Attribute-based choice

Francine W. Goh
ORCID.org/0000-0002-7364-4398

Jeffrey R. Stevens
ORCID.org/0000-0003-2375-1360

University of Nebraska-Lincoln

Abstract

Alternative-based approaches to decision making generate overall values for each option in a choice set by processing information within options before comparing options to arrive at a decision. By contrast, attribute-based approaches compare attributes (such as monetary cost and time delay to receipt of a reward) across options and use these attribute comparisons to make a decision. Because they compare attributes, they may not use all available information to make a choice, which categorizes many of them as heuristics. Choice data have suggested that attribute-based models can better predict choice compared to alternative-based models in some situations (e.g., when there are many options in the choice set, when calculating an overall value for an option is too cognitively taxing). Process data comparing alternative-based and attribute-based processing obtained from eye-tracking and mouse-tracking technology support these findings. Data on attribute-based models thus align with the notion of bounded rationality that people make use of heuristics to make good decisions when under time pressure, informational constraints, and computational constraints. Further study of attribute-based models and processing would enhance our understanding of how individuals process information and make decisions.

Author note

Department of Psychology, Center for Brain, Biology and Behavior, University of Nebraska-Lincoln, Lincoln, Nebraska, USA

Correspondence concerning this article should be addressed to Jeffrey R. Stevens, B83 East Stadium, University of Nebraska-Lincoln, Lincoln, Nebraska, 68588 USA. E-mail: jeffrey.r.stevens@gmail.com

Goh, F., & Stevens, J. R. (2021). Attribute-based choice. In R. Viale (Ed.), *Routledge Handbook of Bounded Rationality* (pp. 242–253). Routledge. https://doi.org/10.4324/9781315658353-16.

When sitting at your favorite café, you face the choice between a small cup of your favorite beverage for \$3.50 or a large cup for \$3.75. Many of us would choose the large cup. But how might we arrive at this choice? One method could generate a value for each option by combining the amount of beverage received and the cost of that beverage (Figure 1). After repeating this process for the second option, one could then compare the two options' values. This is an example of *alternative-based processing* because information is primarily processed within each alternative or option and options are processed in a sequential manner (Payne, Bettman, & Johnson, 1993).

Another way to make the choice is to compare within attributes and across options. *Attribute-based processing* primarily processes information within attributes or dimensions of information used in choice. In the beverage example, the amount of beverage and cost are the two relevant attributes. This method would compare the prices and may determine that they are quite similar. However, the amounts are noticeably different, and you prefer more to less beverage, so you choose the larger beverage (Figure 1).

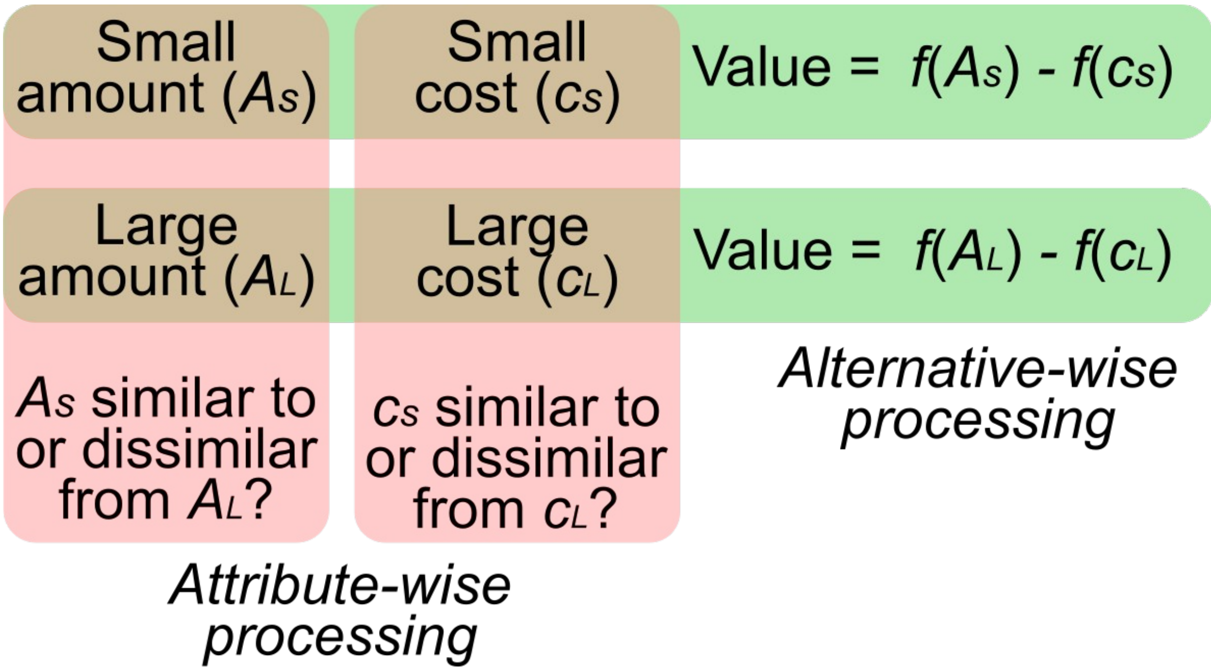

Figure 1: Approaches to choice. Alternative-wise processing integrates attributes (in this case, by applying some function *f* to the attributes) within alternatives to generate a composite value. Attribute-wise processing compares attributes across alternatives using a process such as similarity.

These two types of processing use the same information, but they use them in different ways. Alternative-wise processing integrates within alternatives and considers options sequentially, while attribute-wise processing compares within attributes and considers options simultaneously. Though many models of choice do not explicitly define the decision-making process, they typically imply either alternative- or attribute-wise processing.

Herbert Simon (1957) proposed the notion of *bounded rationality*, which states that decision makers face constraints on information availability, time to make a decision, and computational abilities. Including all information or processing it in complicated ways may be difficult for decision makers. Instead, they may use *heuristics* that ignore information and use simpler computations to make the best possible choice given the constraints of their current situation (Payne et al., 1993; Gigerenzer, Todd, & the ABC Research Group, 1999; Selten, 2002). Models of choice include both optimization models that use all information and combine it in complex ways, as well as heuristic models. Many alternative-based models of decision making use all informational cues and combine them in a way to generate something akin to a subjective value for each option. But many heuristics are attribute-based models. Though there are exceptions in both directions, alternative-based approaches tend to use optimization and attributed-based approaches tend to be heuristics. Here, we briefly review alternative-based approaches to choice, then explore attribute-based approaches and what they can offer the study of decision making.

Alternative-based choice

Alternative-based models are often *compensatory* because they make tradeoffs across attributes: high values in low-weighted attributes can compensate for low values in high-weighted attributes. Though alternative-based models can sometimes involve complex calculations, these models can lead to sharper distinctions between choice options and thus facilitate optimal decision making (Russo & Dosher, 1983). Thus, most normative models of choice are alternative-based models. These models have been used to account for a range of types of decisions, including multiattribute choice, risky choice, and intertemporal choice.

Multiattribute choice refers to situations in which decision makers must choose between two or more options, and each option has values for a number of different attributes. For example, one might choose between apartments that differ in their price, location, security deposit, and amenities. A normative model of optimal multiattribute choice is the weighted additive (WADD) rule (or weighted sum model) (Keeney & Raiffa, 1976). WADD is effectively a regression model that generates an overall value for each option in a choice set based on attributes that are weighted by their importance to the decision maker (Payne et al., 1993). The overall value for an option is determined by multiplying the value of each attribute by that attribute's weight and summing all of the weighted attribute values for that option. All possible options are then compared and the option with the highest overall value is selected. WADD, therefore, uses all available information, involves complex computational steps, and requires a high degree of cognitive effort (Payne et al., 1993). The equal weight (EW) rule (or Dawes' rule) is a variation of WADD in which all attributes are equally weighted (Dawes, 1979), thereby simplifying the decision-making process (Payne et al., 1993). Satisficing is another decision-making strategy that involves finding an option that satisfies a threshold or set of thresholds (Simon, 1955). Decision makers first determine minimally acceptable threshold values (or aspiration levels) for each attribute. Each option is then considered sequentially by comparing the option's attribute values to their corresponding predetermined thresholds. Options that contain any attributes that do not meet the thresholds are excluded and the first option that contains attributes which satisfy all of the attribute thresholds is selected (Payne et al., 1993). Though satisficing is considered a type of heuristic because it does not necessarily assess all options, it uses alternative-wise processing by evaluating options in the sequence in which they occur in the choice set.

Risky choice refers to situations in which options include different outcomes occurring with different probabilities. For example, would you prefer a 100% chance of receiving $100 or a 50% chance of $200 and a 50% chance of $0? Researchers have proposed many models of risky choice, and most of them are alternative-based approaches using a modification of expected value. The expected value approach multiplies two attributes—the probability of an outcome and the reward amount of that outcome—and sums these over all outcomes within an option to generate an expected value (Pascal, 1654, as cited in Smith, 1984). Many other models modify the expected value approach by applying a function to the probability and/or outcome (e.g., expected utility, subjective utility, prospect theory; see Stott, 2006). The key feature of these models is that each option is summarized into a value that is compared across options.

Intertemporal choice refers to sets of options that differ in the reward amount and time delay to receiving that reward. For example, would you prefer $100 today or $150 in one year? Like risky choice models, most intertemporal choice models integrate two attributes to generate a value for each option. For intertemporal choice, the attributes are reward amount and the time delay to receiving the reward. Models of intertemporal choice apply different functions to the reward amounts and time delays and different operations to combine them (Doyle, 2013; Regenwetter et al., 2018). These operations have the effect of discounting the value of the reward amount based on the time delay. These discounting models (e.g., exponential, hyperbolic, quasi-hyperbolic, additive) generate discounted values for each option and compare them to select the least discounted option.

Attribute-based choice

Attributed-based models have also been developed to account for multiattribute, risky, and intertemporal choice. Many attribute-based models are *non-compensatory* because they do not use all available information and therefore can avoid tradeoffs across attributes. Low-weighted attributes may be ignored and, therefore, cannot compensate for low values in high-weighted attributes. Attribute-based models can also allow for intransitive preference cycles in which option A is preferred to B, B is preferred to C, and C is preferred to A. Though alternative-based models have gained the majority of interest in the field, research on attribute-based models has grown. Here, we survey a subset of attribute-based models of multiattribute, risky, and intertemporal choice.

Lexicographic heuristic

In the lexicographic heuristic, decision makers first decide on the attribute that is most important to them. They then compare the values of that attribute across all choice options before selecting the option with the highest value on that attribute. In instances where two options have the same value on the most important attribute, individuals will have to compare the options on the next most important attribute. This comparison process continues until one option is deemed to be better than the other option on an attribute of importance (Fishburn, 1974). Several studies have found empirical support for the usage of the lexicographic heuristic during decision making (Slovic, 1975; Tversky, Sattah, & Slovic, 1988; Kohli & Jedidi, 2007; Yee, Dahan, Hauser, & Orlin, 2007). A variation of the lexicographic heuristic is the lexicographic semi-order, where the ranking of each option's value on an attribute depends on a just noticeable difference (Tversky, 1969). Specifically, if the values of options fall within the just noticeable threshold for the target attribute, the attribute values of these options will be ranked as equal and the decision maker will have to consider the next most important attribute to break the tie.

Elimination-by-aspects heuristic

The elimination-by-aspects (EBA) heuristic combines the lexicographic heuristic with the conjunctive rule. The conjunctive rule states that decision makers make a choice by establishing minimally acceptable threshold values for attributes and then eliminating choice options that do not meet these threshold values (Dawes, 1964; Einhorn, 1970). Similar to the lexicographic heuristic, decision makers using the EBA heuristic first select the attribute (or aspect) that is most important to them. A threshold value for each attribute is then determined and the value of each option on that attribute is compared to the threshold value. Choice options that do not meet the threshold value for the attribute are eliminated and the process continues with the next most important attribute until there is only one option that meets the threshold values for all of the attributes (Tversky, 1972). Additionally, the EBA heuristic has been suggested as a heuristic used by decision makers to reduce cognitive effort when they have to make a decision from several choice options (Payne, 1976). The EBA heuristic is considered to violate the principle of rational choice because the final decision is determined by a single attribute. On the other hand, the EBA heuristic is also considered a rational heuristic because it comprises the ranking of attributes in order of their importance (Tversky, 1972; Payne et al., 1993).

Proportional difference model

The proportional difference (PD) model was initially developed to predict decision-making behavior in a risky choice setting. The PD model posits that individuals compare the values of options along the same attributes in a proportional manner (i.e., the monetary outcome and probability of receiving that outcome of one option relative to those of the other option). During this comparison process, individuals add the advantages and subtract the disadvantages for each option to obtain an adjusted difference variable. To reach a decision, individuals compare their difference variable to a decision threshold that reflects the importance of each attribute (González-Vallejo, 2002). Such decision thresholds can vary according to individual wealth status and the context of the situation (González-Vallejo, 2002; González-Vallejo, Reid, & Schiltz, 2003; González-Vallejo & Reid, 2006). The PD model has since been extended to the domain of intertemporal choice by replacing the probability dimension with the time delay to receiving the monetary outcome (Cheng & González-Vallejo, 2016). In addition, the PD model accounts for the magnitude effect (where individuals exhibit less discounting when values are larger), violations of stochastic dominance (which states that when two options are similar on one attribute, individuals will choose the option that is dominant on the differing attribute), transitivity of preferences, reflection effect (which states that individuals are risk averse when they have to make a choice among gains and risk seeking when they have to make a choice among losses), and additivity (which holds that preference for a delayed option should be consistent regardless of how the delay period is segmented) (González-Vallejo, 2002; González-Vallejo et al., 2003; González-Vallejo & Reid, 2006; Cheng & González-Vallejo, 2016).

Tradeoff model

The tradeoff model proposes that individuals choose from options by weighing the advantage of the monetary outcome of one option against the advantage of the time value of the other option in intertemporal choice (Scholten & Read, 2010). The tradeoff model thus also suggests that time can be converted to the same scale of measurement used for monetary outcome (Scholten, Read, & Sanborn, 2014). The tradeoff model accounts for the magnitude effect, common difference effect (the tendency for individuals to exhibit more discounting when a delay period begins sooner compared to later), violations of transitivity of preferences, additivity, and inseparability (which states that individuals consider the value of the time delay of an option based on the value of that option's monetary outcome). In contrast to the PD model which uses the absolute monetary and time delay values of options to carry out comparisons between two options, the tradeoff model includes additional parameters that calculate value- and time-weighing functions that capture individuals' subjective perceptions of monetary values and time delays respectively (Scholten & Read, 2010; Cheng & González-

Vallejo, 2016). Despite the use of a more complex formula to predict choice, the ability of the tradeoff model to predict intertemporal choice is similar to that of the PD model (Cheng & González-Vallejo, 2016).

Difference-ratio-interest-finance-time (DRIFT) model

The difference-ratio-interest-finance-time (DRIFT) model suggests that decisions in intertemporal choice are affected by how choice options are framed. Specifically, the weighted average of the absolute difference between monetary values, relative difference between monetary values, experimental interest rate offered, and extent to which individuals view the experimenter's offer as an investment rather than a consumption are balanced against the importance assigned to time (Read, Frederick, & Scholten, 2013). Read and colleagues (2013) found in their analysis of the DRIFT model that the framing of monetary outcomes as investments increased individuals' patience for small monetary values ($700) but reduced patience for large monetary values ($70,000), which suggests that the manner in which intertemporal choices are framed affects decision-making behavior. The DRIFT model can account for the magnitude effect and delay effect (which states that individuals discount less when the time delay is described in a calendar date format instead of units of delay) when the difference and ratio between monetary values and the experimental interest rates are varied (Read et al., 2013).

Intertemporal choice heuristic (ITCH) model

The intertemporal choice heuristic (ITCH) model makes use of arithmetic operations to predict choice. Individuals compare available options by first subtracting and dividing option values along their respective monetary and time dimensions to obtain absolute and relative differences. Weights that reflect the level of importance assigned to these dimensions are then added to each of the four variables and their sum calculated to arrive at a decision (Ericson, White, Laibson, & Cohen, 2015).

Although the ITCH model is similar to the DRIFT model, the two models differ in that the ITCH model calculates both absolute and relative differences in time delay whereas the DRIFT model calculates only absolute differences (Ericson et al., 2015). The ITCH model accounts for the property of additivity and the magnitude, common difference, and delay effects.

Similarity model

The similarity model was initially developed to study decision making in a risky choice setting (Rubinstein, 1988; Leland, 1994). Rubinstein (1988) suggested that individuals who have to make a decision between two lottery options will do so by comparing the similarity of monetary outcomes and similarity of probability of receiving those outcomes for both options. The similarity model has also been extended to the strategic choice domain where it suggests that individuals make a decision by comparing the similarity of payoff options (Leland, 2013) and to the intertemporal choice domain where it posits that individuals arrive at a decision by comparing the similarity of monetary outcomes and time delays of choice options (Leland, 2002; Rubinstein, 2003; Stevens, 2016).

In the domain of intertemporal choice, the version of the similarity model developed by Leland (2002) suggests that individuals compare the similarity of monetary outcomes and similarity of time delays for options. These similarity comparisons can then result in one of three decision consequences: (1) a choice is made because one option dominates the other option on one attribute but has similar values on the other attribute, (2) the choice between the two options is inconclusive because both options offer similar values on the monetary and time delay attributes, or (3) the choice between the two options is inconsequential because one option dominates the other option on one attribute but is dominated on the other attribute. When a decision is either inconclusive or inconsequential, Leland (2002) proposed that individuals will proceed to make a choice at random, whereas Rubinstein (2003) suggested that a choice must be made using another (unspecified) criterion.

Stevens (2016) added a second stage of existing discounting models if similarity analysis was inconclusive or inconsequential. The two-stage similarity models predicted individual choice better than Leland's (2002) similarity model and other discounting models alone. Finally, the similarity model accounts for the magnitude, reflection, and common difference effects, violations of stochastic dominance, and transitivity of preferences (Leland, 1994, 1998, 2002; Stevens, 2016).

Fuzzy-trace theory

Fuzzy-trace theory posits that individuals encode information presented to them in both verbatim and gist representations (Reyna & Brainerd, 1995, 2011). Verbatim representations refer to the exact remembrance of information, such as remembering a note word-for-word or the exact digits of a telephone number. On the other hand, gist representations refer to memory for the general meaning of concepts, such as one's principles or cultural norms (Reyna & Brainerd, 2011; Reyna, 2012). Several studies have shown that individuals tend to rely on gist compared to verbatim representations when they have to make decisions and that individuals prefer to make use of the simplest gist level (or categorical distinctions) whenever possible (Reyna & Farley, 2006; Reyna & Lloyd, 2006; Reyna et al., 2011; Reyna & Brainerd, 2011).

Fuzzy-trace theory suggests that decisions made in risky choice and intertemporal choice settings depend on the gist, or core, principles evoked based on the context of the situation. The evoked gist principles then make one option more salient than the other, resulting in a decision. When specifically applied to the context of intertemporal choice, the evoked gist principles will make either the smaller-sooner option or the larger-later option more salient which will in turn affect the intertemporal choice made (Reyna, 2012; Rahimi-Golkhandan, Garavito, Reyna-Brainerd, & Reyna, 2017; Reyna & Wilhelms, 2017). For example, an individual presented with a choice of either receiving $5 today or $7 in 3 days may think of these options in the gist representations of "receiving some money today" and "receiving some money later" respectively. According to fuzzy-trace theory, if this individual possesses a gist principle akin to "living in the moment", his gist principle would make the option to receive $5 today more attractive than the other option, resulting in him choosing the smaller-sooner option. Fuzzy-trace theory can thus be considered an attribute-based model since it compares choice options across attributes.

Process data

While many researchers have compared alternative-based and attribute-based models in terms of their ability to accurately predict choice, the two classes of models also provide an important distinction in the *process* of choice—that is, the cognitive steps required to make a choice. Therefore, it can be useful to investigate process data to explore these models, particularly data that reveal how decision makers acquire information. Researchers have used eye tracking and mouse tracking to measure information acquisition with respect to alternative- or attribute-based information processing (Schulte-Mecklenbeck, Kühberger, & Ranyard, 2010).

Eye tracking

Eye-tracking techniques monitor how individuals attend to different types of information (Duchowski, 2017). As individuals look at visual stimuli, an eye tracker records the direction and path of eye movements, thus allowing researchers insight into which information individuals consider to be important (Figure 2). In the first use of eye tracking to study the decision-making process, Russo and Rosen (1975) studied how individuals chose in a multialternative choice setting. The researchers concluded that participants compared the options presented to them in pairs and preferred to use options that were similar to one another to form these pairs whenever they could. In a similar vein, Russo and Dosher (1983) found that participants preferred to compare options along attributes in a multiattribute choice setting. Participants also made use of attribute-wise comparisons in gambles that were expected to follow an expected value rule where the expected monetary outcome and probability of receiving that outcome are combined to calculate an overall value for each option. These eye-tracking studies thus support an attribute-based decision-making process.

Arieli, Ben-Ami, and Rubinstein (2011) used a risky choice task to investigate whether individuals used an alternative-based or similarity-based approach to make decisions. They hypothesized that participants who used an alternative-based approach when evaluating lottery options would move their eyes within options because they were formulating an overall value for each option (Figure 1). On the other hand, participants who used a similarity-based approach would move their eyes within attributes because they were comparing the options along each attribute (i.e., monetary outcome and probability).

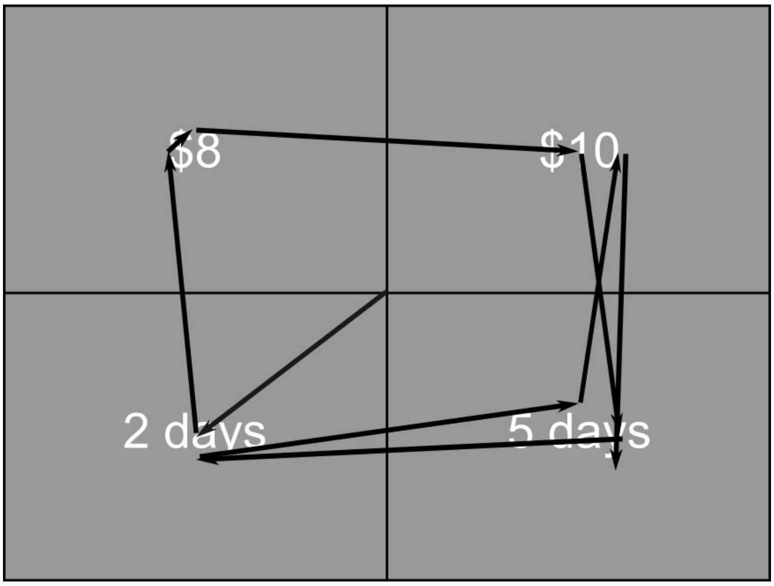

Figure 2: Example eye-tracking screenshot. Eye trackers record the direction and path of eye movements when individuals view information presented on a screen.

Arieli and colleagues (2011) found that participants used attribute-based processing to make decisions in a risky choice setting when the values of the monetary outcomes and probabilities made the calculation of the overall value of each option using the alternative-based process difficult. A follow-up study conducted by Aimone, Ball, and King-Casas (2016) supported Arieli et al.'s (2011) finding and also found that attribute-based processing was associated with risk-aversive choice preferences. Further, Arieli et al. (2011) found that participants maintained attribute-based processing to make a decision when the context of the lottery options was changed from risky choice (i.e., with the dimensions being monetary outcome and probability of receiving the monetary outcome) to intertemporal choice (i.e., with the dimensions being monetary outcome and time delay of monetary outcome).

Mouse tracking

Mouselab is a computer program that allows researchers to monitor how individuals acquire information in the decision-making process by using a computer mouse as a tracking tool (Johnson, Payne, Bettman, & Schkade, 1989; Willemsen & Johnson, 2009). The information for each attribute for all options in the choice set is presented in a matrix in which the cells are covered by overlays. When individuals hover their mouse over a cell of the matrix, the overlay disappears to reveal the underlying information; when the mouse moves out of the cell, the overlay reappears and covers the information again (Figure 3). Mouselab also records the amount of time that individuals spend viewing each "opened" section, the order in which sections are viewed and the number of times each section is viewed, thus allowing researchers to ascertain the importance of each attribute to individuals during the decision-making process.

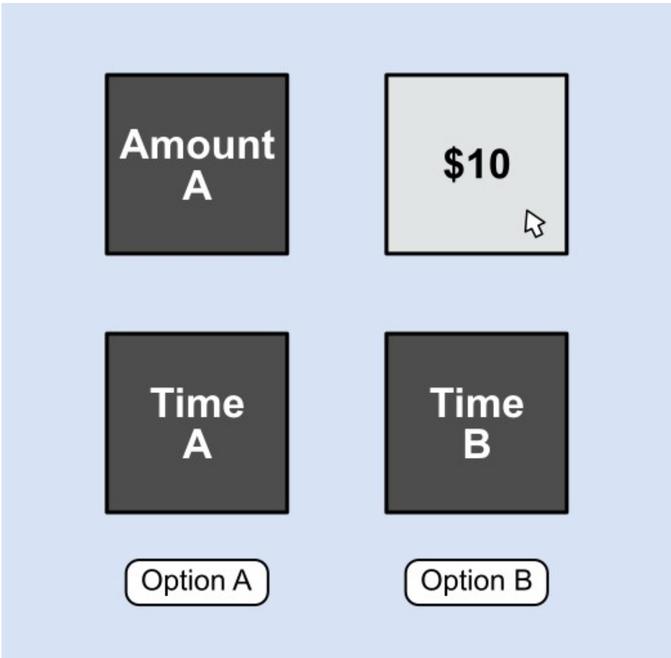

Figure 3: Recreated screenshot of MouselabWEB. Individuals move their mouse over each section of the matrix to display information for each option that is hidden by the overlay. The overlay reappears—and the information disappears again—when the mouse is moved out of the section.

In a comparison of the Mouselab and eye-tracking process-tracing techniques, Lohse and Johnson (1996) found that for both techniques, participants used attribute-based processing when the *number of options* in a choice set was increased in both risky choice and multiattribute choice settings. By contrast, participants used alternative-based processing when the *number of attributes* for each option in the choice set was increased (Lohse & Johnson, 1996). Reeck, Wall, and Johnson (2017) used Mouselab and eye tracking to study variations in search strategies in an intertemporal choice setting. They found that participants who used an attribute-based search strategy to compare options had a higher tendency to choose the larger-later option and were more susceptible to option-framing effects compared to participants who used an alternative-based search strategy. Additionally, they found that participants who spent more time looking at the amount dimension compared to time dimension of options were more patient as they chose the larger-later option more often than other participants in the study. In a study that combined risky and intertemporal choices, Konstantinidis, van Ravenzwaaij, and Newell (2017) used a computer program similar to Mouselab to study individuals' decision making in risky intertemporal choice. Participants in their study had to choose between two lottery options that differed in the dimensions of monetary outcome, probability of receiving the monetary outcome, and delay to receiving the monetary outcome. Process data demonstrated that participants preferred to use an attribute-based approach over an alternative-based approach when making their decisions.

Research using eye tracking and mouse tracking has further elucidated our understanding of how individuals acquire and process information when making decisions. Evidence from process data has shown that individuals make use of both alternative-based and attribute-based models of choice processing, and that the choice strategy that they use depends on the context of the situation at hand.

Conclusion

While the study of decision making has historically focused on alternative-based models, attribute-based models have experienced a resurgence of interest from researchers for a number of reasons. First, they follow from Simon's notion of bounded rationality because they often reflect real-world limitations faced by decision makers by using less information and simpler computations. This is especially pertinent in instances where decision makers have to make a choice from myriad options or when there is risk involved in the decision-making process. Second, they capture choice data quite well, predicting multiattribute, risky, intertemporal, and strategic choices while accounting for, or bypassing, anomalies regularly encountered in the use of alternative-based models. Third, in addition to capturing choice data, attribute-based models can capture the decision process by making predictions about eye tracking and information acquisition data. Combined, these lines of evidence suggest that attribute-based models provide a fruitful class of decision-making models that warrant continued investigation.

Acknowledgments

This work was funded in part by the National Science Foundation (SES-1658837).

References

Aimone, J. A., Ball, S., & King-Casas, B. (2016). It's not what you see but how you see it: Using eye-tracking to study the risky decision-making process. *Journal of Neuroscience, Psychology, and Economics*, *9*(3–4), 137–144. doi: 10.1037/npe0000061

Arieli, A., Ben-Ami, Y., & Rubinstein, A. (2011). Tracking decision makers under uncertainty. *American Economic Journal: Microeconomics*, *3*(4), 68–76. doi: 10.1257/mic.3.4.68

Cheng, J., & González-Vallejo, C. (2016). Attribute-wise vs. alternative-wise mechanism in intertemporal choice: Testing the proportional difference, trade-off, and hyperbolic models. *Decision*, *3*(3), 190–215. doi: 10.1037/dec0000046

Dawes, R. M. (1964). Social selection based on multidimensional criteria. *The Journal of Abnormal and Social Psychology*, *68*(1), 104–109. doi: 10.1037/h0047832

Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. *American Psychologist*, *34*(7), 571–582. doi: 10.1037/0003-066X.34.7.571

Doyle, J. R. (2013). Survey of time preference, delay discounting models. *Judgment and Decision Making*, *8*(2), 116–135. doi: 10.2139/ssrn.1685861

Duchowski, A. T. (2017). *Eye tracking methodology: Theory and practice* (3rd ed.). New York, NY: Springer.

Einhorn, H. J. (1970). The use of nonlinear, noncompensatory models in decision making. *Psychological Bulletin*, *73*(3), 221–230. doi: 10.1037/h0028695

Ericson, K. M. M., White, J. M., Laibson, D., & Cohen, J. D. (2015). Money earlier or later? Simple heuristics explain intertemporal choices better than delay discounting. *Psychological Science*, *26*(6), 826–833. doi: 10.1177/0956797615572232

Fishburn, P. C. (1974). Lexicographic orders, utilities and decision rules: A survey. *Management Science*, *20*(11), 1442–1471. doi: 10.1287/mnsc.20.11.1442

Gigerenzer, G., Todd, P. M., & the ABC Research Group. (1999). *Simple heuristics that make us smart.* New York, NY: Oxford University Press.

González-Vallejo, C. (2002). Making trade-offs: A probabilistic and context-sensitive model of choice behavior. *Psychological Review*, *109*(1), 137–155. doi: 10.1037//0033-295X.109.1.137

González-Vallejo, C., & Reid, A. A. (2006). Quantifying persuasion effects on choice with the decision threshold of the stochastic choice model. *Organizational Behavior and Human Decision Processes*, *100*(2), 250–267. doi: 10.1016/j.obhdp.2006.02.001

González-Vallejo, C., Reid, A. A., & Schiltz, J. (2003). Context effects: The proportional difference model and the reflection of preference. *Journal of Experimental Psychology. Learning, Memory & Cognition*, *29*(5), 942–953. doi: 10.1037/0278-7393.29.5.942

Johnson, E. J., Payne, J. W., Bettman, J. R., & Schkade, D. A. (1989). *Monitoring information processing and decisions: The Mouselab system* (Report No. 89-4). Retrieved from http://www.dtic.mil/docs/citations/ADA205963

Keeney, R. L., & Raiffa, H. (1976). *Decisions with multiple objectives: Preferences and value tradeoffs*. New York, NY: John Wiley & Sons.

Kohli, R., & Jedidi, K. (2007). Representation and inference of lexicographic preference models and their variants. *Marketing Science*, *26*(3), 380–399. doi: 10.1287/mksc.1060.0241

Konstantinidis, E., van Ravenzwaaij, D., & Newell, B. R. (2017). Exploring the decision dynamics of risky intertemporal choice. In G. Gunzelmann, A. Howes, T. Tenbrink, & E. J. Davelaar (Eds.), *Proceedings of the 39th Annual Conference of the Cognitive Science Society* (pp. 694–699). Austin, TX: Cognitive Science Society.

Leland, J. W. (1994). Generalized similarity judgments: An alternative explanation for choice anomalies. *Journal of Risk and Uncertainty*, *9*(2), 151–172. doi: 10.1007/BF01064183

Leland, J. W. (1998). Similarity judgments in choice under uncertainty: A reinterpretation of the predictions of regret theory. *Management Science, 44*(5), 659–672. doi: 10.1287/mnsc.44.5.659

Leland, J. W. (2002). Similarity judgments and anomalies in intertemporal choice. *Economic Inquiry*, *40*(4), 574–581. doi: 10.1093/ei/40.4.574

Leland, J. W. (2013). Equilibrium selection, similarity judgments, and the "nothing to gain/nothing to lose" effect. *Journal of Behavioral Decision Making, 26*(5), 418–428. doi: 10.1002/bdm.1772

Lohse, G. L., & Johnson, E. J. (1996). A comparison of two process tracing methods for choice tasks. *Organizational Behavior and Human Decision Processes*, *68*(1), 28–43. doi: 10.1006/obhd.1996.0087

Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance*, *16*(2), 366–387. doi: 10.1016/0030-5073(76)90022-2

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. New York, NY: Cambridge University Press.

Rahimi-Golkhandan, S., Garavito, D. M. N., Reyna-Brainerd, B. B., & Reyna, V. F. (2017). A fuzzy-trace theory of risk and time preferences in decision making: Integrating cognition and motivation. In J. R. Stevens (Ed.), *Impulsivity: How time and risk influence decision making, Nebraska symposium on motivation* (Vol. 64, pp. 115–144). New York, NY: Springer. doi: 10.1007/978-3-319-51721-6_4

Read, D., Frederick, S., & Scholten, M. (2013). DRIFT: An analysis of outcome framing in intertemporal choice. *Journal of Experimental Psychology. Learning, Memory & Cognition*, *39*(2), 573–588. doi: 10.1037/a0029177

Reeck, C., Wall, D., & Johnson, E. J. (2017). Search predicts and changes patience in intertemporal choice. *Proceedings of the National Academy of Sciences*, *114*(45), 11890–11895. doi: 10.1073/pnas.1707040114

Regenwetter, M., Cavagnaro, D. R., Popova, A., Guo, Y., Zwilling, C., Lim, S. H., & Stevens, J. R. (2018). Heterogeneity and parsimony in intertemporal choice. *Decision*, *5*(2), 63–94. doi: 10.1037/dec0000069

Reyna, V. F. (2012). A new intuitionism: Meaning, memory, and development in fuzzy-trace theory. *Judgment and Decision Making*, *7*(3), 332–359.

Reyna, V. F., & Brainerd, C. J. (1995). Fuzzy-trace theory: An interim synthesis. *Learning and Individual Differences*, *7*(1), 1–75. doi: 10.1016/1041-6080(95)90031-4

Reyna, V. F., & Brainerd, C. J. (2011). Dual processes in decision making and developmental neuroscience: A fuzzy-trace model. *Developmental Review, 31*(2–3), 180–206. doi: 10.1016/j.dr.2011.07.004

Reyna, V. F., Estrada, S. M., DeMarinis, J. A., Myers, R. M., Stanisz, J. M., & Mills, B. A. (2011). Neurobiological and memory models of risky decision making in adolescents versus young adults. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *37*(5), 1125–1142. doi: 10.1037/a0023943

Reyna, V. F., & Farley, F. (2006). Risk and rationality in adolescent decision making: Implications for theory, practice, and public policy. *Psychological Science in the Public Interest*, *7*(1), 1–44. doi: 10.1111/j.1529-1006.2006.00026.x

Reyna, V. F., & Lloyd, F. J. (2006). Physician decision making and cardiac risk: Effects of knowledge, risk perception, risk tolerance, and fuzzy processing. *Journal of Experimental Psychology: Applied*, *12*(3), 179–195. doi: 10.1037/1076-898X.12.3.179

Reyna, V. F., & Wilhelms, E. A. (2017). The gist of delay of gratification: Understanding and predicting problem behaviors. *Journal of Behavioral Decision Making*, *30*(2), 610–625. doi: 10.1002/bdm.1977

Rubinstein, A. (1988). Similarity and decision-making under risk (is there a utility theory resolution to the Allais paradox?). *Journal of Economic Theory*, *46*(1), 145–153. doi: 10.1016/0022-0531(88)90154-8

Rubinstein, A. (2003). “Economics and psychology”? The case of hyperbolic discounting. *International Economic Review*, *44*(4), 1207–1216. doi: 10.1111/1468-2354.t01-1-00106

Russo, J. E., & Dosher, B. A. (1983). Strategies for multiattribute binary choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *9*(4), 676–696. doi: 10.1037/0278-7393.9.4.676

Russo, J. E., & Rosen, L. D. (1975). An eye fixation analysis of multialternative choice. *Memory & Cognition*, *3*(3), 267–276. doi: 10.3758/BF03212910

Scholten, M., & Read, D. (2010). The psychology of intertemporal tradeoffs. *Psychological Review*, *117*(3), 925–944. doi: 10.1037/a0019619

Scholten, M., Read, D., & Sanborn, A. (2014). Weighing outcomes by time or against time? Evaluation rules in intertemporal choice. *Cognitive Science*, *38*(3), 399–438. doi: 10.1111/cogs.12104

Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (2011). *A handbook of process tracing methods for decision research: A critical review and user’s guide*. New York, NY: Psychology Press.

Selten, R. (2002). What is bounded rationality? In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 13–36). Cambridge, MA: MIT Press.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, *69*(1), 99–118. doi: 10.2307/1884852

Simon, H. A. (1957). *Models of man: Social and rational*. New York, NY: John Wiley & Sons.

Slovic, P. (1975). Choice between equally valued alternatives. *Journal of Experimental Psychology: Human Perception and Performance*, *1*(3), 280–287. doi: 10.1037/0096-1523.1.3.280

Smith, D. E. (1984). *A source book in mathematics*. Mineola, NY: Dover.

Stevens, J. R. (2016). Intertemporal similarity: Discounting as a last resort. *Journal of Behavioral Decision Making*, *29*(1), 12–24. doi: 10.1002/bdm.1870

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty*, *32*(2), 101–130. doi: 10.1007/s11166-006-8289-6

Tversky, A. (1969). Intransitivity of preferences. *Psychological Review*, *76*(1), 31–48. doi: 10.1037/h0026750

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, *79*(4), 281–299. doi: 10.1037/h0032955

Tversky, A., Sattah, S., & Slovic, P. (1988). Contingent weighting in judgment and choice. *Psychological Review*, *95*(3), 371–384. doi: 10.1037/0033-295X.95.3.371

Willemsen, M. C. & Johnson, E. J. (2009). MouselabWEB: Monitoring information acquisition processes on the web. Retrieved from http://www.mouselabweb.org/

Yee, M., Dahan, E., Hauser, J. R., & Orlin, J. (2007). Greedoid-based noncompensatory inference. *Marketing Science*, *26*(4), 532–549. doi: 10.1287/mksc.1060.0213