Exploring the Structure of Predecisional Information Search in Risky Choice

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Abstract

It is commonly assumed that there are qualitatively distinct cognitive strategies that underlie decision making. Because cognitive strategies differ in how information is processed, predecisional information search offers a window onto these strategies. Using a bottom-up approach, we examine whether predecisional information search actually reflects the use of distinct strategies. Specifically, we investigate the extent to which the heterogeneity in people's predecisional information search in a risky choice task reflects qualitatively distinct patterns that should emerge when people use distinct strategies. Our analysis takes into account the distribution of attention across attributes and transitions between attributes. Using cluster analysis, we find just two qualitatively different clusters with low separability: one characterized by balanced attention to all attributes and by transitions occurring mostly within the same option, and one characterized by a focus on outcome information and by frequent attribute-wise transitions. These two clusters were also associated with differences in people's choice behavior. The distribution of these clusters varied considerably across individuals, but less so across choice problems, suggesting that information search is not necessarily guided by features of the choice problem—this result challenges current theories on strategy selection. Our results challenge the common assumption that heterogeneity in predecisional information search is differentiated along clearly distinct information processing policies. Instead, the differentiation seems to fall into just two broad clusters—one resembling rational principles of expectation computation, the other reflecting heuristic principles that neglect probabilities—with considerable variability within each cluster.

Keywords: decision making; information search; heuristics; process tracing; clustering; decision strategies

Research on human decision making has a long tradition of investigating the information processing underlying people's choices. One important methodological approach for studying information processing is analyzing predecisional information search, recorded with eye tracking or information-board procedures such as Mouselab (Payne, Bettman, & Johnson, 1993; Schulte-Mecklenbeck, Kühberger, & Johnson, 2019). This approach is based on the eye–mind assumption (Just & Carpenter, 1980), according to which there is a close link between looking at information and mentally processing it.

Two of the key properties of predecisional information search that have been used to characterize people's attentional policies during decision making are the extent to which information inspection proceeds in an attribute-wise versus an option-wise manner, and how people distribute their attention across the various attributes (Payne, Braunstein, & Carroll, 1978; Rosen & Rosenkoetter, 1976; Russo & Dosher, 1983; Su et al., 2013). Predecisional information search data have been used to test process models of decision strategies, as well as to test how these strategies deviate from the rational principle of expectation computation (i.e., summing up the possible outcomes of a risky option, each weighted by its probability; Glöckner & Herbold, 2011; Johnson, Schulte-Mecklenbeck, & Willemsen, 2008; Pachur, Hertwig, Gigerenzer, & Brandstätter, 2013; Venkatraman, Payne, & Huettel, 2014). Moreover, patterns of predecisional information search have helped to map individual differences in decision making (e.g., Pachur, Schulte-Mecklenbeck, Murphy, & Hertwig, 2018; Patalano, Juhasz, & Dicke, 2010)—as has been done in other areas of cognitive science, such as categorization (Kruschke, Kappenman, & Hetrick, 2005) and reading (Staub, 2021).

An implicit assumption in process-tracing research in decision making is that predecisional information search data provides a diagnostic signal for inferring which strategy people use (e.g., Glöckner & Herbold, 2011; Pachur et al., 2013). For example, a balanced inspection of both outcome and probability information with most transitions occurring between outcomes and probabilities of the same option could indicate the weighted-additive strategy, which weights outcomes by their probability (in line with the rational principle of expectation computation). In contrast, a decision maker using a minimax strategy, which ignores probabilities and simply chooses the option with the more attractive outcome, should show a focus on inspecting outcome information with transitions that reflect comparisons of outcome information both within and between options.

Here we scrutinize this assumption by analyzing how distinct patterns of predecisional information search actually are. Using a clustering technique, we investigate the patterns of predecisional information search in risky choice. Whereas research on cognitive processes in decision making tends to be top-down, using existing models of strategies to describe people's behavior (Glöckner & Herbold, 2011; Johnson et al., 2008; Lee, Gluck, & Walsh, 2019; Pachur et al., 2013), we take a bottom-up approach, aiming to identify empirical patterns of predecisional information search without making prior assumptions of what these patterns might look like. This approach allows us to test the signal arising from predecisional information search data at face value and to potentially detect patterns that have not been hypothesized previously.

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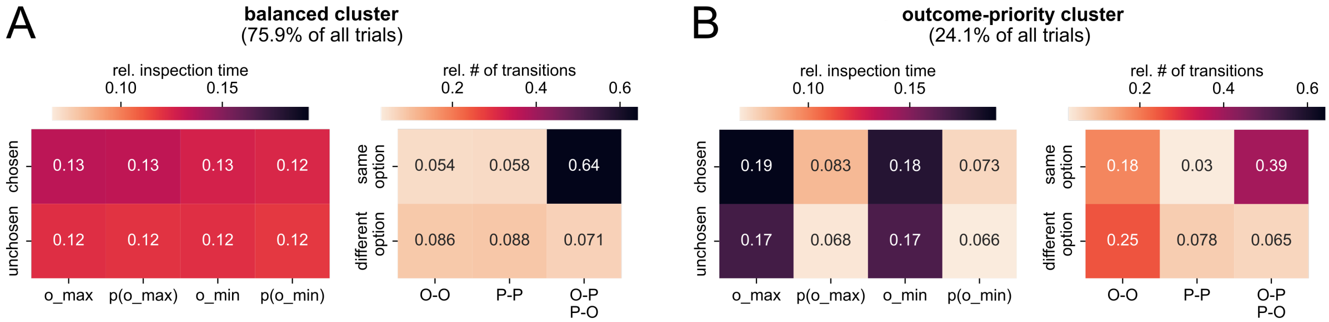

Figure 1: Cluster centroids. Variables refer to relative inspection time of boxes and relative number of transitions between boxes. Darker colors indicate higher values. O = outcome attribute, P = probability attribute

If predecisional information search data reflects the information processing of distinct decision strategies, then it should be separable into distinct clusters. Also, since decision strategies may predict different choices, different patterns of predecisional information search should also be associated with differences in choice behavior. For instance, trials in which choices are more consistent with the minimax strategy should be associated with a stronger focus on outcome information compared to trials in which choices are more consistent with a weighted-additive strategy.

In addition to identifying distinct patterns of predecisional information search, we are interested in analyzing sources of variability in these patterns. Theories of metareasoning suggest that decision makers adapt their decision strategies to the characteristics of the choice problem (Lieder & Griffiths, 2017; Payne, Bettman, & Johnson, 1988); on this account, patterns of predecisional information search should therefore vary between choice problems. Moreover, individuals might use different strategies (Mohnert, Pachur, & Lieder, 2019), which should lead to different patterns of predecisional information search between individuals. Previous research has found variability of information processing across individuals (Pachur et al., 2018) as well as across choice problems (Payne et al., 1993), but so far the extent of this variability has not been compared directly.

Methods

Data

For our analysis, we used data from Pachur et al. (2018), in which 90 participants completed a set of 91 risky choice problems twice in two sessions three weeks apart. At each trial, a choice problem consisting of two options was presented. Most options were risky options offering two outcomes with some probability (e.g., a 34% chance of winning €24 and a 66% chance of winning €59 vs. a 42% chance of winning €47 and a 58% chance of winning €64). The choice problems included 35 pure-gain choice problems, 25 pure-loss choice problems and 31 mixed choice problems.

The choice problems were presented with the process-tracing software Mouselab Payne et al. (1993). In Mouselab, information about probabilities and outcomes are hidden behind boxes but can be revealed by moving the mouse cursor over the box; the information disappears once the cursor is moved away. By recording how long each box is open and how the decision maker transitions between boxes, Mouselab traces patterns in predecisional information search.

Box openings shorter than 100 ms were discarded from the analysis. We excluded 0.7% of all trials from analysis because no decision was recorded or fewer than two boxes were opened. On average, 26 boxes were opened per trial.

For every trial, we computed a total of 14 variables characterizing the predecisional information search. Eight variables reflected the amount of attention allocated to the options' different attributes: the relative inspection time of the maximum outcome (o_max), of the minimum outcome (o_min), and of their respective probabilities (p[o_max], p[o_min]), separately for the chosen and the unchosen option. Six variables referred to how participants moved between the boxes during predecisional information search: the relative number of transitions between two outcomes (O-O), between two probabilities (P-P) and between one outcome and one probability (O-P/P-O), separately for transitions within one option and between the two options. We focused on this set of variables because inspection times and transitions between attributes are among the most commonly studied properties of process data in risky choice (Glöckner & Herbold, 2011; Johnson et al., 2008; Pachur et al., 2013). All variables were z-standardized across all participants.

Analytic Approach

To identify clusters of predecisional information search, we used k-means clustering on all trials from all participants. In k-means clustering, every observation (in this case, every trial) is assigned to the cluster with the closest cluster centroid. The algorithm sets a specified number of k cluster centroids such that the total within-cluster variance is minimized. Here, we performed clustering with $1 \leq k \leq 15$, and for each k, we computed the silhouette coefficient to assess between-cluster separation.

Results

With increasing number of clusters k, there was no identifiable "elbow" after which decreases in the within-cluster variance were only marginal. Silhouette coefficients, which express how clearly the clusters are separated, ranged between 0.10 and 0.17, suggesting that separation was low and that on average, data points were close to neighbouring clusters. These results indicate that the predecisional information search data do not display strongly distinct clusters; instead, the boundaries between clusters are continuous. For all subsequent analyses, we used $k = 2$, as this resolution yields the highest separation between clusters according to the silhouette coefficient while enabling clear interpretability of the differences between clusters.

Figure 1 shows the centroids of the two resulting clusters. One cluster (Figure 1A) was characterized by balanced attention to all outcome and probability information and by most transitions occurring between outcome and probability information of the same option. We therefore refer to it as the *balanced cluster*. The other cluster (Figure 1B) was characterized by a focus on outcome information and transitions between outcome and probability information of the same option; there were also frequent transitions between outcome information, both within one option and between the two options. We refer to this cluster as the *outcome-priority cluster*.

Many clustering solutions with higher values of k included a cluster similar to the outcome-priority cluster and clusters in which some outcome-probability pairs were inspected for longer than others (but not the more general balanced cluster).

How Do the Search Clusters Vary Across Choice Problems and Across Participants?

We compared two possible sources of variability in predecisional information search: choice problems and participants. Figure 2A plots the cluster distribution across choice problems. There was strong evidence against the cluster distribution differing between choice problems ($BF_{10} = 7.6 \times 10^{-40}$). Figure 2B plots the cluster distribution across participants. There was strong evidence that cluster distribution differed between participants ($BF_{10} = 8.0 \times 10^{730}$). These findings suggest that the qualitative differences in predecisional information search are primarily driven by differences between individuals, and not by choice problems.

Are the Search Clusters Associated With Differences in Choice?

Differences in information processing—and by extension in predecisional information search—might lead to systematically different decisions. We therefore tested whether the balanced cluster and the outcome-priority cluster were linked to differences in choice behavior. Separately for each choice problem, we compared the distribution of chosen options in trials assigned to the balanced cluster with the distribution of chosen options in trials assigned to the outcome-priority cluster. For 18 of 91 choice problems, there was strong evidence for a different distribution between chosen options ($BF_{10} > 10$) and one choice problem showed strong evidence against a difference in choice ($BF_{10} < 0.1$). The remaining problems did not show sufficient evidence for or against differences in choices between the clusters. Overall, these results indicate that the two clusters in predecisional information search are linked to differences in choices.

In a further step, we aimed to characterize these differences in choice behavior in more detail. For each choice problem, we computed the decision quality (defined as the proportion of choices of the option with the higher expected value), separately for trials assigned to the balanced cluster and the outcome-priority cluster. Decision quality did not differ between the two clusters ($M_{balanced} = 0.46, M_{outcome-priority} = 0.50, BF_{10} = 0.12$). Next, for each choice problem, we computed risk attitude (defined as the proportion of choices of the option with the higher coefficient of variation), separately for trials assigned to each of the two clusters. There was moderate evidence that for pure-gain problems choices on trials assigned to the outcome-priority cluster were more risk-seeking than in the balanced cluster ($M_{balanced} = 0.48, M_{outcome-priority} = 0.54, BF_{10} = 5.1$); there were no differences in risk attitude for pure-loss problems ($M_{balanced} = 0.49, M_{outcome-priority} = 0.50, BF_{10} = 0.23$) and mixed problems ($M_{balanced} = 0.45, M_{outcome-priority} = 0.54, BF_{10} = 1.86$).

In sum, differences in predecisional information search were associated with differences in choice behavior for some of the choice problems. Predecisional information search was not linked to differences in choice quality.

How Are the Clusters Related to Existing Strategies of Risky Choice?

Finally, we investigated how the choices associated with the identified clusters in predecisional information search corresponded to existing models of strategies for risky choice. We determined the predicted choices of 11 strategies for risky choice (see Table 1) and computed, for each cluster, the proportion of trials in which people's choices matched the strategies' predictions (Figure 3). The choices of the least-likely strategy ($BF_{10} = 1.4 \times 10^{23}$) and the tallying strategy ($BF_{10} = 52,070$) more closely matched the choices in the balanced cluster than those in the outcome-priority cluster. These two strategies consider both outcome and probability information when making a choice and thus are consistent with predecisional information search that attends to both types of information. The maximax strategy ($BF_{10} = 2.0 \times 10^{17}$) and the equal-weight strategy ($BF_{10} = 4.9 \times 10^{31}$) better matched the choices in the outcome-priority cluster than those in the balanced cluster. These two strategies consider only outcome information when making a choice and are thus consistent with predecisional information search that primarily attends to outcome information. Choices were therefore consistent with existing decision strategies that resembled the predicted predecisional information search.

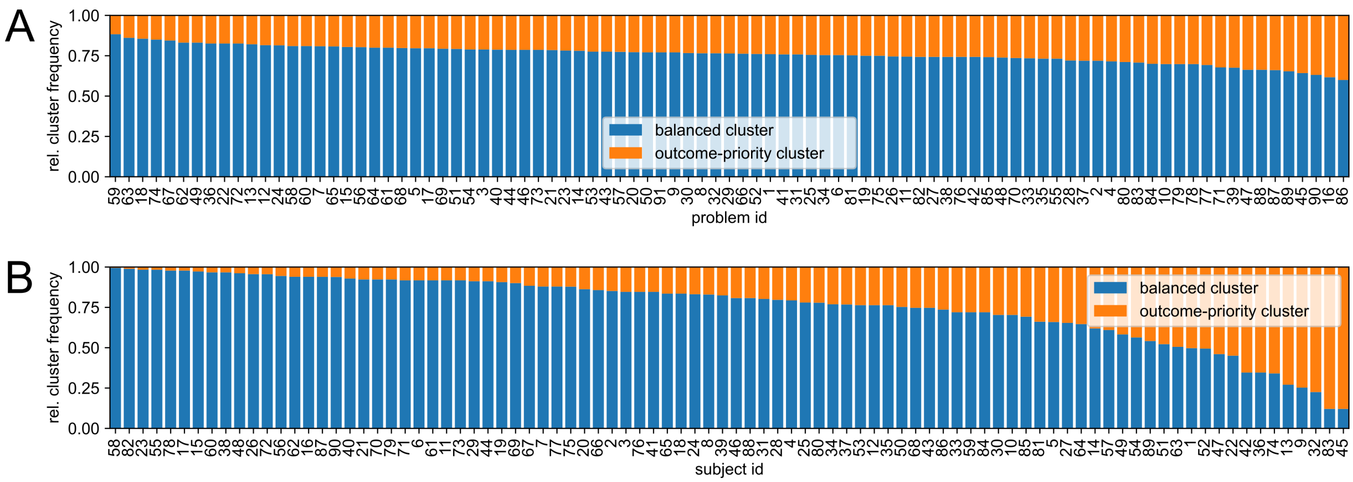

Figure 2: Cluster distribution across choice problems (Panel A) and across participants (Panel B).

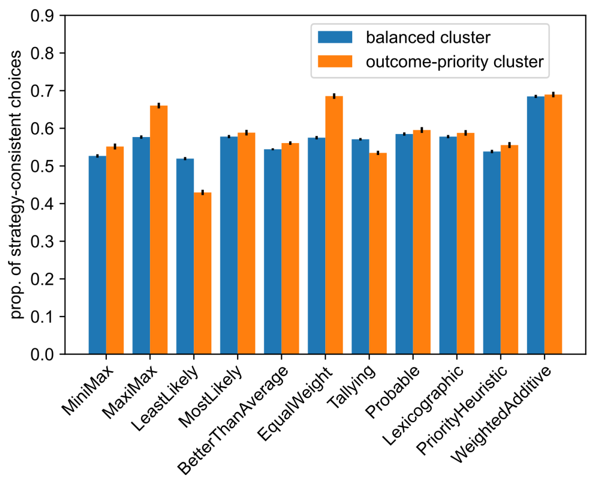

Figure 3: Proportion of choices that were consistent with each of the tested strategies. Error bars represent standard error of the mean.

Discussion

We employed a bottom-up, data-driven approach to examine patterns in predecisional information search in risky choice. The analysis revealed two general clusters. The balanced cluster was characterized by a balanced attention to outcome and probability information and transitions occurring mostly between outcome and probability information of the same option. The outcome-priority cluster was characterized by a stronger focus on outcome information and frequent attribute-wise transitions. The outcome-priority cluster may reflect a heuristic strategy that ignores part of the information (Gigerenzer, Hertwig, & Pachur, 2011). Although even in the outcome-priority cluster probability was inspected to some degree, this could reflect an initial reading (or encoding) phase that is often assumed to precede the actual decision-making process (e.g., Brandstätter, Gigerenzer, & Hertwig, 2008; Goldstein & Einhorn, 1987; Kahneman & Tversky, 1979; Pachur et al., 2013).

Overall, the clusters displayed low separability, indicating that the boundaries between them are blurred. This suggests that predecisional information search does not fall into distinct categories; instead, differences in predecisional information search seem to be gradual. An important question for future research will be to examine how well this finding generalizes to decision making in other domains. For example, in multi-attribute choice, where attributes are less interdependent than in risky choice (where normatively an outcome is closely tied to its corresponding probability; Rosen & Rosenkoetter, 1976), the patterns of predecisional information search might be less homogeneous and the evidence for distinct strategies stronger.

While there were pronounced individual differences in predecisional information search across participants, there were hardly any qualitative difference in predecisional information search across choice problems. This finding is at odds with the assumption in metareasoning theories that strategy selection (and consequently predecisional information search) is guided by the characteristics of the choice problem (Lieder & Griffiths, 2017; Payne et al., 1988). The set of choice problems used in our data set should be sufficiently diverse to elicit the use of different strategies for different choice problems; previous modeling work showed that choices on a similar set of choice problems were best described by people employing a toolbox of different strategies (Mohnert et al., 2019). However, we cannot rule out that the patterns identified by our clustering analysis subsume strategies that are similar in how they search information but different in terms of the mental operations involved. Also, given the considerable variance in predecisional information search within each of the identified clusters, our findings do not rule out more continuous differences in predecisional information search between choice problems—for instance, that people's atten-

Table 1: Models of strategies of risky choice.

Strategy	Description
Minimax	Choose the option with the highest minimum outcome.
Maximax	Choose the option with the highest outcome.
Least-likely	Identify each option's worst outcome. Then choose the option with the lowest probability of the worst outcome.
Most-likely	Identify each option's most likely outcome. Then choose the option with the highest most likely outcome.
Better-than-average	Calculate the grand average of all outcomes from all gambles. For each gamble, count the number of outcomes equal to or above the grand average. Then select the gamble with the highest number of such outcomes.
Equal-weight	Calculate the sum of all outcomes within a gamble. Choose the gamble with the highest sum.
Tallying	For gamble problems in the gain domain, give a tally mark to the gamble with (a) the higher minimum gain, (b) the higher maximum gain, (c) the lower probability of the minimum gain, and (d) the higher probability of the maximum gain. For gamble problems in the loss domain, replace "gain" by "loss" and "higher" by "lower" (and vice versa). Select the gamble with the highest number of tally marks.
Probable	Categorize probabilities as "probable" (i.e., $p \geq .5$ for a two-outcome gamble) or "improbable." Cancel improbable outcomes. Then calculate the arithmetic mean of the probable outcomes for each gamble. Finally, select the gamble with the highest average payoff.
Lexicographic	Determine the most likely outcome of each gamble and their respective payoffs. Then select the gamble with the highest most likely payoff. If all payoffs are equal, determine the second most likely outcome of each gamble and select the gamble with the highest (second most likely) payoff.
Priority heuristic	Go through attributes in the following order: minimum gain, probability of minimum gain, and maximum gain. Stop examination if the minimum gains differ by $1/10$ or more of the maximum gain; otherwise, stop examination if the probabilities differ by $1/10$ or more of the probability scale. Choose the option with the most attractive gain (probability).
Weighted-additive	For each gamble, sum up the possible outcomes weighted by their probabilities. Choose the option with the highest weighted sum.

Note. Descriptions of strategies are adapted from Brandstätter, Gigerenzer, and Hertwig (2006).

tion to outcome and probability information depends in a gradual fashion on the magnitude of these attributes. In any case, our analysis suggests that the signal contained in data about decision makers' predecisional information search—though clearly displaying systematic structures (Pachur et al., 2018)—might be less specific about qualitatively distinct processing strategies than is commonly assumed.

Clusters were associated with differences in choice behavior, indicating a link between the information attended and the final choice (Orquin & Loose, 2013). However, the different choice patterns did not result in differences in decision quality, showing that both types of predecisional information search could lead to similarly good decisions. The association between clusters and choices was observed for only a subset of the choice problems, maybe because the choice problems were not specifically designed to differentiate between the two clusters and different ways of predecisional information search might have led to similar decisions for some choice problems. The choices associated with the clusters overlapped with the choice predictions of previously suggested strategies that correspond to the type of information considered in each cluster: While strategies that consider both outcome and probability information better explained choices in the balanced cluster, strategies that only consider outcome information better explained choices in the outcome-priority cluster. Thus, while there seems to be a link between the clusters identified in our analysis and existing models of decision making, there is no simple one-on-one match between clusters and strategies.

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