple but sensitive analytical procedure for scanpath analysis in testing decision-making models, where the step-by-step procedure is potentially standardized in terms of algorithm selection, parameter combination based on the principle of parsimony, and typical trial identification. In this way, we also overcome the limitation of applying a similarity score, that is, that it is difficult to choose an appropriate relative weighting for each parameter (Mathôt et al., 2012). Without a standardized step-by-step procedure, the absolute values of similarity scores obtained from different studies that used different parameters cannot be directly compared and evaluated. The results of our robustness checks suggest that it is safe to calculate a reliable similarity score if the present analytical procedure for scanpath analysis is employed and that such a potentially standardized procedure may provide a simple, validated, and methodological standard to generalize the finding in future decision-making studies. Second, we defined the relationship of ROIs based on the attribute of option, which makes the method more appropriate for decision-making research. It can be seen that scanpath analysis is traditionally used in visual-based tasks (e.g., reading and viewing natural scenes), with the logic relationships between ROIs being principally based on spatial considerations. Meanwhile, in risky decision-making tasks, the logic relationships between ROIs are based on not only spatial considerations but also the scan orders between different attributes (e.g., probability or outcome) or between options, which are presumably ruled by different decision strategies. In the latter case, the scanpaths between the same attributes or options might be calculated differently depending on their positions. The cross-validation of the findings from our study using scanpath analysis and the previous studies using conventional analysis (Su et al., 2013; Sun et al., 2014; Wang & Li, 2012) indicated the validity of defining the relationship of ROIs based on attributes.

Scanpath analysis for examining risky-decision models

Compared with the traditional analytical methods of eye tracking, utilizing scanpath analysis to examine models of risky decision-making has unique merits. First, no specific hypothesis on the local details of eye movements is required, particularly for research attempting to determine whether two processes differ. Based on the pattern generated by the scanpath (Norman & Schulte-Mecklenbeck, 2010), we can investigate the process of risky choice from a global perspective. Unlike in previous eye-tracking studies, we do not need to develop specific hypotheses regarding the local detail of eye movements (Glöckner & Herbold, 2011; Su et al., 2013). Second, scanpaths are free from the presentation of stimuli. The results derived by traditional eye-tracking analysis are subject to the "presentation effect" (Shieh, Hsu, & Lin, 2005). That is, the presentation modes of stimuli interfere with the eye-movement results. According to scanpath theory, cognitive models are assumed to control the eye-movement scanpath (Noton & Stark, 1971a, 1971b). The influence of stimulus presentation on scanpath analysis is therefore relatively small.

Specifically, scanpath analysis simplifies the process of model testing. Numerous theories have been developed to reconcile violations of the expectation-maximization rule with experimental data and demonstrate that with the transformation of outcomes or of outcome probabilities, the expectation-maximization rule is applicable to risky choices. When the Allais paradox (Allais, 1953) questioned the maximization assumption in risky decision making, expectation-maximization proponents argued that any definite rule for choosing between risky prospects could be described as a maximization of some function. Therefore, the issue is not whether choice can be described as a maximization but rather which function is being maximized (for a more detailed argument, see S. Li, 1996). Using scanpath analysis, we were able to test the core expectation-maximization rule directly rather than testing which function (e.g., rank-dependent and sign-dependent or not) with which parameter (e.g., $\delta = 0.31$, 0.61, and 0.91 in the inverse S-shaped weighting function of cumulative prospect theory (Tversky & Kahneman, 1992)) is being maximized. Expectation-based risky-decision models hypothesize a single well-defined decision-making strategy (e.g., Pascal, 1670; von Neumann & Morgenstern, 1947; Kahneman & Tversky, 1979). However, our results indicate that the internal consistency of the scanpath pattern in

DOI: 10.1002/bdm

the proportion task (i.e., performing an expectation computation is definitely required) is higher than that in the probability task, implying that decision-makers may adopt a relatively flexible strategy in making risky choices rather than using a single strategy, as prescribed by the family of expectation models.

Moreover, a potential "rule-specific" contribution of scanpath analysis is its utilization to evaluate the degree of consistency of the internal patterns of decision tasks and therefore to examine the deterministic/stochastic decision rule. At present, we can note that a specific eye-movement pattern has been utilized to investigate the compensatory/non-compensatory and holistic/dimensional rule underlying the decision-making process. For example, a saccade between an outcome and its probability is required for a weighting process, whereas a saccade between the outcomes of two options is an index indicating a dimensional process. To our knowledge, however, no eye-movement pattern has been identified as satisfactorily usable to examine the deterministic/stochastic rule. As the likelihood that a deterministic/stochastic rule will be employed by a decision maker increases, the similarity score that would be derived from the decision maker increases/decreases; therefore, the similarity score developed in this paper might serve as a useful index for testing whether making a risky choice is based on a stochastic process. The analysis of Su et al.'s (2013) data, which indicated that the intra-condition similarity score for the *proportion* task (which definitely requires a deterministic rather than a stochastic strategy) was significantly higher than that of the probability task, supports this possibility.

Prospects and limitations

Scanpath analysis has been successfully used in applied research to examine individuals' search-process patterns and decision strategies (Bradley et al., 2011; Day, 2010; Engbert & Kliegl, 2001; Ni et al., 2011; Pieters et al., 1999). It is worth attempting to use scanpath analysis to examine decision-making models in fields other than risky decision making (e.g., decision making under uncertainty and intertemporal choice) to provide new evidence for the mechanisms of decision making. Scanpath analysis might also be a good candidate for studying decision making based on strategies, including experience-based decision making (Glöckner, Fiedler, Hochman, Ayal, & Hilbig, 2012; Yechiam & Busemeyer, 2005), web-based decision making (Ehmke & Wilson, 2007), and decision making in extreme environments, such as emergencies (Sun et al., 2014), space flight (Bock, Weigelt, & Bloomberg, 2010; Rao, Jiang, Liang, Zhou, & Li, 2014), and simulated microgravity (Jiang et al., 2013).

This study can surely be improved because it suffers from some limitations. First, the similarity between two tasks is measured by the similarity score in scanpath analysis. It is difficult to evaluate the meaning of an absolute similarity score within a task. Second, the core features of the typical trial were heavily based on the direct observation of the scanpath pattern. To generalize the result based on a typical trial, proper statistical analysis is needed in future research. Finally, although the similarity score might serve as a promising index for testing the process hypothesized by DDM, DFT, and other models based on stochastic information accumulation, it is still not clear how such an index can be utilized appropriately because these models ultimately did not yield an explicit and precise prediction regarding sequential information processing.

In summary, the present study verified that scanpath analysis is reliable and valid for examining the process of risky decision-making models. The typical scanpath pattern we developed can visualize the diagnostic crux of a decision-making process and allow the direct and rapid inspection of whether two decision-making processes differ. Given that scanpath analysis is a non-invasive method for examining the decision-making process, it is a good candidate for application in decision-making research.

ACKNOWLEDGEMENTS

This research was partially supported by the National Basic Research Program of China (973 Program, No. 2011CB711000), the National Natural Science Foundation of China (Nos. 71071150, 71471171, 70871110, 31170976, 31070904, 31200791), the Foundation for the Supervisor of Beijing Excellent Doctoral Dissertation (No. 20138012501), and the Key Project of the Chinese Academy of Sciences (No. KJZD-EW-L04). We thank Yin Su, Hong-Yue Sun, Lei Zhang and Chu-Guang Wei for discussion and data analysis assistance.

REFERENCES

Allais, M. (1953). Le comportement de l'homme rationel devant le risque: Critique des postulats et axioms de l'école americaine [Rational man's behavior in face of risk: Critique of the American School's postulates and axioms]. *Econometrica*, *21*, 503–546.

Altmann, G. T. M., & Kamide, Y. (2009). Discourse-mediation of the mapping between language and the visual world: Eye movements and mental representation. *Cognition*, *111*, 55–71. 10.1016/j.cognition.2008.12.005.

Birnbaum, M. H., & LaCroix, A. R. (2008). Dimension integration: Testing models without trade-offs. *Organizational Behavior and Human Decision Processes*, *105*, 122–133. 10.1016/j.obhdp.2007.07.002.

Bock, O., Weigelt, C., & Bloomberg, J. J. (2010). Cognitive demand of human sensorimotor performance during an extended space mission: A dual-task study. *Aviation, Space, and Environmental Medicine*, *81*, 819–824. 10.3357/ASEM.2608.2010.

Bradley, M. M., Houbova, P., Miccoli, L., Costa, V. D., & Lang, P. J. (2011). Scan patterns when viewing natural scenes: Emotion, complexity, and repetition. *Psychophysiology*, *48*, 1544–1553. 10.1111/j.1469-8986.2011.01223.x.

Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2006). The priority heuristic: Making choices without trade-offs. *Psychological Review*, *113*, 409–432. 10.1037/0033-295X.113.2.409.

Brandstätter, E., & Gussmack, M. (2012). The cognitive processes underlying risky choice. *Journal of Behavioral Decision Making*, *26*, 185–197. 10.1002/bdm.1752.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*, 432–459. 10.1037/0033-295X.100.3.432.

DOI: 10.1002/bdm

Colbert, G., Murray, D., & Nieschwietz, R. (2009). The use of expected value in pricing judgments. *Journal of Risk Research*, *12*, 199–208. 10.1080/13669870802488925.

Cristino, F., Mathôt, S., Theeuwes, J., & Gilchrist, I. D. (2010). ScanMatch: A novel method for comparing fixation sequences. *Behavior Research Methods*, *42*, 692–700. 10.3758/BRM.42.3.692.

Day, R.-F. (2010). Examining the validity of the Needleman–Wunsch algorithm in identifying decision strategy with eye-movement data. *Decision Support Systems*, *49*, 396–403. 10.1016/j.dss.2010.05.001.

DeKay, M. L., Hershey, J. C., Spranca, M. D., Ubel, P. A., & Asch, D. A. (2006). Are medical treatments for individuals and groups like single-play and multiple-play gambles? *Judgment and Decision Making*, *1*, 134–145.

Dshemuchadse, M., Scherbaum, S., & Goschke, T. (2013). How decisions emerge: Action dynamics in intertemporal decision making. *Journal of Experimental Psychology: General*, *142*, 93–100. 10.1037/a0028499.

Edwards, W. (1954). The theory of decision making. *Psychological Bulletin*, *51*, 380–417. 10.1037/h0053870.

Ehmke, C., & Wilson, S. (2007). *Identifying web usability problems from eye-tracking data*. Proceedings of the 21st British HCI Group Annual Conference on People and Computers. *UK*, *1*, 119-128.

Engbert, R., & Kliegl, R. (2001). Mathematical models of eye movements in reading: A possible role for autonomous saccades. *Biological Cybernetics*, *85*, 77–87. 10.1007/PL00008001.

Feldt, S., Waddell, J., Hetrick, V. L., Berke, J. D., & Żochowski, M. (2009). Functional clustering algorithm for the analysis of dynamic network data. *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, *79*, 056104.

Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: an eye-tracking analysis. *Frontiers in Psychology*, *3*, 1–18. 10.3389/fpsyg.2012.00335.

Foulsham, T., & Kingstone, A. (2013). Fixation-dependent memory for natural scenes: An experimental test of scanpath theory. *Journal of Experimental Psychology: General*, *142*, 41–56. 10.1037/a0028227.

Foulsham, T., & Underwood, G. (2009). Does conspicuity enhance distraction? Saliency and eye landing position when searching for objects. *Quarterly Journal of Experimental Psychology*, *62*, 1088–1098. 10.1080/17470210802602433.

Fred, A. (2002). Similarity measures and clustering of string patterns. In Chen, D., & Cheng, X. (Eds.), Pattern Recognition and String Matching (pp. 155–193). The Netherlands: Kluwer Academic Publishers.

Gbadamosi, J., & Zangemeister, W. H. (2001). Visual imagery in hemianopic patients. *Journal of Cognitive Neuroscience*, *13*, 855–866. 10.1162/089892901753165782.

Glaholt, M. G., & Reingold, E. M. (2011). Eye movement monitoring as a process tracing methodology in decision making research. *Journal of Neuroscience, Psychology, and Economics*, *4*, 125–146. 10.1037/a0020692.

Glöckner, A., & Betsch, T. (2008). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*, 1055–1075. 10.1037/0278-7393.34.5.1055.

Glöckner, A., Fiedler, S., Hochman, G., Ayal, S., & Hilbig, B. E. (2012). Processing differences between descriptions and experience: A comparative analysis using eye-tracking and physiological measures. *Frontiers in Psychology*, *3*, 1–15. 10.3389/fpsyg.2012.00173.

Glöckner, A., & Herbold, A. K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making*, *24*, 71–98. 10.1002/bdm.684.

Harte, J. M., Westenberg, M. R., & van Someren, M. (1994). Process models of decision making. *Acta Psychologica*, *87*, 95–120. 10.1016/0001-6918(94)90046-9.

Hayhoe, M., & Ballard, D. (2005). Eye movements in natural behavior. *Trends in Cognitive Sciences*, *9*, 188–194. 10.1016/j.tics.2005.02.009.

Henderson, J. M., & Hollingworth, A. (1999). High-level scene perception. *Annual Review of Psychology*, *50*, 243–271. 10.1146/annurev.psych.50.1.243.

Hilbig, B. E. (2008). One-reason decision making in risky choice? A closer look at the priority heuristic. *Judgment and Decision Making*, *3*, 457–462.

Holmqvist, K., Andrà, C., Lindström, P., Arzarello, F., Ferrara, F., Robutti, O., et al. (2011a). A method for quantifying focused versus overview behavior in AOI sequences. *Behavior Research Methods*, *43*, 987–998. 10.3758/s13428-011-0104-x.

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Van de Weijer, J. (2011b). Eye tracking: A comprehensive guide to methods and measures. UK: Oxford University Press.

Holyoak, K. J., & Simon, D. (1999). Bidirectional reasoning in decision making by constraint satisfaction. *Journal of Experimental Psychology: General*, *128*, 3–31. 10.1037/0096-3445.128.1.3.

Jain, A. K., Duin, R. P. W., & Mao, J. (2000). Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*, 4–37. 10.1109/34.824819.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An Introduction to Statistical Learning with Applications in R. New York: Springer.

Jiang, C.-M., Zheng, R., Zhou, Y., Liang, Z.-Y., Rao, L.-L., Sun, Y., … & Li, S. (2013). Effect of 45-day simulated microgravity on the evaluation of orally reported emergencies. *Ergonomics*, *56*, 1225–1231. 10.1080/00140139.2013.809481

Johnson, E. J., Schulte-Mecklenbeck, M., & Willemsen, M. C. (2008). Process models deserve process data: Comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychological Review*, *115*, 263–273. 10.1037/0033-295X.115.1.263.

Josephson, S., & Holmes, M. E. (2002). *Visual attention to repeated internet images*: *Testing the scanpath theory on the world wide web*. Proceedings of the 2002 Symposium on Eye Tracking Research & Applications, 43-49. 10.1145/507072.507081.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–291. 10.2307/1914185.

Keren, G. (1991). Additional tests of utility theory under unique and repeated conditions. *Journal of Behavioral Decision Making*, *4*, 297–304. 10.1002/bdm.3960040407.

Klos, A., Weber, E. U., & Weber, M. (2005). Investment decisions and time horizon: Risk perception and risk behavior in repeated gambles. *Management Science*, *51*, 1777–1790. 10.1287/mnsc.1050.0429.

Koop, G. J., & Johnson, J. G. (2013). The response dynamics of preferential choice. *Cognitive Psychology*, *67*, 151–185. 10.1016/j.cogpsych.2013.09.001.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*, 1292–1298. 10.1038/nn0911-1217b.

Krajbich, I. & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based choice. *Proceedings of the National Academy of Sciences*, *108*, 13852–3857. 10.1073/pnas.1101328108.

Langer, T., & Weber, M. (2001). Prospect theory, mental accounting, and differences in aggregated and segregated evaluation of lottery portfolios. *Management Science*, *47*, 716–733. 10.1287/mnsc.47.5.716.10483.

Li, S. (1996). What is the price for utilizing deductive reasoning? A reply to generalized expectation maximizers. *Journal of Economic Behavior and Organization*, *29*, 355–358. 10.1016/0167-2681(95)00069-0.

Li, S. (2003). The role of expected value illustrated in decision-making under risk: Single-play vs. multiple-play. *Journal of Risk Research*, *6*, 113–124. 10.1080/1366987032000078893.

Li, S. (2004). A behavioral choice model when computational ability matters. *Applied Intelligence*, *20*, 147–163. 10.1023/B:APIN.0000013337.01711.c7.

Li, X., Logan, G. D., & Zbrodoff, N. J. (2010). Where do we look when we count? The role of eye movements in enumeration. *Attention, Perception, & Psychophysics*, *72*, 409–426. 10.3758/APP.72.2.409.

Li, S., & Xie, X. (2006). A new look at the "Asian disease" problem: A choice between the best possible outcomes or between the worst possible outcomes? *Thinking and Reasoning*, *12*, 129–143. 10.1080/13546780500145652.

Liang, Z.-Y., Xu, L.-J., Rao, L. -L., Jiang, T.-Z., & Li, S. (2012). "20%的概率获得"="蛋糕" = "获得蛋糕的 20%" ? 检验风险决策的期望法则假设 ["20% probability to gain a cake" = "gain 20% of the cake"? Testing the expectation rule of risky decision making]. *Chinese Science Bulletin*, *57*, 3421–3433. 10.1360/972012-691.

Loftus, G. R., & Mackworth, N. H. (1978). Cognitive determinants of fixation location during picture viewing. *Journal of Experimental Psychology: Human Perception and Performance*, *4*, 565–572. 10.1037/0096-1523.4.4.565.

Lopes, L. L. (1981). Decision making in the short run. *Journal of Experimental Psychology: Human Learning and Memory*, *7*, 377–385. 10.1037/0278-7393.7.5.377.

Mathôt, S., Cristino, F., Gilchrist, I. D., & Theeuwes, J. (2012). A simple way to estimate similarity between pairs of eye movement sequences. *Journal of Eye Movement Research*, *5*, 1–15.

Needleman, S. B., & Wunsch, C. D. (1970). A general method applicable to the search for similarities in the amino acid sequence of two proteins. *Journal of Molecular Biology*, *48*, 443–453. 10.1016/0022-2836(70)90057-4.

Ni, J., Jiang, H., Jin, Y., Chen, N., Wang, J., Wang, Z., . . . Hu, X. (2011). Dissociable modulation of overt visual attention in valence and arousal revealed by topology of scan path. *PLoS ONE*, *6*, e18262. 10.1371/journal.pone.0018262

Norman, E., & Schulte-Mecklenbeck, M. (2010). Take a quick click at that! Mouselab and eye-tracking as tools to measure intuition. In Glöckner, A., & Witteman, C. (Eds.), Foundations for tracing intuition: Challenges and methods (pp. 24–44). New York, NY: Psychology Press.

Noton, D., & Stark, L. (1971a). Scanpaths in eye movements during pattern perception. *Science*, *171*, 308–311. 10.1126/science.171.3968.308.

Noton, D., & Stark, L. (1971b). Scanpaths in saccadic eye movements while viewing and recognizing patterns. *Vision Research*, *11*, 929–942. 10.1016/0042-6989(71)90213-6.

Nuthmann, A., & Kliegl, R. (2009). An examination of binocular reading fixations based on sentence corpus data. *Journal of Vision*, *9*, 1–28. 10.1167/9.5.31.

Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, *144*, 190–206. 10.1016/j.actpsy.2013.06.003.

Pachur, T., Hertwig, R., Gigerenzer, G., & Brandstätter, E. (2013). Testing process predictions of models of risky choice: A quantitative model comparison approach. *Frontiers in Psychology*, *4*, 646. 10.3389/fpsyg.2013.00646.

Pascal, B. (1670). *Pensées* (W. F. Trotter, Trans.). Retrieved October 25, 2012, from http://oregonstate.edu/instruct/phl302/texts/pascal/pensees-contents.html.

Payne, J. W., & Bettman, J. R. (2004). Walking with the scarecrow: The information processing approach to decision research. In Koehler, D. J., & Harvey, N. (Eds.), Blackwell handbook of judgment and decision making (pp. 110–132). New York, NY: John Wiley and Sons.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). The adaptive decision maker. Cambridge, England: Cambridge University Press. 10.1017/CBO9781139173933

Payne, J. W., & Venkatraman, V. (2010). Opening the black box: Conclusions to a handbook of process tracing methods for decision research. In Schulte-Mecklenbeck, M. (Ed.), A handbook of process tracing methods for decision research: A critical review and user's guide (pp. 223–249). New York: Taylor & Francis.

Pieters, R., Rosbergen, E., & Wedel, M. (1999). Visual attention to repeated print advertising: A test of scanpath theory. *Journal of Marketing Research*, *36*, 424–438. doi: 10.2307/3151998

Quené, H., & Van den Bergh, H. (2004). On multi-level modeling of data from repeated measures designs: A tutorial. *Speech Communication*, *43*, 103–121. 10.1016/j.specom.2004.02.004.

Rao, L., Jiang, C., Liang, Z., Zhou, Y., & Li, S. (2014). High-risk decision-making in space. In Sander, S., & Chen, S. (Eds.), Human Performance in Space: Advancing Astronautics Research in China (pp. 38–39). Washington, DC: Science/AAAS.

Rao, L.-L., Li, S., Jiang, T., & Zhou, Y. (2012). Is payoff necessarily weighted by probability when making a risky choice? Evidence from functional connectivity analysis. *PLoS ONE*, *7*, e41048. 10.1371/journal.pone.0041048.

Rao, L.-L., Liu, X.-N., Li, Q., Zhou, Y., Liang, Z.-Y., Sun, H.-Y., … Li, S. (2013). Toward a mental arithmetic process in risky choices. *Brain and Cognition*, *83*, 307–314. doi: 10.1016/j.bandc.2013.09.009

Rao, L.-L., Zhou, Y., Xu, L., Liang, Z.-Y., Jiang, T., & Li, S. (2011). Are risky choices actually guided by a compensatory process? New insights from fMRI. *PLoS ONE*, *6*, e14756. 10.1371/journal.pone.0014756.

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, *9*, 347–356. 10.1111/1467-9280.00067.

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. *The Quarterly Journal of Experimental Psychology*, *62*, 1457–1506. 10.1080/17470210902816461.

Redelmeier, D. A., & Tversky, A. (1992). On the framing of multiple prospects. *Psychological Science*, *3*, 191–193. 10.1111/j.1467-9280.1992.tb00025.x.

Russo, J. E., & Leclerc, F. (1994). An eye-fixation analysis of choice processes for consumer nondurables. *Journal of Consumer Research*, *21*, 274–290. 10.1086/209397.

Scarpa, R., Zanoli, R., Bruschi, V., & Naspetti, S. (2013). Inferred and stated attribute non-attendance in food choice experiments. *American Journal of Agricultural Economics*, *95*, 165–180. 10.1093/ajae/aas073.

Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (Eds) (2011a). A handbook of process tracing methods for decision research: A critical review and user's guide. New York: Taylor & Francis.

Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (2011b). The role of process data in the development and testing of process models of judgment and decision making. *Judgment and Decision Making*, *6*(8), 733–739.

Shi, S. W., Wedel, M., & Pieters, R. (2013). Information acquisition during online decision making: A model-based exploration using eye-tracking data. *Management Science*, *59*, 1009–1026. 10.1287/mnsc.1120.1625.

Shieh, K. K., Hsu, S. H., & Lin, Y. C. (2005). Dynamic Chinese text on a single-line display: Effects of presentation mode. *Perceptual and Motor Skills*, *100*, 1021–1035. 10.2466/PMS.100.4.1021-1035.

Stevenson, M. K., et al. (1990). Judgment and decision-making theory. In Dunnette, D. M., & Hough, L. M. (Eds.), Handbook of industrial and organizational psychology (2nd ed., Vol. *1*, pp. 283–374). CA, US: Consulting Psychologists Press.

Su, Y., Rao, L.-L., Sun, H.-Y., Du, X.-L., Li, X., & Li, S. (2013). Is making a risky choice based on a weighting and adding process? An eye-tracking investigation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *39*, 1765–1780. 10.1037/a0032861.

Sun, H.-Y., Rao, L.-L., Zhou, K., & Li, S. (2014). Formulating an emergency plan based on expectation-maximization is one thing, but applying it to a single case is another. *Journal of Risk Research*, *17*, 785–814. 10.1080/13669877.2013.816333.

Suter, R. S., Pachur, T., & Hertwig, R. (2015). How affect shapes risky choice: Distorted probability weighting versus probability

DOI: 10.1002/bdm

neglect. *Journal of Behavioral Decision Making*. Advance online publication.. 10.1002/bdm.1888.

Thorngate, W. (1980). Efficient decision heuristics. *Behavioral Science*, *25*, 219–225. 10.1002/bs.3830250306.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*, 453–458. 10.1007/BF00122574.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*, 297–323. 10.1007/BF00122574.

Underwood, G., Foulsham, T., & Humphrey, K. (2009). Saliency and scan patterns in the inspection of real-world scenes: Eye movements during encoding and recognition. *Visual Cognition*, *17*, 812–834. 10.1080/13506280902771278.

Underwood, G., Humphrey, K., & Foulsham, T. (2008). Knowledge-based patterns of remembering: Eye movement scanpaths reflect domain experience. *HCI and Usability for Education and Work*, *5298*, 125–144. 10.1007/978-3-540-89350-9_10.

von Neumann, J., & Morgenstern, O. (1947). Theory of games and economic behavior. Princeton, NJ: Princeton University Press.

Wang, Z.-J., & Li, S. (2012). 对整合模型和占优启发式模型的检验：基于信息加工过程的眼动研究证据 [Tests of the integrative model and priority heuristic model from the point of view of choice process: Evidence from an eye-tracking study]. *Acta Psychologica Sinica*, *44*, 179–198. 10.3724/SP.J.1041.2012.00179

Watson, M. R., Brennan, A. A., Kingstone, A., & Enns, J. T. (2010). Looking versus seeing: Strategies alter eye movements during visual search. *Psychonomic Bulletin & Review*, *17*, 543–549. 10.3758/PBR.17.4.543.

Wedell, D. H., & Böckenholt, U. (1994). Contemplating single versus multiple encounters of a risky prospect. *American Journal of Psychology*, *107*, 499–518. 10.2307/1422997.

Yarbus, A. L. (1967). Eye movements and vision. New York, NY: Plenum Press.

Yechiam, E., & Busemeyer, J. R. (2005). Comparison of basic assumptions embedded in learning models for experience-based decision making. *Psychonomic Bulletin & Review*, *12*, 387–402. 10.3758/BF03193783.

Zangemeister, W., Sherman, K., & Stark, L. (1995). Evidence for a global scanpath strategy in viewing abstract compared with realistic images. *Neuropsychologia*, *33*, 1009–1025. 10.1016/0028-3932(95)00014-T.

Authors' biographies:

Lei Zhou is a Ph.D. Student at Institute of Psychology, Chinese Academy of Sciences. Her research interests focus on the underlying decision process of risky choice and intertemporal choice with eye-tracking method.

Yang-Yang Zhang is a Ph.D. Student at Institute of Psychology, Chinese Academy of Sciences. He holds a B.S. in Psychology from Northeast Normal University and a M.S. in Psychology from East China Normal University. His research interests include intertemporal choice, risky decision making and neuroeconomics.

Zuo-Jun Wang is currently an Associate Professor in the Department of Psychology, Ningbo University. His research interests are in the area of judgment and decision making, emotion and group behavior.

Li-Lin Rao is an Associate Professor at Institute of Psychology, Chinese Academy of Sciences. She holds a B.S. in Psychology from Beijing Normal University, and a Ph.D. in Psychology from the Chinese Academy of Sciences. She has published articles on judgment and decision making in international refereed journals such as *Judgment and Decision Making*, *Evolution and Human Behavior*, and *the Journal of Experimental Psychology*: *Learning*, *Memory*, *and Cognition*.

Wei Wang is a Lecturer in Medicine at Brigham and Women's Hospital and Harvard Medical School. Her research interest expands many areas of statistics, such as experimental design, longitudinal and time series data analysis, and survival data analysis.

Shu Li (*Ph.D. UNSW*) is currently Professor and Chairman of the Academic Committee at the Institute of Psychology, Chinese Academy of Sciences. His research interests are in the area of behavioral decision making. He published his research both in Chinese and English which has appeared in over five-dozen journals such as *Journal of Behavioral Decision Making*, *Organizational Behavior and Human Decision Processes*, *Judgment and Decision Making*, *Thinking and Reasoning*, and *Evolution and Human Behavior*.

Xingshan Li is a Professor at Institute of Psychology, Chinese Academy of Sciences. His major research interests include language processing and eye movement control during high-level cognitive processes such as reading, decision making and scene perception.

Zhu-Yuan Liang is an Assistant Professor of Psychology at the Institute of Psychology, Chinese Academy of Sciences, China. Her research interests include intertemporal choice, risky decision making, neuroeconomics, and individual differences in judgment and decision making.

Authors' addresses:

Lei Zhou, Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China; University of Chinese Academy of Sciences, Beijing, China.

Yang-Yang Zhang, Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China; University of Chinese Academy of Sciences, Beijing, China.

Zuo-Jun Wang, Department of Psychology, Ningbo University, Ningbo, China.

Li-Lin Rao, Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China.

Wei Wang, Department of Medicine, Brigham and Women's Hospital, Harvard Medical School, MA, USA.

Shu Li, Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China.

Xingshan Li, Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China.

Zhu-Yuan Liang, Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China.

DOI: 10.1002/bdm