

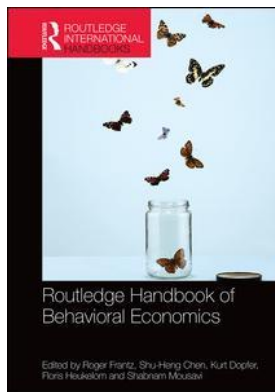
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Publisher: *Routledge*

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## **Routledge Handbook of Behavioral Economics**

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### **Rethinking Behavioral Economics Through Fast-and-Frugal Heuristics**

Publication details

<https://test.routledgehandbooks.com/doi/10.4324/9781315743479.ch20>

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**Published online on: 27 Jul 2016**

**How to cite :-** Shabnam Mousavi, Gerd Gigerenzer, Reza Kheirandish. 27 Jul 2016, *Rethinking Behavioral Economics Through Fast-and-Frugal Heuristics* from: Routledge Handbook of Behavioral Economics Routledge

Accessed on: 22 Mar 2023

<https://test.routledgehandbooks.com/doi/10.4324/9781315743479.ch20>

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## 20

# RETHINKING BEHAVIORAL ECONOMICS THROUGH FAST- AND-FRUGAL HEURISTICS

*Shabnam Mousavi, Gerd Gigerenzer, and Reza Kheirandish*

How do humans reason when the conditions for rationality postulated by the model of neoclassical economics are not met?

*Herbert A. Simon, 1989*

## Introduction

The goal of behavioral economics is to develop models that extend the explanatory and predictive power of economic theory, to address violations of expected utility theory, and to account more realistically for individual choice behavior that does not adhere to calculative rationality. In mainstream behavioral economics, two defining practices have been to list so-called cognitive fallacies and to extend existing expected utility models by adding parameters to account for behavioral factors. Both practices have met their limits. Many cognitive fallacies have been shown to be most likely error on the part of researchers, and adding parameters has been shown to improve fitting but not necessarily the predictive power of the revised utility model. In view of this situation, we review fast-and-frugal heuristics as an alternative vision of behavioral economics that leads to testable process models with superior predictive power. Such a theory satisfies Herbert Simon's criteria of developing process models rather than as-if Bernoulli functions, deals with genuine uncertainty rather than reducing uncertainty to calculable risk, and postulates ecological rather than logical rationality.

In their opening chapter of *Advances on Behavioral Economics* (2004), Camerer and Loewenstein present their "final thoughts":

Critics have pointed out that behavioral economics is not a unified theory, but is instead a collection of tools or ideas. This is true. It is also true of neoclassical economics. A worker might rely on a "single" tool—say, a power drill—but also use a wide range of drill bits to do various jobs. Is this one tool or many? . . . The goal of behavioral economics is to develop better tools that, in some cases, can do both jobs at once . . . *all too often economists fail to conduct intellectual trade with those who have a comparative advantage in understanding individual human behavior.* . . . Our hope is that behavioral models will gradually replace simplified models based on stricter rationality, as the behavioral models

prove to be tractable and useful in explaining anomalies and making surprising predictions. Then strict rationality assumptions now considered indispensable in economics will be seen as useful special cases . . . , they help illustrate a point which is truly established only by more general, behaviorally grounded theory.

*(pp. 41–2, emphasis added)*

What is called behavioral economics consists of two different programs. The first catalogues a list of cognitive fallacies, and the second accounts for psychological phenomena through minimal alterations of expected utility theory. This twin research program has run into two severe problems. First, many so-called cognitive fallacies have since been shown to be mainly statistical or measurement artifacts and thus do not represent genuine psychological phenomena that provide insight into human behavior. For example, the hot hand fallacy introduced by Gilovich, Vallone, and Tversky (1985), which attributed systematic errors to coaches and players, has been argued to result from researchers' systematic error in measurement (Miller & Sanjurjo, 2015). Likewise, overconfidence defined as miscalibration (Lichtenstein, Fischhoff, & Phillips, 1982) has been shown to be mainly due to researchers' misinterpretation of regression to the mean (see Erev, Wallsten, & Budescu, 1994); the same holds for Slovic, Fischhoff, and Lichtenstein's (1982) reported overestimation of low risk and underestimation of high risk (see Hertwig, Pachur & Kurzenhäuser, 2005). In both cases, researchers mistook the participants' unsystematic errors for systematic ones. Other alleged systematic errors have been similarly set in a different light (see Gigerenzer, 2015; Gigerenzer, Fiedler & Olsson, 2012). Equally important, systematic literature searches show lack of evidence that these cognitive illusions, even if they existed, would cause actual harm in terms of less wealth, health, or happiness (Arkes, Gigerenzer & Hertwig, 2016; Berg & Gigerenzer, 2010).

The second problem has to do with an issue inherent to the functional form underlying behavioral economics models. Behavioral economists have attempted to build behavioral models by adding free parameters to expected utility models that generally have Bernoulli functional forms. Adding parameters to Bernoulli functions can increase their data fitting power but is no remedy for their poor out-of-sample prediction power (Friedman, Isaac, James & Sunder, 2014). On the contrary, adding more adjustable parameters ultimately decreases the predictive power because of increasing estimation error (Geman, Bienenstock & Doursat, 1992). Thus, achieving better prediction power for behavioral models developed through such practices is problematic. An alternative can be found in a program of study inspired by Herbert Simon's version of behavioral economics, which differs from the described two practices in three respects: by developing process models rather than as-if Bernoulli functions to achieve higher predictive power, openly dealing with genuine uncertainty rather than reducing uncertainty to risk, and utilizing an ecological notion of rationality that rectifies mistaken claims of cognitive fallacies. These properties characterize the fast-and-frugal heuristics study program.

This chapter provides a selective survey of fast-and-frugal heuristics (Gigerenzer, Hertwig & Pachur 2011; Gigerenzer, Todd and the ABC Research Group, 1999) that addresses the characteristics and goals of behavioral economics as described in the above passage by Camerer and Loewenstein, which are still valid today (Pope & Sydnor, 2016). Our respective position can be summarized as follows. We partially share the tool-with-bits view, wholeheartedly agree that understanding individual behavior is central to developing a behavioral theory, and seriously doubt that such a theory will develop around the "strict rationality" maxim. To clarify our position, we introduce the concept of the mind as an adaptive toolbox replete with tools, including heuristics (Gigerenzer & Selten, 2001). However, we regard heuristics not as a defective tool or merely a drill bit but as an altogether new set of tools (or drills) for the study of

human behavior at par with logic and statistics. This characterization of heuristics emerges from studying them with respect to their match to the environment in which they are used, which constitutes their *ecological rationality*, as opposed to exclusively evaluating them against logic or statistical benchmarks (Gigerenzer, 2008). Moreover, we advocate comparative evaluation of models based on predictive accuracy, demonstrate the high explanatory power of fast-and-frugal heuristics and tractability of heuristic models, and highlight normative implications of their ecological rationality.

In the development and examination of testable models of heuristic decision making, conditions have been brought to light under which less information, calculation, and in general expenditure of cognitive, technical, and material resources can lead to higher predictive accuracy, more efficiency, and easier attainment of goals. This seeming paradox is referred to as the less-is-more phenomenon. The important realization that heuristics do not necessarily trade accuracy for effort opens the way to a better understanding of the phenomenon through exploring environmental structures that favor heuristic strategies, that is, through revealing conditions under which heuristics are ecologically rational. Note that an accuracy–effort trade-off is commonly assumed in traditional heuristics/adaptive behavior literature (see Payne, Bettman & Johnson, 1993, for a rational account of such trade-offs based on the cost of effort; see Shah & Oppenheimer, 2008, for an argument to the same effect based on cognitive limitations).

Alternatively, the study of fast-and-frugal heuristics focuses on exploring the criteria for functionally matching a strategy with the environment in which it succeeds in completing a task, making a good choice, or resolving a problem. These conditions signify the ecological rationality of a strategy in a given environment. In this framework, the mind is seen as an adaptive toolbox that includes heuristics, their building blocks, and the capacities that they exploit. By exploiting evolutionary or learned capacities, heuristic strategies can be frugal, fast, and robust while simple. Additionally, heuristics are not universal rules but rather elements in the adaptive toolbox that contains both domain-specific heuristics and non-heuristic strategies. In this view, bias is not simply predisposition to make error. A complete statistical configuration of predictive error—composed of both “bias” and “variance” (see below)—clarifies why retaining some bias can play a beneficial role in reducing the total error of prediction models by reducing error due to variance. Notably, the study of less-is-more effects calls for new norms that adequately reflect environmental structures. We elaborate on the superior predictive power of heuristic models in relation to particular environmental structures such as dominance and noncompensatoriness. The evaluation of heuristic models in comparison with traditional models in terms of their predictive power is a promising but underexplored path, which we aim to bring to researchers’ attention.

In the very same manner that simple heuristics can help people make better decisions under uncertainty, some simple models and modeling techniques offer a wealth of explanatory power to scientists. By way of example, we introduce the priority heuristic. For the assessment of choice behavior through gambling tasks, the priority heuristic as a model of preferential choice considers payoffs and probabilities one at a time in a lexicographic order rather than by adding flexible parameters that add analytical sophistication to value maximization. Brandstätter, Gigerenzer, and Hertwig (2006) explain how they derived the order of this sequence from psychological insights into human inclinations such as regret aversion as opposed to value maximization based on transitive preference. This simple lexicographic model with no free parameters responds directly to Camerer and Loewenstein’s (2004) vision of behaviorally grounded models in more than one way. The priority heuristic model both yields a surprisingly high explanatory power and logically implies the Allais paradox, the certainty effect, the fourfold pattern of risk attitudes, and other so-called anomalies. Hence, moving beyond

calculative rationality does not necessitate adding to the complexity of models. Several testable and empirically verified models of heuristics listed in this chapter are evidence of this claim.

The rest of this chapter is organized in three sections, which are followed by closing remarks. The first section focuses on definitions and characteristics of heuristics in the adaptive toolbox, which constitutes the descriptive study of heuristics. In it, we provide clarifying explanations as to why the widely presumed economics-based principles of accuracy–effort trade-off and more-is-better constitute common misunderstandings within the study and analysis of heuristic decision making. Picking up from there, the second section formally discusses less-is-more effects and the bias–variance dilemma. This section describes the normative study of the ecological rationality of heuristics and presents a novel direction not yet explored in mainstream behavioral economics. Here, we elaborate on situations in which less information and computation can lead to more predictive accuracy and present three environmental structures that lend themselves to heuristic exploitation. The third section then leads the reader through the steps of constructing a heuristic process model—the priority heuristic—for preferential choice, the very type of problem that preoccupies many economists. The priority heuristic is a simple lexicographical model that logically implies a number of behavioral puzzles. Finally, a few remarks and highlights close the chapter.

### Adaptive toolbox: models of heuristics

The Oxford dictionary defines *heuristic* (adj.) as “enabling a person to discover or learn something for themselves.” Used as a noun, *heuristic* refers to “a heuristic process or method.” A survey by Groner, Groner, and Bischof (1983) shows the extensive and long ongoing use of the term across disciplines in relation to theories of rationality, knowledge, and action. The behavioral economics literature largely follows the tradition of the heuristics-and-biases program (Tversky & Kahneman, 1974), which considers heuristics as mental shortcuts that are the source of cognitive illusions. Dividing the “architecture of cognition” into two systems, Kahneman (2003) classifies heuristics into the low- or no-effort category of System 1, in contrast to the deliberate reasoning of System 2 that consumes cognitive resources:

The difference in effort provides the most useful indications of whether a given mental process should be assigned to System 1 or System 2. Because the overall capacity for mental effort is limited, effortful processes tend to disrupt each other, whereas effortless processes neither cause nor suffer much interference when combined with other tasks.

(p. 1451)

Attributing the use of heuristics to saving on effort is not our position. In fact, we hold the idea of a general accuracy–effort trade-off (as proposed by Payne et al., 1993; and Shah & Oppenheimer, 2008) to be an enduring misconception associated with heuristic mental processes (this point will be further elaborated on in our discussion of the bias–variance dilemma). Instead, we promote analyzing heuristics with respect to their degree of adaptation to the environment (ecological rationality) and developing testable models of heuristic judgment. Moreover, unlike proponents of Systems 1 and 2, we view heuristics as strategies that can be used both consciously and subconsciously.

Here, we focus on heuristics as simple rules of thumb that effectively ignore less relevant information and exploit environmental uncertainty. This shifts the focus from avoiding uncertainty to yielding efficient results (Neth, Meder, Kothiyal & Gigerenzer, 2014). Consequently,

uncertainty does not necessarily have to be reduced to a calculable representation of risk in the study of choice behavior (Neth & Gigerenzer, 2015: 6).

*Definition:* Heuristics are adaptive tools that ignore information to make fast-and-frugal decisions that are accurate and robust under conditions of uncertainty. A heuristic is considered ecologically rational when it functionally matches the structure of environment.

Many strategies, including heuristic ones, can be understood when they are decomposed into: (i) a *search rule* that provides direction to the search in the information space, (ii) a *stopping rule* that defines when to stop search, and (iii) a *decision rule* that defines the final choice. Each of these three rules itself can be a heuristic rule (Gigerenzer et al., 1999). For example, search can be nonexhaustive, it can stop before all pieces of information are looked up (as in satisficing behavior), and a decision can be made based on a rule of thumb. Search rules, stopping rules, and decision rules are referred to as *building blocks* in the adaptive toolbox. Below is an example of decomposing the take-the-best heuristic—which represents a process of sequential binary comparisons—into its building blocks (Gigerenzer, 2006: 125):

1. *Search rule:* Search through cues in order of their validity. Look up the cue value with the highest validity first.
2. *Stopping rule:* If one object has a positive cue value and the other does not (or is unknown), then stop search and proceed to Step 3. If no more cues are found, guess.
3. *Decision rule:* Predict that the object with the positive cue value has the higher value on the criterion.

The take-the-best heuristic was the first in a series of formal models generated in the fast-and-frugal heuristics study program (Gigerenzer & Goldstein, 1996). Gigerenzer and Gaissmaier (2011) surveyed the literature on testable models of heuristics with a focus on inferential judgment. Drawing on this survey in addition to other work (references herein), Table 20.1 provides a classification of heuristics alongside examples in each class and related studies in the fields of economics and business decision making. Here, heuristics are assigned to four classes: recognition-based decision making, sequential consideration, satisficing, and equal weighting. This classification is neither complete nor unique. It provides a frame of reference for our discussion and serves as an example of the type of work that brings us closer to theorizing heuristics.

Recognition-based heuristics process the information on alternative options based on recognition and assign a higher value to the recognized option. Table 20.1 lists two heuristics in this class that have been studied in economic and other domains. The recognition heuristic was formally introduced by Goldstein and Gigerenzer (2002).

*Recognition heuristic:* If one of two alternatives is recognized and the other is not, then infer that the recognized alternative has the higher value with respect to the criterion.

Ortmann, Gigerenzer, Borges, and Goldstein (2008) show the merits of simple and low-cost strategies such as the recognition heuristic that outperform sophisticated analysis of financial markets, drawing on a study in which portfolios of stocks recognized by laypeople in the US and Germany outperformed the market index, whereas experts-recognized based portfolios did not (Borges, Goldstein, Ortmann & Gigerenzer, 1999). One reason for their failure is that experts

Table 20.1 A classification of models of heuristics and examples of economic applications

<i>Classes of heuristics in the adaptive toolbox</i>	<i>Example heuristics</i>	<i>Applications in economics/business</i>
<i>Recognition-based decision making:</i> Evaluate options based on their being recognized	Recognition heuristic	Investment portfolio performance (Borges et al., 1999; Ortmann et al., 2008)
	Fluency heuristic	Performance of IPOs, and value estimates in the market (Alter & Oppenheimer, 2006, 2008)
<i>Sequential consideration:</i> Consider cues in a simple order such as lexicographical; stop consideration as soon as a decision can be made (Special case: Base decision on a single cue)	One-clever-cue heuristics	Identifying active customers: the hiatus heuristic (Wübben & von Wangenheim, 2008)  Pricing by intuition (Rusetski, 2014)  Crisis management: the credibility heuristic (MacGillivray, 2014)
	Priority heuristic	Logically implies the Allais paradox, certainty effect, and four-fold pattern of risk attitudes (Brandstätter et al., 2006)
	Take-the-best	Forming consideration sets for purchase (Hauser, 2014)
	Setting and adjusting aspiration levels	Aspiration adaptation theory (Selten, 1998)  Investing in malls/high-rises (Berg, 2014) Pricing used cars (Artinger & Gigerenzer, 2016)
<i>Satisficing:</i> Choose the first option that meets an aspiration level. (Information consideration does not follow a sequence ordering.)	Tallying	Emergency room decisions (Kattah et al., 2009)
	1/N heuristic	Equal allocation of resources to investment options (DeMiguel et al., 2009)

\*Equal weighting can be perceived as a special case of a larger class of heuristics with rules that assign simple weights to cues. This is a potential area for future studies.

cannot benefit from the recognition heuristic in the same way that laypeople do; experts know too much. The other heuristic in this class, the fluency heuristic, assigns a higher value to the option that is recognized more rapidly (Schooler & Hertwig, 2005).

*Fluency heuristic:* If both alternatives are recognized but one is recognized faster, then infer that this alternative has the higher value with respect to the criterion.

Alter and Oppenheimer (2006) report that the fluency of pronouncing the name of a stock has a clear positive correlation with its immediate performance in initial public offerings. In 2008, the same authors report experimental studies wherein the valuation process is based on familiarity and fluency, and extend the implications of their findings to marketing experts and policymakers.

Sequential heuristics consider cues/reasons (or pieces of information) in a simple sequence, such as a lexicographic order, and stop as soon as a decision can be made. A subclass of these, one-clever-cue heuristics, ignores all but one of the observable cues. Wübben and von Wangenheim (2008) report the use of one threshold value, which they call the hiatus heuristic, to identify active customers in an airline industry, an online CD retailer, and in an apparels business.

*Hiatus heuristic:* If a customer has not purchased within a certain number of months (the hiatus), the customer is classified as inactive; otherwise, the customer is classified as active.

They showed that this heuristic, which uses only one threshold and ignores all else, is as good as or better than complex algorithms such as Pareto/NBD at identifying active customers.<sup>1</sup> Similarly, Rusetski (2014) finds no evidence for the use of complex compensatory algorithms by brand managers when making price decisions. His survey of more than 100 managers reveals a simple pricing strategy that considers only the competitors' price levels, followed by a consistent positioning above, equal to, or below that price. In the area of crisis management, MacGillivray (2014) introduces the credibility heuristic used by managers in detecting contaminated water sources and presents evidence from the field on how these decisions are made based simply on "the perceived trustworthiness of the message conveyor." The credibility heuristic can be effective because situations in crisis management are subject to a high level of uncertainty and decisions need to be made without delay.

In the class of sequential heuristics, two further heuristic models are listed in Table 20.1: the priority and take-the-best heuristics. The priority heuristic models information processing for the preferential choice between gambles, as discussed in detail later in this chapter. The take-the-best heuristic, whose building blocks were described above, orders cues unconditionally without taking their interdependencies into account. In a similar manner, consumers who are faced with many products and/or several attributes for each product follow a sequential consider-then-choose process in a heuristic-based form (for a survey of evidence and literature on this topic see Hauser, 2014). Hauser (2014) emphasizes that understanding this process of choice, which he names *consideration set heuristic*, is essential to successful managerial decisions on product development and marketing communication, where "consideration sets are key to business strategy" (p. 1688). The heuristic process used in the formation of consideration sets is particularly prevalent and successful in noncompensatory environments (see the next section for a definition).

Famously proposed by Simon (1955), satisficing is a heuristic-based behavior and the initial inspiration for many studies in heuristic decision making. Here, the search among options follows no specific order and stops simply once the option under consideration *satisfices*, that is, is "good enough" to meet an aspiration level. This does not rule out the possibility of adjusting an initial aspiration level during the process of search/examination.

*Satisficing:* Set an aspiration level  $\alpha$  and start the search in any order. Choose the first object with value  $\geq \alpha$ . If no object is found after time  $\beta$ , lower aspiration level by  $\delta$ . Continue search with the updated aspiration level  $\alpha - \delta$ . Repeat the process until a choice can be made.



Theorized by Selten (1998), this nonoptimizing process is described under the title of *aspiration adaptation*. Its noteworthy distinction lies in satisficing an aspiration level as opposed to satisfying a mathematical criterion, the latter requiring strict adherence to the criterion but the former accepting “good enough” adherence. Configuration of behavior as a satisficing process especially fits the way in which humans resolve ill-defined problems such as choice of a lifetime partner or a job/career. Two empirical studies listed in Table 20.1 provide evidence from markets for satisficing behavior. In one of these, Berg (2014) interviewed entrepreneurs to discover the process of information that leads to the choice of location for large construction investments such as building commercial high-rises. His data could not be described by a model of search cost but instead support simple satisficing search and limited consideration of information. Interestingly, “locations are frequently discovered by chance.” Developers reportedly make high-impact decisions based on satisficing a simple aspiration criterion such as a fixed return over a fixed period of time. Moreover, they do not update their initial aspirations in the process of search, thereby resorting to the simplest form of satisficing behavior. Another example for satisficing behavior is found in the market for second-hand cars, where BMW dealers set the price by determining an initial aspiration level, followed by gradual (in fixed percentage) adjustments over fixed (monthly) intervals (Artinger & Gigerenzer, 2016).

The last class of heuristics in Table 20.1 is the class of *equal weighting*, where equal weights are allocated to all cues or options in order to reduce the error incurred when estimating weights. The efficiency of simple unit weighting schemes when dealing with small samples has been long investigated in mathematical psychology and organizational behavior (Einhorn & Hogarth, 1975), but relatively rarely incorporated in econometrics. Tallying heuristics belong to this class. A simple tallying heuristic counts only the favored cues, that is, assigns them a weight of one and ignores the rest by assigning them a zero weight. Tallying is routinely used, for instance, in emergency rooms for making vital calls (Kattah, Talkad, Wang, Hsieh & Newman-Toker, 2009), and by hikers for avoiding avalanche accidents (McCammon & Hægeli, 2007). Another member of this class is the  $1/N$  heuristic, which allocates resources to  $N$  options equally. Although equal allocation of resources to options has been observed as a frequent behavior, behavioral economists have considered it an inferior allocation strategy. For example, Benartzi and Thaler (2001) refer to equal allocation of assets in retirement portfolios as *naïve diversification*. Yet when empirically tested,  $1/N$  outperformed Markowitz’s mean-variance portfolio in six out of seven tests and could not be consistently outperformed by any of another dozen sophisticated portfolio diversification algorithms (DeMiguel, Garlappi & Uppal, 2009).

Situations where simple strategies can outperform complex ones are instances of the less-is-more effect. The study of the ecological rationality of heuristics explains when and why less can be more.

### **Ecological rationality: bias–variance dilemma and less-is-more effects**

The goal of the study of ecological rationality is to specify the environmental conditions under which a given strategy or heuristic can be expected to succeed compared to competitors. It is based on two methodological principles: to test a model in its predictive accuracy (as opposed to data fitting) and to test a model competitively against the best existing models. In our view, these two methodological principles should become standard in behavioral economics.

Error in predictive accuracy stems from two sources: (i) bias, that is, the difference between the true value and the average predicted value; and (ii) variance, that is, the variance of the predictions around the average predicted value. Bias corresponds to the mis-specification of a model, and variance to overfitting. Variance is influenced by sample size. Predictive accuracy

increases when the sum of both errors is reduced, and it is subject to a trade-off between the two. Total systematic error in prediction can be expressed as

$$\text{Error} = \text{Bias}^2 + \text{Variance}. \quad (1)$$

This bias–variance dilemma (Geman et al., 1992; Grenander, 1952) can be best understood in the context of over- and underfitting for prediction models (Hastie, Tibshirani & Friedman, 2009). An optimum level of model complexity corresponds to the optimal trade-off between bias reduction and variance reduction. When the complexity of the model exceeds this optimum level, overfitting occurs, whereas underfitting occurs when complexity is inadequate. These relations are depicted in Figure 20.1.

Simple heuristic models for binary comparisons can reduce total prediction error by beneficially trading less variance for more bias (or, if certain environmental conditions hold—see below—, without increasing bias). In their analysis of the relative predictive accuracies of take-the-best and other simple strategies with respect to the way in which cues are weighted, choice sets characterization, and error, Hogarth and Karelaia (2006: 237) called for future studies to address a crucial question:

An important question ... is to understand the types of environments that people encounter in their decision making activities. For example, to what extent do the data sets compiled by Czerlinski et al. (1999) characterize the kinds of situations people face in their natural ecologies? *We simply do not know.* (emphasis added)

Şimşek (2013) responded to this call. First, we now know of three environmental structures for which the “bias” component of error is the same for a lexicographic heuristic as for a linear model (assuming same order of cue weights). These are defined in Table 20.2. Dominance is the most obvious: if the cue (attribute) values of option *A* are never smaller than those of option *B*, and at least one value is larger, then *A* dominates *B*. Here, every strategy will arrive at the same choice. Cumulative dominance extends dominance to the cumulative values of the cues, and noncompensatoriness holds if the cue weights (assuming, without loss of generalization, that the

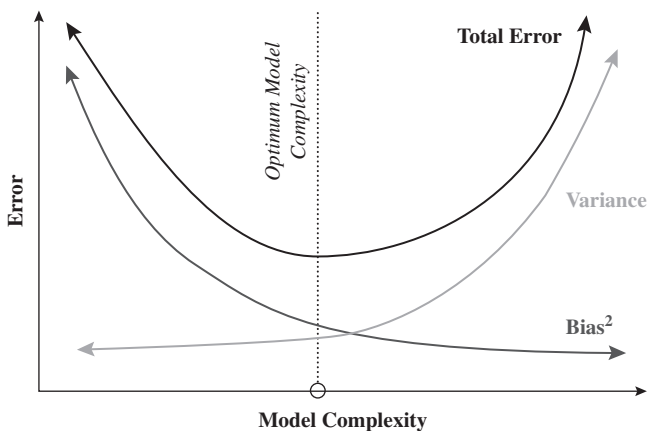


Figure 20.1 Bias–variance trade-off versus model complexity

Source: Adapted from Fortman–Roe (2012).

cues are binary and weights are nonnegative) are ordered in decreasing value, each weight is greater than the sum of all weights that come after it. An example is the set of weights 1, 1/2, 1/4, and 1/8. In this case, a lexicographic strategy that relies only on the first cue that allows for a decision will always end up with the same choice as a linear model (that has the same cue order). The question is how prevalent are these conditions in natural environments?

For paired comparison tasks, Şimşek (2013) examined the structure of 51 data sets from online repositories, textbooks, research publications, field data, and packages for R statistical software. These diverse areas span business, economics, engineering, and medicine. How often was one or more of these three structures—dominance, cumulative dominance, and non-compensatoriness—satisfied? The median for the 51 data sets was 90 percent. That is, in half of the data sets, a lexicographic heuristic yielded the same choice as a linear model for more than 90 percent of the decisions encountered, but more quickly and with less effort. When the cues (predictors) were dichotomized at the median, this number increased to 97 percent (Şimşek, 2014). In other words, in the majority of decisions, a lexicographic heuristic has the same bias as a linear model. Together with lexicographic heuristics’ potential for reducing variance, this result explains why and when simple heuristics outperform linear models in prediction.

This section provided a case study in ecological rationality<sup>2</sup> by specifying the conditions under which simple heuristics can outperform more information-greedy strategies. It explains why the accuracy-effort trade-off does not generally hold and why the bias-variance trade-off allows for a better understanding of the rationale of heuristics. In addition, these results clarify that there is nothing irrational per se about relying on heuristics. If one of the conditions in Table 20.2 is in place and people rely on lexicographic heuristics instead of linear rules, this does not imply a lack of rationality because of cognitive limitations, as has been commonly assumed in the heuristics-and-biases program. On the contrary, due to higher estimation error, choosing a simple rule can lead to better predictions.

In the next section, we address in detail the question of how to build a model of heuristics based on empirical data and the objective to reduce error due to variance.

Table 20.2 Environmental structures that lexicographic heuristics exploit (in paired comparison tasks). If one of these structures holds, a lexicographic heuristic has the same “bias” as a linear model

<i>Environmental structure</i>	<i>Definition</i>
Dominance	For two options $A$ and $B$ with $k$ attributes $x_{iA}$ and $x_{iB}$ , where $\Delta x_i = (x_{iA} - x_{iB})$ , $A$ dominates $B$ if $w_i \Delta x_i \geq 0, \forall i, \text{ and } w_i \Delta x_i > 0, \exists i.$ <i>Example:</i> In the decimal system, $A = 642$ does not dominate $B = 351$ because $6 > 3$ and $2 > 1$ , but $4 < 5$ .
Cumulative dominance	For two options $A$ and $B$ with attributes $x_{iA}$ and $x_{iB}$ , where $\Delta x_i = (x_{iA} - x_{iB})$ , $\Delta x'_i = \sum_{j=1}^i \Delta x_j, \forall i$ , and $w'_i = w_i - w_{i+1}, 1 \leq i < k$ . $A$ cumulatively dominates $B$ if $w'_i \Delta x'_i \geq 0, \forall i, \text{ and } w'_i \Delta x'_i > 0, \exists i.$ <i>Example:</i> In the decimal system, $A=642$ cumulatively dominates $B=351$ because $6 > 3$ , $6+4 > 3+5$ , and $6+4+2 > 3+5+1$ .
Noncompensatoriness	For an option with binary attributes $x_i$ that take values 0 or 1, a set of (nonnegative) weights is called noncompensatory if $w_i > \sum_{j=i+1}^k w_j, i = 1, 2, \dots, k-1.$ <i>Example:</i> 1, 0.5, 0.25, 0.125.

Source: Extracted from Şimşek (2013).

## Building a heuristic model for preferential choice: the priority heuristic

The classes of heuristics listed in Table 20.1 can be used for both inference and preference. Studying inferential choice requires an external metric and thus avoids the difficulty of uniquely specifying a metric as in the study of preferential choice. However, preferential choice is the centerpiece of economic modeling of human behavior. Paul Samuelson, who redefined and mainstreamed modern economics, developed the theory of revealed preferences (Samuelson, 1938a, 1938b, 1948), which remains to date the cornerstone for theoretical analysis and empirical testing of choice behavior in accordance with utility maximization. Its underlying idea is that people consider all options and have a clear and stable order of preferences for the options. The act of rational choice simply reflects such an order.

The behavioral revolution in economics ensued from accumulation of evidence on systematic violations of rationality axioms such as stable ordering of options, transitivity of choices, and other requirements of internal logical consistency. Formal attempts to capture the observed violations, such as intransitivity and inconsistency of preferences, have been chiefly shaped by adding free or adjustable parameters to the expected utility model (Berg & Gigerenzer, 2010). Cumulative prospect theory (Tversky & Kahneman, 1992) is a case in point, where three parameters fit the shape of the value function, and another two the shape of the probability weighting function.<sup>3</sup> In this approach, flexible parameters are modeling elements that extend the explanatory power of the expected utility theory to account for the observed violations. Yet cumulative prospect theory is not meant to model the process of decision making but is used instead as an as-if model that demands estimations and computations that are even less realistic than expected utility theory (Berg & Gigerenzer, 2010). Moreover, although such models may fit the data better as a result of using more parameters, the very practice can cause overfitting and even reduce the predictive power. The bias-variance dilemma accounts for why adding free parameters can increase error due to “variance” and diminish predictive power.

Rather than adding parameters, the idea that led to the development of the priority heuristic model took another approach: Why not study what people actually do when they make decisions? What if people actually use simple rules when the problem at hand becomes more complex? If that is the case, then a model without adjustable parameters can potentially capture such processes and should logically imply systematic deviations from expected utility theory. In pursuit of this conjecture, Brandstätter, Gigerenzer, and Hertwig (2006, BGH herein) constructed the priority heuristic by taking the following steps.

*Step 1:* Which heuristic form? From the set of all possible heuristics for two-alternative choice problems, the candidates were narrowed down to lexicographic rules and tallying (see Table 20.1 for definitions). Then, tallying was ruled out because empirical evidence does not support equal treatment of reasons in choice between monetary gambles. Once the lexicographic form was chosen, reasons for consideration needed to be specified.

*Step 2:* Which reasons? Start with simple gambles that contain only nonnegative payoffs, or “gains.” These contain three separate reasons: (i) a maximum gain,  $M$ ; (ii) a minimum gain,  $m$ ; and (iii) the probability of minimum gain  $p_m$ , where  $p_M + p_m = 1$ . Three reasons have six possible orderings, from which one order must be chosen by investigating the evidence on choice behavior.

*Step 3:* Which order? Choice experiments by Brandstätter and Kühberger (2005) suggest that people consider value of gains before their probabilities. This eliminates

two possible orders in which probabilities are the first reason, leaving four. Because people are risk averse in the gain domain (Edwards, 1954), they consider  $m$  first in order to avoid the worst outcome. Which of the remaining two possible orders is actually followed needs to be further elicited. To examine the remaining two orders of consideration,  $m$ - $p$ - $M$  versus  $m$ - $M$ - $p$ , BGH conducted an experiment in which  $m$  was kept constant to elicit the order for  $p$  and  $M$ . Their results agree with Slovic, Griffin, and Tversky (1990, Study 5) in that  $p$  preceded  $M$  in consideration order. Thus, the order of reasons was specified as  $m$ - $p$ - $M$  which is called the priority (or search) rule.

*Step 4: When to stop search?* This can be determined by finding empirically supported satisficing rules. For two simple gambles  $A$  and  $B$ , one starts by comparing their minimum gain values,  $\Delta m = |m_A - m_B|$ . Evidence suggests that whether  $\Delta m$  is considered large enough to stop the consideration of reasons depends on the maximum gain. Taking a simple aspiration that corresponds to the decimal system, BGH postulated that people stop search if  $\Delta m$  is larger than or equal to  $0.1M$ , where  $M = \max\{M_A, M_B\}$ . Notice that 0.1 is an empirically informed fixed (not flexible) parameter. (i) if  $\Delta m < 0.1M$  then consider the second reason (probabilities of minimum gains). If  $\Delta p_m = |p_{m_A} - p_{m_B}| \geq 0.1$  then stop; otherwise consider the last reason (maximum gains).

*Step 5: Which gamble to choose?* For the choice between gambles BGH defined a decision rule based on “attractiveness.” Once the search is stopped, the priority heuristic predicts that the gamble with the more attractive decisive feature, either gain or probability, will be chosen.

Steps 1 to 5 describe the procedure of constructing the priority heuristic model, which is a lexicographic model for preferential choice. The resulting model has the following three building blocks (BGH, 2006: 413):

*Priority Rule:* Go through reasons in the order of minimum gain, probability of minimum gain, maximum gain.

*Stopping Rule:* Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain; otherwise stop examination if probabilities differ by 1/10 (or more) of the probability scale.

*Decision Rule:* Choose the gamble with the more attractive gain (probability).

This model is generalized to both gambles with nonpositive gains (losses) and nonnegative gambles with more than two outcomes. How does this simple model with no flexible parameters fare in predicting choice behavior, where systematic violations of expected utility are prevalent? Because one can always construct a set of choices between gambles in which one’s model fares well, BGH (2006) tested the priority heuristic using four “hostile” data sets designed by Kahneman, Tversky, and others. The competitors were three modifications of expected utility theory, including cumulative prospect theory, and ten previously studied heuristics, including tallying. Across all 260 problems, the priority heuristic topped them all with a predictive accuracy of 87 percent; cumulative prospect theory predicted only 77 percent of people’s choices correctly. Note that cumulative prospect theory excelled in data fitting, that is, explaining data already known, but not in prediction. The reason for that discrepancy follows from the bias–variance

dilemma: Cumulative prospect theory suffers from prediction error due to the variance in parameter estimation, whereas the priority heuristic, having no free parameters, incurs no error from variance but only from bias.

The priority heuristic is not the only heuristic people use. A detailed analysis showed that different strategies are adapted to either easy or difficult choices (BGH, 2006). Choices are considered easy when the expected values differ by a factor of 2 or more and difficult when the factor is smaller ( $<2$ ). Whereas the priority heuristic predicted people's behavior best for difficult choices, cumulative prospect theory was better at predicting easy choices. For easy choices, however, the best strategy was simple expected value theory. Thus, two strategies—each with zero adjustable parameters—might be sufficient to predict the data for difficult and simple problems, respectively. This shows how risky choice can be modeled without Bernoulli functions, which are notoriously unreliable in out-of-sample prediction (Friedman et al., 2014; Stewart, Reimers & Harris, 2014).

In summary, BGH (2006) showed how to construct a process model from empirical observations. The resulting priority heuristic was better at predicting people's choices for two- and multiple-outcome gambles and for certainty equivalent problems than are cumulative prospect theory and similar modifications of expected utility theory, and logically implies the major violations of utility theory (Katsikopoulos & Gigerenzer, 2008). This model is emphatically not meant to be the last word but rather exemplifies a new behavioral economics that builds realistic process models rather than more complicated as-if models and that can be more successful in predicting actual choice behavior.

### Final remarks

In the past, heuristics were commonly associated with cognitive biases and generally considered to be second-best strategies. This view focused on reducing the bias—and developing debiasing techniques—while ignoring the variance component of errors. As we illustrated, however, reducing either component of error can reduce the total prediction error. Fast-and-frugal heuristics are simple yet robust tools in the adaptive toolbox of individuals and institutions that produce a beneficial trade-off between bias and variance so that people can make effective choices under uncertainty. This trade-off highlights the importance of two methodological principles: to test models in out-of-sample prediction, not by fitting their parameters to known data; and to test models competitively against the best existing candidates.

In this chapter, we introduced several testable models of heuristics. Particularly, by going through the steps of formulating the priority heuristic model, we illustrated the way in which a simple model is constructed that logically implies violations of the expected utility theory without adding more free parameters. Thus we established that heuristic models can satisfy the eventualities required by economists for proper formalization. However, the methodology we introduced here takes an alternative, algorithmic approach in that optimization is not the main method. Nor are flexible parameters added to account for the psychological aspects of behavior. Viewed in perspective, examination of constructing the priority heuristic demonstrates that the methodology of investigation is never neutral. It directs and limits the type and shape of the outcomes of scientific inquiry, as can be observed in the emerging trends in behavioral economics in comparison with the study of fast-and-frugal heuristics.

Whereas behavioral economics operates mainly in the explanatory domain, the fast-and-frugal heuristics program works in parallel on explanatory and normative aspects of a science of heuristics. Indeed, what humans ought to do cannot be understood without acknowledging what

they can do. And what humans can do is the most reliable basis for developing norms for what they should do. As such, our position concurs with that of James March:

If behavior that apparently deviates from standard procedures of calculated rationality can be shown to be intelligent, then it can plausibly be argued that models of calculated rationality are deficient not only as descriptors of human behavior but also as guides to intelligent choice.

(1978: 593)

In particular, we maintain that extending behavioral insights to policy design and to recommendations for improving individual and collective choice necessarily entails an ecological approach to human behavior, including the development of a systematic theory of behavior that regards heuristics at par with logical and statistical rules. Steps in this direction have been taken in finance (Forbes, Hudson, Skerratt & Soufian, 2015) and business (a series of papers in *Journal of Business Research*, 67, 2014).

In this chapter, we provided a classification of heuristics and an introduction to the normative study of heuristics, that is, their ecological rationality. These heuristics are empirically found to produce robust and effective outcomes by ignoring information, using less calculation, and relying on exploitation of human capacities and environmental uncertainty. Given that informational efficiency is at the heart of the formal study and modeling of markets in economics, the analysis of heuristics that efficiently ignore information can provide a new framework for behavioral economics.

### Acknowledgments

We are thankful to Özgür Şimşek and Konstantinos Katsikopoulos for their careful feedback and suggestions, and to Rona Urnau for providing many helpful improvements to our article.

### Notes

- 1 NBD stands for negative binomial distribution.
- 2 Two forms of rationality in economics à la Smith (2008) are constructivist and ecological forms. Whereas Smith adopts the definition of ecological rationality formulated in the study of fast-and-frugal heuristics, his account remains descriptive. The shared definition and juxtaposition of these two views is reported in Mousavi and Kheirandish (2014).
- 3 *Prospects* are gambles. Gambles have been used to represent risky decision making in a tradition that can be traced back to the origins of probability theory in the seventeenth century (Hacking, 1975).

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