Journal of Applied Research in Memory and Cognition 5 (2016) 215–231

Contents lists available at ScienceDirect

Journal of Applied Research in Memory and Cognition

journal homepage: www.elsevier.com/locate/jarmac

Applied Decision Making With Fast-and-Frugal Heuristics☆

Sebastian Hafenbrädl*
Yale University, New Haven, United States
University of Lausanne, Lausanne, Switzerland

Daniel Waeger
University of Amsterdam, Amsterdam, Netherlands

Julian N. Marewski
University of Lausanne, Lausanne, Switzerland

Gerd Gigerenzer
Max Planck Institute for Human Development, Berlin, Germany

In applied settings, such as aviation, medicine, and finance, individuals make decisions under various degrees of uncertainty, that is, when not all risks are known or can be calculated. In such situations, decisions can be made using fast-and-frugal heuristics. These are simple strategies that ignore part of the available information. In this article, we propose that the conceptual lens of fast-and-frugal heuristics is useful not only for describing but also for improving applied decision making. By exploiting features of the environment and capabilities of the decision makers, heuristics can be simple without trading off accuracy. Because decision aids based on heuristics build on how individuals make decisions, they can be adopted intuitively and used effectively. Beyond enabling accurate decisions, heuristics possess characteristics that facilitate their adaptation to varied settings. These characteristics include accessibility, speed, transparency, and cost effectiveness. Altogether, the article offers an overview of the literature on fast-and-frugal heuristics and their usefulness in diverse applied settings.

Keywords: Fast-and-frugal heuristics, Professional decision making, Applied decision making, Decision aids, Ecological rationality, Bounded rationality, Optimization

On January 15th, 2009, Chesley B. Sullenberger and Jeffrey Skiles, the pilots of US Airways Flight 1549, found themselves in a dramatic situation. Shortly after takeoff, a flock of geese hit the two turbofans of their Airbus A320, resulting in a complete engine failure. Within seconds, the pilots had to decide whether they would be able to return to LaGuardia Airport in New York or whether they would have to seek a more risky emergency landing spot. They decided against returning. Instead, Sullenberger conducted a spectacular landing in the Hudson River, saving the lives of all 155 passengers on board.

Sitting in the cockpit of a modern aircraft, you might feel overwhelmed by all the information on display. Avionics systems measure and monitor myriad pieces of information: from airspeed, altitude, heading, vertical speed, and yaw to navigational, weather, and engine indications. In modern airplanes, everything is connected to onboard computers, and there is

Author Note

We thank Rona Unrau for many helpful comments and for editing this article. We also thank Claire Lauren Tepper and Benjamin Schmitt for helping to edit a previous version of this article. The first author is grateful for financial support from the Swiss National Science Foundation (Grant nos. 100014 140503 and P2LAP1_161922). This article summarizes selected examples from the literature on fast-and-frugal heuristic, thereby synthesizing, among others, Gigerenzer (2007, 2014), Gigerenzer and Gaissmaier (2011), Marewski, Gaissmaier, and Gigerenzer (2010), and Marewski and Gigerenzer (2012).

☆ Please note that this paper was handled by the current editorial team of JARMAC.

* Correspondence concerning this article should be addressed to Sebastian Hafenbrädl, Yale University, School of Management, Evans Hall, 165 Whitney Avenue, New Haven, CT 0651, United States. Contact: Sebastian.Hafenbraedl@Yale.edu.

plenty of computing power in the control towers that manage flight traffic. Given that these large amounts of information are available and ready to be processed by computers, decisions such as those made by the pilots of Flight 1579 might appear to be textbook examples of the successful use of optimization control techniques.

But when trying to find out whether they could make it back to LaGuardia Airport, Sullenberger and Skiles did not simply rely on their computers and flight instruments. As co-pilot Skiles later explained, “It’s not so much a mathematical calculation as visual, in that when you are flying in an airplane, things that—a point that you can’t reach will actually rise in your windshield. A point that you are going to overfly will descend in your windshield.” (Charlie Rose, *The Charlie Rose Show*, February 11, 2009). What Skiles describes is a simple rule of thumb known as the *gaze heuristic* (Gigerenzer, 2014; Gigerenzer, Hertwig, & Pachur, 2011):

> Fix your gaze on a potential landing spot. If this spot rises in your windshield, then you will not be able to reach it.

This simple rule of thumb does not draw on the aforementioned information provided from the instrument panels. Instead, it considers the angle of gaze. The gaze heuristic has been reported to describe how dogs and humans, including professional baseball players, catch balls; sailors use a variant of this strategy as well. It belongs to a class of highly efficient decision strategies that have been dubbed *fast-and-frugal heuristics* (e.g., Gigerenzer, Todd, & The ABC Research Group, 1999).

The goal of this article is to make the case that the conceptual lens of fast-and-frugal heuristics is well suited to describing and improving applied decision making. We contend that the story of Flight 1549 is not an anomaly in this respect. In many naturally occurring situations, fast-and-frugal heuristics can aid decision making, and people (justifiably) rely on them. This conceptual lens can, we argue, more generally serve as a starting point for investigating and attempting to improve applied decision making in domains as wide-ranging as aviation, medicine, and business.

The structure of this article is as follows. We begin by providing a brief introduction to optimization and fast-and-frugal heuristics, two conceptual lenses often employed by researchers of applied decision making. Second, we discuss how fast-and-frugal heuristics can be simple and accurate at the same time. Third, we argue that because they are built on how individuals make decisions, fast-and-frugal heuristics can be useful in prescribing individual decision-making strategies. Fourth, we explore several characteristics that enable fast-and-frugal heuristics to be adapted to various situational requirements. These characteristics make fast-and-frugal heuristics particularly useful for improving applied decision making. In conclusion, we reflect on how this conceptual lens allows improving decision making even in situations when decision makers are better off to not rely on heuristics.

Conceptual Lenses for Describing and Improving Applied Decision Making

Instead of testing theories of decision making in experimental ‘toy tasks’ in which all options and probabilities are known for certain, researchers of applied decision making prioritize practical relevance. They seek to describe and improve decision making in real-life situations, in which appropriate courses of action often need to be determined under considerable uncertainty (e.g., Brown, 2015; Hoffrage & Marewski, 2015; Klein, 2015). In many cases, researchers of applied decision making might not deliberately select the conceptual lens through which they try to understand a specific problem. Yet the conceptual lens they inevitably employ directs their attention and determines which elements they address and which elements they exclude from their analysis. Conceptual lenses also establish a framework of assumptions needed in order to move from mere description of phenomena toward explanation, prediction, and prescription. Allison (1969, p. 690) uses the following metaphor: “Conceptual models both fix the mesh of the nets that the analyst drags through the material in order to explain a particular action or decision and direct him to cast his net in select ponds, at certain depths, in order to catch the fish he is after”. We advocate that researchers actively select a useful conceptual lens. For researchers interested in applied decision making, conceptual lenses can be useful for (at least) two different purposes: first, to describe how people actually make decisions, and, second, to prescribe how people should make decisions under the constraints they face. Prescriptive measures include engineering decision aids and designing decision environments such that people can make good decisions.

Optimization

One family of conceptual lenses that many academics in business, economics, biology, and psychology rely on is called *optimization*. Optimization models represent the classical approach to human decision making and rationality, dating back to the Enlightenment and thinkers such as Blaise Pascal, Pierre Fermat, and Daniel and Nicholas Bernoulli. Prominent representatives of this approach are models of *Bayesian inference* and the *maximization of (subjective) expected utility* (e.g., Arrow, 1966; Edwards, 1954; Savage, 1954; von Neumann & Morgenstern, 1947; see also Becker, 1993; Chater & Oaksford, 2008, for more recent approaches). In the social sciences, these resulted in statistical tools such as linear models that estimate coefficients while minimizing errors. The resulting tools are not only widely used, but have also been transformed into theories of decision making (Gigerenzer, 1991).

By employing the conceptual lenses of optimization, researchers assume that they are in a world of *risk* (Knight, 1921). A world of risk is a world in which probabilities are known or can be reliably estimated; by definition, optimization is possible only in such worlds. Examples of worlds of risk with well-defined and predictable problems are lotteries, roulette, and card games. Savage (1954), the father of modern Bayesian Decision Theory, introduced the notion of *small worlds* to refer to such situations of perfect knowledge. They typically abound in economics and in business textbooks that instruct students how to use optimization methods.

In contrast to a world of risk, a world of *uncertainty* implies that the probabilities are unknown, unknowable, or not mathematically precise. Such fuzzy situations are what Binmore (2009) – in allusion to Savage's small worlds – referred to as *large* (or *uncertain*) *worlds*. We define uncertainty as situations where not all alternatives, consequences, and probabilities are known, and/or where the available information is not sufficient to estimate these reliably. In such situations, surprises can occur, leaving the premises of a rational (e.g., Bayesian) decision theory unfulfilled. Not only does uncertainty lead to optimization becoming unfeasible or inappropriate, but it also invalidates optimization as a gold standard to which other decision processes are compared. In our view, beyond the neat examples one finds in textbooks, much if not most applied decision making involves degrees of uncertainty, not just calculable risks. Problems that at first sight seem to entail risk alone often entail uncertainty as well.

What is the Conceptual Lens of Fast-and-Frugal Heuristics?

The fast-and-frugal heuristics research program follows the lead of Herbert Simon's work, in which he pointed out that it is often impossible to optimize in the real world. Instead, he argued, decision making can be described by models of bounded rationality (e.g., Simon, 1956). Such models are geared toward *satisficing*, meaning that they obtain solutions that suffice to satisfy the decision maker's goals. That is precisely what fast-and-frugal heuristics do.

Simon also pointed out that performance and behavior depend on both cognition and the environment: "Human rational behavior . . . is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990, p. 7). Specifically, given that people perform different tasks in different environments, the assumption of the fast-and-frugal heuristics approach is that people do not rely on a single cognitive strategy but rather select an adequate heuristic from what has been dubbed an *adaptive toolbox*. Each of the heuristics (decision-making tools) in this cognitive "toolbox" is suitable for a different class of environments. By relying on a heuristic that fits a particular environment, people can make efficient decisions in little time and based on little information (hence 'fast-and-frugal').

The fast-and-frugal heuristics framework, so we contend, can be useful with respect to both the descriptive and prescriptive aspects of research on decision making. First, the descriptive accuracy of fast-and-frugal heuristics can be assessed by comparing their predictions to actual decisions. Heuristics make precise and testable predictions and are typically formulated as computational models (e.g., Marewski & Olsson, 2009). They consist of building blocks, such as a *search rule* that specifies how information is searched for, a *stopping rule* that defines when information search is stopped, and a *decision rule* that determines how a decision is made.

Second, the question of how to improve decision making can be addressed by comparing how people should ideally make decisions with how people actually make them; the results highlight potential for improvement. From the perspective of the fast-and-frugal heuristics framework, this question is not addressed by analyzing differences between people's decisions and the predictions of optimization algorithms in an attempt to document humans' presumed irrationality, as is often done in other frameworks (e.g., Kahneman, 2011). Instead, the analysis of *ecological rationality* tries to understand in which environments people's reliance on a specific heuristic leads to accurate or otherwise satisfactory decisions, extending Simon's approach of modeling how people's decision strategies fit with the environment. As the "Miracle on the Hudson River" (Curkin & Monek, 2009) illustrated, it can be ecologically rational for pilots to ignore the information necessary to estimate the trajectory of an airplane when they can solve a task faster and more safely using a fast-and-frugal heuristic.

Third, by analyzing the environment in which a decision will be taken, researchers can develop decision strategies that are ecologically rational in that specific environment. Such engineered fast-and-frugal heuristics are particularly useful as prescriptive decision aids because they 'pick up people where they stand' and make improvements to the decision process that people already follow. That is, in place of requiring people to learn a new process from scratch, one can develop prescriptive aids for intuitive and effective use. Moreover, in many domains, speed, transparency, and efficiency – all characteristics of fast-and-frugal heuristics – are crucial for successfully applied decision making, as we will discuss further below.

How Fast-and-Frugal Heuristics can be Simple and Accurate

The conceptual lens of fast-and-frugal decisions starts from the premise that in situations of uncertainty, accurate decisions do not generally require high effort or complex strategies. This premise, among others, differentiates fast-and-frugal heuristics from other approaches such as the *heuristics-and-biases framework* (e.g., Kahneman, Slovic, & Tversky, 1982) or the *adaptive decision maker* approach (e.g., Payne, Bettman, & Johnson, 1993). According to the latter frameworks, decision makers rely on heuristics in order to reduce effort. From the vantage point of fast-and-frugal heuristics, however, reducing effort is not the main goal but rather a (welcome) by-product. What is more, heuristics can be simple without sacrificing accuracy because of their ability to exploit intrinsic properties of the two blades of Simon's scissors: the decision environment and the individual capabilities of the decision maker. We will now turn to a more detailed discussion of these two blades.

The Decision Environment

The Statistical Structure of the Decision Environment. Many naturally occurring decision environments have structures that allow fast-and-frugal heuristics to ignore part of the available information. One example is the principle of the 'vital few and the trivial many,' which is also known as the *Pareto principle*, a term coined by Joseph Juran. He explains it in the following words: "In any series of elements to be controlled, a selected small fraction, in terms of numbers of elements, always accounts for a large fraction, in terms of effect" (Juran, 1954, p. 758). The distribution of many quantities follows a power law and can thus be described by this principle. Environments with corresponding distributions are labeled *noncompensatory* in the literature on decision strategies (Martignon & Hoffrage, 1999). In these environments, the prediction of each predictor cannot be overruled by the combined predictions of all less important predictors together. This condition is met, for example, by assigning binary predictors the weights of 1/2, 1/4, 1/8, 1/16 or the weights 100, 10, 1, 0.1. As can be seen, no trade-offs among predictor variables can be made with these noncompensatory weights (e.g., 1/2 cannot be overruled by 1/4, 1/8, 1/16; 1/4 cannot be overruled by 1/8, 1/16; and so on). In such an environment, simply relying on the best predictor will lead to the same choice as trying to weigh and add all predictors.

When there is doubt as to what the most important predictor is, it makes sense to consider more predictor variables. Doing so allows for novices to explore the usefulness of the predictors, thereby learning which of them is the most valuable. Experts, in contrast, may have already acquired sufficient knowledge. They can thus often immediately exploit this knowledge by considering only the most important predictor variables (Pachur & Marinello, 2013). To illustrate this, Garcia-Retamero and Dhami (2009) asked laypeople and professional burglars who had committed burglary on an average of about 57 occasions to judge which of two residential properties was more likely to be burgled. Decisions made by a group of laypeople, composed of graduate students, were mostly consistent with a compensatory *weighted additive model*. Such a model weighs each predictor variable according to its importance, then adds up the weighed predictors for each option, and finally chooses the option with the higher sum score. In contrast, the professional burglars' decisions were most consistent with noncompensatory strategies such as the *take-the-best heuristic* (Gigerenzer & Goldstein, 1996) or a *fast-and-frugal classification tree* (Laskey & Martignon, 2014; Martignon, Vitouch, Takezawa, & Forster, 2003), as were those of another expert group, namely police officers who had worked for about 19 years on average.

Let us explain how the take-the-best heuristic simplifies decision making in more detail for the case of binary predictors: It searches through predictors, and considers them in the order of their importance, one at a time. An inference is made based on the first predictor that discriminates between the two options, that is, when one option has a positive value on the predictor (suggesting a high criterion value), and the other does not (i.e., indicating a low or unknown criterion value). Unlike many more complex models (e.g., regressions) that estimate 'optimal' (e.g., beta) weights for the multiple predictors, take-the-best determines the importance of predictors based on their validity v, with $v = C/(C + W)$. C is the number of correct inferences and W the number of wrong inferences when a predictor discriminates (i.e., when one alternative has a positive value and another does not). The building blocks for the take-the-best heuristic are the following:

Search rule: Search through predictor variables in order of their validity.
Stopping rule: Stop when finding the first predictor that discriminates between the alternatives.
Decision rule: Infer that the alternative with the positive predictor value has the higher value on the criterion.

This heuristic exploits a particular structure that many naturally occurring environments share by ignoring all but the most important predictor variable, if that variable already enables a decision to be made. Other heuristics ignore other pieces of information. For instance, the *tallying heuristic* (Gigerenzer & Goldstein, 1996) leaves aside the importance of predictor variables and treats them equally by simply counting which option has more positive predictor variables and choosing that option. Which heuristic is ecologically rational to use hence depends on the specific properties of the decision environment. In addition, heuristics can be more robust to variations in environments than optimization approaches, as Walsh, Einstein, and Gluck (2013) recently demonstrated in a series of computer simulations (see also Walsh & Gluck, 2015 and Gluck et al., 2012 on the notion of robustness).

The Signal to Noise Ratio in the Decision Environment. In many naturally occurring decision environments, irregular and random fluctuations (noise) obscure the systematic and predictable relationships between variables. In turn, more complex decision strategies, which for instance aim to estimate (more) free parameters, need larger amounts of information to ensure that these parameters actually pick up systematic relationships instead of random noise. A practical example of the role the signal to noise ratio in the decision environment plays in explaining the surprising accuracy of fast-and-frugal heuristics can be found in investment decision making.

Naïve Diversification: 1/N. Consider the situation of investors facing the decision of allocating their money among a set of retirement funds that are on offer. This task is fraught with uncertainties about the likely returns and risks. One candidate heuristic would be *1/N*. According to this "naïve" diversification strategy, the money is divided equally among the funds in question. The rationale of this heuristic follows that of the folk wisdom 'Do not put all your eggs in the same basket.'

1/*N*: Allocate your money equally to each of *N* funds.

How successful is 1/*N*? For seven investment problems, DeMiguel, Garlappi, and Uppal (2009) compared the performance of 1/*N* to that of 14 alternative models, including Bayesian ones and the mean–variance portfolio, which won Harry Markowitz the Nobel Memorial Prize in economics. Unlike 1/*N*, these optimization models try to estimate their many *free parameters* from stock data, which are often highly unreliable. Free parameters are variables in the model that are typically estimated based on past observations. To estimate these parameters, DeMiguel et al. fitted them to 10 years of stock data. All models then had to predict the next month's performance. This procedure was repeated using a moving window to fit past data first and then predict future data. As it turned out, none of the optimization models fared consistently better than 1/*N* for these out-of-sample predictions. On financial criteria such as certainty-equivalent returns, turnover, and the Sharpe ratio, 1/*N* ranked first, second, and fifth, respectively. In six out of the seven investments, 1/*N* outperformed the mean–variance portfolio.

The performance of 1/*N* relative to optimization methods hinges on a number of environmental factors. For instance, computer simulations suggest that the smaller the number of assets, the better optimization models will predict relative to 1/*N*. Optimization models are also more likely to perform better if more past stock data are at hand. How much more data would one need in order for the mean–variance portfolio to outperform 1/*N*? On the U.S. equity market, the mean–variance approach for a portfolio with 50 assets would likely beat 1/*N* if investors had 500 years of stock data available to estimate the free parameters of the portfolio.

The Bias–Variance Dilemma. How can less be more? Let us illustrate the general conditions. For decision makers such as investors in the example discussed above, it is important how well a model is able to predict what will happen in the future (Goldstein & Gigerenzer, 2009) rather than fit only a particular subsample of existing (e.g., past) observations. The ability of a model to predict new, unknown (e.g., future) observations has been dubbed *generalizability* (e.g., Pitt, Myung, & Zhang, 2002). A model's generalizability can be diminished by two main factors: bias and variance. If a model's predictions consistently deviate from the true state of nature (i.e., if one uses a linear regression although the true function is parabolic), then the model has a "bias." As the true state is typically unknown a priori, it is not possible to simply select an unbiased model. Because models with free parameters can accommodate a larger variety of true states, increasing a model's complexity (e.g., the number and kinds of free parameters) will likely reduce its bias. However, this reduction in bias often comes at a price: models with more free parameters (or an otherwise higher model complexity; see Pitt et al., 2002) will fit better not only to the true underlying structure but also to the noise in the specific sample of observations from which it estimates its parameters ("overfitting"). This second type of error, called *variance*, is different from bias and is defined as the variance of the sample estimates around their mean. Thus, the total error when predicting new cases is due to bias and variance. For instance, because 1/*N* does not try to estimate expected returns, volatility, and correlations from stock data, it has no error due to variance, only to bias. Figure 1 illustrates how too much complexity systematically leads to less accuracy in prediction. It also shows that evaluating models in terms of data fitting ("hindsight") is a misleading strategy.

In summary, when choosing the complexity of one's model, there is a tradeoff between bias and variance. This *bias–variance dilemma* (Brighton, 2006; Geman, Bienenstock, & Doursat, 1992; Gigerenzer & Brighton, 2009) can be illustrated as an inversely U-shaped function between complexity and accuracy in prediction. For environments in which more data are available or when the available data are less noisy, the model is better able to separate signal from noise. In such environments, the peak of the inversely U-shaped function is further to the right (e.g., Pitt & Myung, 2002). For many decision makers in applied domains, however, such extensive information is usually not available. Investors, for instance, do not have unlimited data or even 500 years of stock data, which they would need to benefit from complex optimization models. Optimization models might look good 'on paper' because their high flexibility allows them to fit past data very well. But for professionals concerned with predicting new (future) observations, hindsight is not important. Given that, in noisy environments, models with lower complexity are likely more accurate in the absence of abundant data, simple heuristics such as 1/*N*, take-the-best or tallying often represent a good starting point to model and aid applied decision making. The idea is that decision makers do not rely on simple heuristics because they shy away from the effort more complexity would imply but because under uncertainty, more complexity might lead to less accurate predictions.

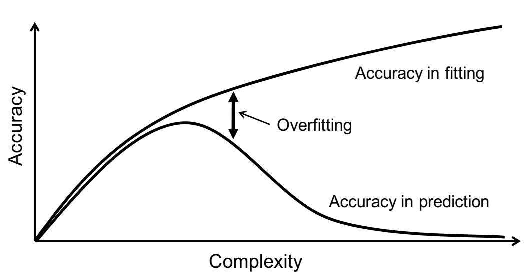

Figure 1. Schematic illustration of how the complexity of a model (e.g., number and kind of free parameters) can influence its accuracy in fitting existing observations and in predicting new ones.
Figure adapted from Pitt and Myung (2002).

The Capabilities of the Decision Maker

Heuristics exploit not only the statistical structures of the decision environment, but also features of how the human mind works, such as in terms of memory and cognition – the second blade in Simon's scissors. The visual system, as it is exploited by the gaze heuristic, is one example. Memory is another.

Memory – the environment within us. One memory-based decision strategy is known as the *recognition heuristic* (Goldstein & Gigerenzer, 2002). This particularly simple strategy operates on just one predictor variable: recognition, that is, remembering whether an alternative's name has been encountered before or not.[1] In doing so, the heuristic exploits the workings of memory, for example the ability to recall information that is presented frequently and recently in the environment, using environmentally shaped characteristics of memory retrieval as cues in decision making (Marewski & Schooler, 2011; Schooler & Hertwig, 2005). As a result, the heuristic also lends itself to applied problems such as predicting sport outcomes (e.g., Herzog & Hertwig, 2011; Scheibehenne & Bröder, 2007) or polling.

To foreshadow the outcomes of political elections, all a pollster has to do is to ask people which names of political parties and candidates they recognize:

> Predict that parties and candidates that are recognized by more people will win more votes than those that are recognized by fewer people.

[1] For a distinction between different notions of "recognition," including familiarity, see Marewski, Gaissmaier, Schooler, Goldstein, and Gigerenzer (2010b, p. 290), Hertwig, Pachur, and Kurzenhauser (2005, p. 623), and Marewski and Schooler (2011, p. 395).

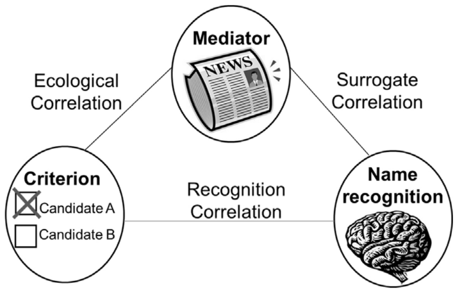

Figure 2. When is it ecologically rational to rely on the recognition heuristic? The recognition heuristic can be expected to lead to accurate inferences when alternatives with high criterion values occur more often in the environment (e.g., in newspapers, on TV, or in conversations). In these cases, people more likely encounter alternatives with large criterion values. The ecological rationality of the recognition heuristic can be understood in terms of three correlations: between the criterion and an environmental mediator (e.g., the news), between the mediator and recognition, and between recognition and the criterion.
Figure adapted from Goldstein and Gigerenzer (2002).

A study series on German federal and state elections (Gaissmaier & Marewski, 2011) suggests that generating recognition-based election forecasts may not require collecting large, representative – and hence expensive – samples of voters. Predictions can instead be based on small and cheap convenience samples, for instance, collected on the streets or in shopping centers.

As with all heuristics, relying on recognition is ecologically rational in particular environments (e.g., Davis-Stober, Dana, & Budescu, 2010). Specifically, it is rational when the recognition of names of alternatives (e.g., candidates) correlates with the values that these alternatives score on a given criterion (e.g., votes), as illustrated in Figure 2. This seems to be the case in German elections. While the causal mechanisms are not conclusively known, those correlations might emerge, for example, when political parties obtain financial resources as a function of past success in elections. The amount of votes gained in the past might then fuel future success via greater media presence and improved future campaign funding, which in turn would increase name recognition. Moreover, unlike intention polls (e.g., asking citizens whom they will vote for), the recognition heuristic benefits from the relative stability of its predictor variable: Although name recognition can be easily induced (e.g., by advertising), once established, it is likely harder to manipulate than voting intentions (Gaissmaier & Marewski, 2011).

Exploiting processing speed. The recognition heuristic exploits an outcome of memory retrieval: whether an object is recognized or not. Other memory-based strategies exploit different outcomes, including a degraded sense of recognition or retrieval fluency (e.g., Hertwig, Herzog, Schooler, & Reimer, 2008; Herzog & Hertwig, 2013; Schooler & Hertwig, 2005) or processing speed in general. One such strategy is the *take-the-first heuristic* (Johnson & Raab, 2003). In decision making under uncertainty, such as competitive sports games, this strategy can allow appropriate responses to be selected quickly:

Choose the first alternative that comes to mind.

This heuristic exploits the cognitive processes of experts, which are already geared toward generating good ideas first. In a study by Johnson and Raab (2003), experienced handball players watched short video sequences of competitive game situations. When the video image was frozen, they were asked to imagine that they were the player with the ball and to generate options about how to proceed. Professional league handball coaches then rated the quality of these options. The sooner an option came to mind, the higher the likelihood that it was rated as appropriate.

Fast-and-Frugal Heuristics are Built on How Individuals Make Decisions

Unlike optimization, the usefulness of heuristics is not limited to situations of risk. Because heuristics can also be relied on in situations of uncertainty, they are more useful than optimization for the many domains of applied decision making under uncertainty. What is more, the conceptual lens of fast-and-frugal heuristics enables researchers to improve decision making by engineering decision strategies. Because such prescriptive heuristics build on the decision processes that people already follow, as we illustrate below, they are easier to rely on and people are more likely to use them successfully.

Fast-and-Frugal Heuristics are Intuitively Understandable

In many businesses, marketers need to decide which of their customers to target with mailings, catalogs, or bonus checks. The problem here is to distinguish between customers who are likely to repurchase from those who are not – a task that requires predicting customers' future behavior (see also Goldstein & Gigerenzer, 2009). In marketing science, one tool for this task is the *Pareto/NBD* (negative binominal distribution) model (e.g., Schmittlein & Peterson, 1994), a complex stochastic model that follows the spirit of optimization approaches. The model assumes, for instance, that active costumers' purchases follow a Poisson process with a purchase rate λ and that each customer is active for a lifetime with an exponentially distributed duration and a dropout rate μ. Customers are heterogeneous, and individual purchase and dropout rates are distributed according to a gamma distribution. In total, the model estimates four parameters to calibrate to a specific customer database. A variant of the Pareto/NBD is the *BG/NBD model*. Well known in academic circles, these two stochastic models appear to be seldom implemented in managerial practice. In a survey among 228 Dutch database marketing companies, Verhoef, Spring, Hoekstra, and Leeflang (2002) found that managers tended to rely instead on simpler techniques such as cross tabulation or the *RFM method*, the latter of which typically classifies customers according to three variables, namely how frequently they purchase, how recently they have purchased, and how much they spend. An even more frugal way to classify customers is the *hiatus heuristic*. This simple rule categorizes every customer as active who has purchased within a certain number of months (the *hiatus*):

If a customer has not made a purchase for 9 months or longer, classify him/her as inactive, otherwise as active.

Wübben and Wangenheim (2008) compared the hiatus heuristic to the Pareto/NBD and BG/NBD models in their ability to accurately classify real-world customers in the apparel, airline, and online CD retail industries as active, inactive, and as future best customers. The hiatus heuristic fared better in the majority of the analyses. In sum, the hiatus heuristic is not only accurate but also easier to understand and implement than the Pareto/NBD and BG/NBD models, and thus more likely to be used.

Fast-and-Frugal Heuristics Simplify the Decision Process

"This phone's price is $600, but the design of this one is nicer; and, wait, yes, my favorite app is already installed, but, oh, the graphical interface is poor. . ., and I am not sure if I will actually need a better camera. . .". Anyone who has visited a cell phone online shop knows how overwhelming the task of choosing from dozens of neat-looking, potentially high-quality phones can be. Many theories of consumer choice posit that consumers simplify such purchasing decisions by using a two-stage process: In the first stage, consumers exclude alternatives from the choice set, and in the second stage, consumers evaluate the remaining alternatives, their *consideration set*, in more detail, until they can make a decision (Alba & Chattopadhyay, 1985; Hafenbrädl, Hoffrage, & White, 2013; Howard & Sheth, 1969; White, Hoffrage, & Reisen, 2015).

In the past decades, formal theories of consideration set construction have typically reflected the spirit of optimization models. For example, consistent with approaches proposing the maximization of expected utility, researchers have assumed that consumers evaluate goods on different attributes, weigh these attributes according to their importance, and add these weighed attribute scores together to determine the good's overall value or utility (e.g., Hauser & Wernerfelt, 1990). By doing so, those researchers try to reduce situations of uncertainty to those of risk. But research also shows that people rely on simpler strategies (Hauser, 1986), such as Tversky's (1972) *elimination-by-aspects heuristic*. This strategy reduces the number of alternatives to consider (e.g., consumer goods). To exclude options from the consideration set, probabilistically selected attributes such as price, color, or size are relied upon. The probability that an attribute is selected depends proportionally on its relative importance. In considering only one attribute at a time, elimination-by-aspects is similar to take-the-best. But it differs from take-the-best, for instance, in that the ordering of attributes is not defined. Let us consider its building blocks:

> Search rule: Look up attributes in an order proportional to their subjective importance.
> Elimination rule: Eliminate all alternatives that do not satisfy a threshold value of the attribute. Proceed with next attribute.
> Stopping rule: Stop search through attributes when all alternatives except one are eliminated. Choose that alternative.

This strategy simplifies the decision process in two ways: first by quickly eliminating many alternatives, and second by considering only one attribute at a time. Nevertheless, even when using simple strategies, people might sometimes defer choice, as we will see next.

Fast-and-Frugal Heuristics Can Explain Both Choice and Choice Deferral

Although the number of new HIV infections has decreased worldwide in recent years, 1.5 million new infections were reported in Sub-Saharan Africa in 2013, which accounts for 70% of all new infections worldwide (UNAIDS, 2014). Not all people in that region, however, know whether they are infected by the virus or not. To make matters worse, health-related uncertainties go hand in hand with social ones: potential infectees might wonder, 'what if my spouse, family, friends, or employers find out that I might have HIV?' In those and similar situations of uncertainty, people might avoid making active decisions and instead rely on the default heuristic, which can be formulated as follows:

> If a policymaker sets a default, then follow it.

When citizens follow the default heuristic, policy makers can induce behavioral change by reversing the default. Such a default reversal took place in 2005, when four hospitals in Chitungwiza, a community close to the Zimbabwean capital Harare decided to test all pregnant women for HIV unless they decided to opt out. Before the reversal, when pregnant women were tested for HIV only if they opted in (i.e., if they actively chose to take the test), only 65% were tested. In contrast, when the test was offered by default to pregnant women, almost all women (99.9%) took it, with only few reporting negative social experiences in the aftermath (Chandisarewa et al., 2007).

For patients, consumers, and other decision makers it is ecologically rational to defer choice and rely on the default heuristic if the policymaker shares their goals and is trustworthy. In this case, so the intuition goes, the default will likely lead to little harm while saving potential effort and time that would be expended in searching for alternatives to the behavior suggested by the default. However, in some situations defaults might be too simplistic, and whether the default heuristic is ecologically rational depends on the details. For example in HIV testing, the default heuristic is ecologically rational only if doctors and patients understand that false positives can occur (i.e., that sometimes uninfected patients receive positive test results; Gigerenzer, 2013). Otherwise patients might suffer for months, erroneously believing that they are infected.

Characteristics that Enable Fast-and-Frugal Heuristics to be Adapted to Situational Requirements

By exploiting the two blades of Simon's scissors, fast-and-frugal heuristics can be both accurate and simple simultaneously. Yet, in many domains, a satisfactory degree of accuracy is only one dimension of ecological rationality. In these domains, situational requirements and constraints strongly influence how decision making can be improved. Fast-and-frugal heuristics possess several characteristics that allow them to be adapted to such situational requirements: accessibility, speed, transparency, and low costs (see e.g., Marewski & Gigerenzer, 2012, for an overview). The importance of the different characteristics varies by goal and situation. For instance, speed and frugality is mostly important under time pressure, and accessibility allows decision strategies to be executed without requiring extensive training.

Accessibility

Fast-and-frugal trees are highly accessible because they are easy to understand, use, and communicate. If experts alone are able to use a proposed decision aid, it will not have an impact in domains where decisions are mainly made by laypeople with limited know-how and experience. For instance, when training micro-entrepreneurs with limited knowledge in accounting in the Dominican Republic, a rule-of-thumb training program outperformed a standard accounting training in improving financial practices, as measured through reporting quality and revenues (Drexler, Fischer, & Schoar, 2014). In light of the financial crisis of 2008, it might be that not only micro-entrepreneurs in the Dominican Republic but also regulators of the financial system could benefit from more accessible und intuitively understandable fast-and-frugal approaches, for instance, to regulate capital requirements of banks. Aikman et al. (2014) proposed and tested such an approach and found that it performs comparably to the more complex standard techniques while being easier to communicate and understand.

How can decision aids for such complex situations be made accessible? Consider the following example. A tearful pupil tells a school counselor that he feels hopeless. The guidance counselor believes that clinical depression can be excluded, but is not entirely sure. If the pupil is erroneously diagnosed as not being depressed, he might not receive the necessary treatment. On the other hand, if the pupil is erroneously classified as depressed, he might not only be treated unnecessarily but also suffer from the social stigma of being in psychiatric treatment. What could help the guidance counselor or other similar professionals to make such decisions? The mental health literature proposes extensive procedures such as structured clinical interviews, which require professional training (First, Spitzer, Gibbon, & Williams, 1995) or questionnaires such as the *Beck Depression Inventory* (Beck, Ward, Mendelson, Mock, & Erbaugh, 1961). One instrument that helps professionals simplify the process without sacrificing accuracy is a fast-and-frugal tree (Martignon, Katsikopoulos, & Woike, 2008; Martignon, Katsikopoulos, & Woike, 2012). Recently, Jenny and colleagues proposed a relevant fast-and-frugal tree that relied on average on only one piece of information yet performed comparably to a less frugal logistic regression and a tallying model (Jenny, Pachur, Lloyd Williams, Becker, & Margraf, 2013).

To illustrate the tree's high accessibility, let us look at it in more detail (see Figure 3). In order to make a decision, at most four questions have to be answered, either with "yes" or with "no". These questions are gone through sequentially, and "no" answers imply an immediate decision. Fast-and-frugal trees are generally composed of three building blocks, similar to take-the-best:

Search rule: Look up predictor variables in the order of their importance.
Stopping rule: Stop search as soon as one predictor allows it.
Decision rule: Classify according to this predictor variable.

Fast-and-frugal trees have a limited number of predictor variables and exits, with n specifying the number of predictor variables, and $n + 1$ the number of exits. The tree in Figure 3, for instance, has 5 exits. In considering only a few binary variables, fast-and-frugal trees, like all other heuristics, simplify decision problems. Optimization procedures, in turn, tend to use more information and, when represented as a tree, have more exits. To illustrate how quickly complexity increases if such simplifications are not built into a decision tree, consider a full tree (Figure 4). Those trees have 2^n exits. As a result, 4 predictors come with 16 exits, 20 with more than 1,000,000, and so on.

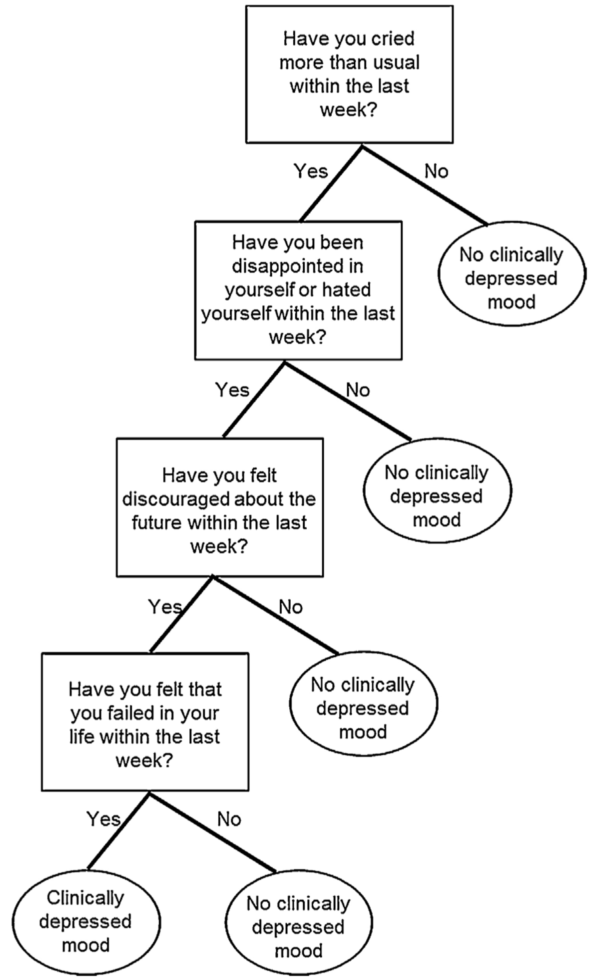

Figure 3. A fast-and-frugal tree for diagnosing a clinically depressed mood. This heuristic consults four predictors sequentially. A person is considered clinically depressed only if all four questions are answered positively.
Figure adapted from Jenny et al. (2013).

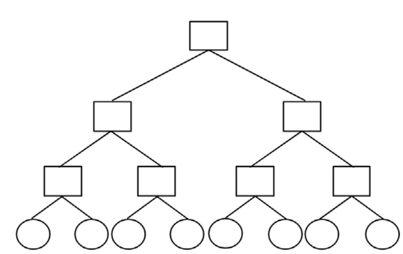

Figure 4. A full decision tree.
Figure adapted from Gigerenzer (2007).

As the number of predictors increases, full trees can become computationally intractable (Gigerenzer, 2007).

When researchers construct a fast-and-frugal tree to improve or aid decision making, signal detection theory can help adapt the tree to the specific cost–benefit structure of the situation in which the tree should be used. As Panel C of Figure 5 shows, according to this theory, observations (e.g., whether the pupil has cried more than usual within the last week) can originate either from *noise* (e.g., reasons that are unrelated to depression) or from a *signal distribution* (e.g., valid indicators of depression). In Jenny et al.'s (2013) study, noise means that the pupil is not depressed, and a signal implies that he is. The counselor's task is to decide whether an observation represents noise or a signal. The strategies for making this decision can be thought of as setting a *decision criterion*, x^c: Any observation that falls to the left of the criterion is classified as noise, and any observation that falls to the right as a signal. The resulting decisions, in turn, can have four possible outcomes (Figure 5A): hits (classifying a signal as a signal), false positives (classifying noise as a signal), false negatives (classifying a signal as noise), and

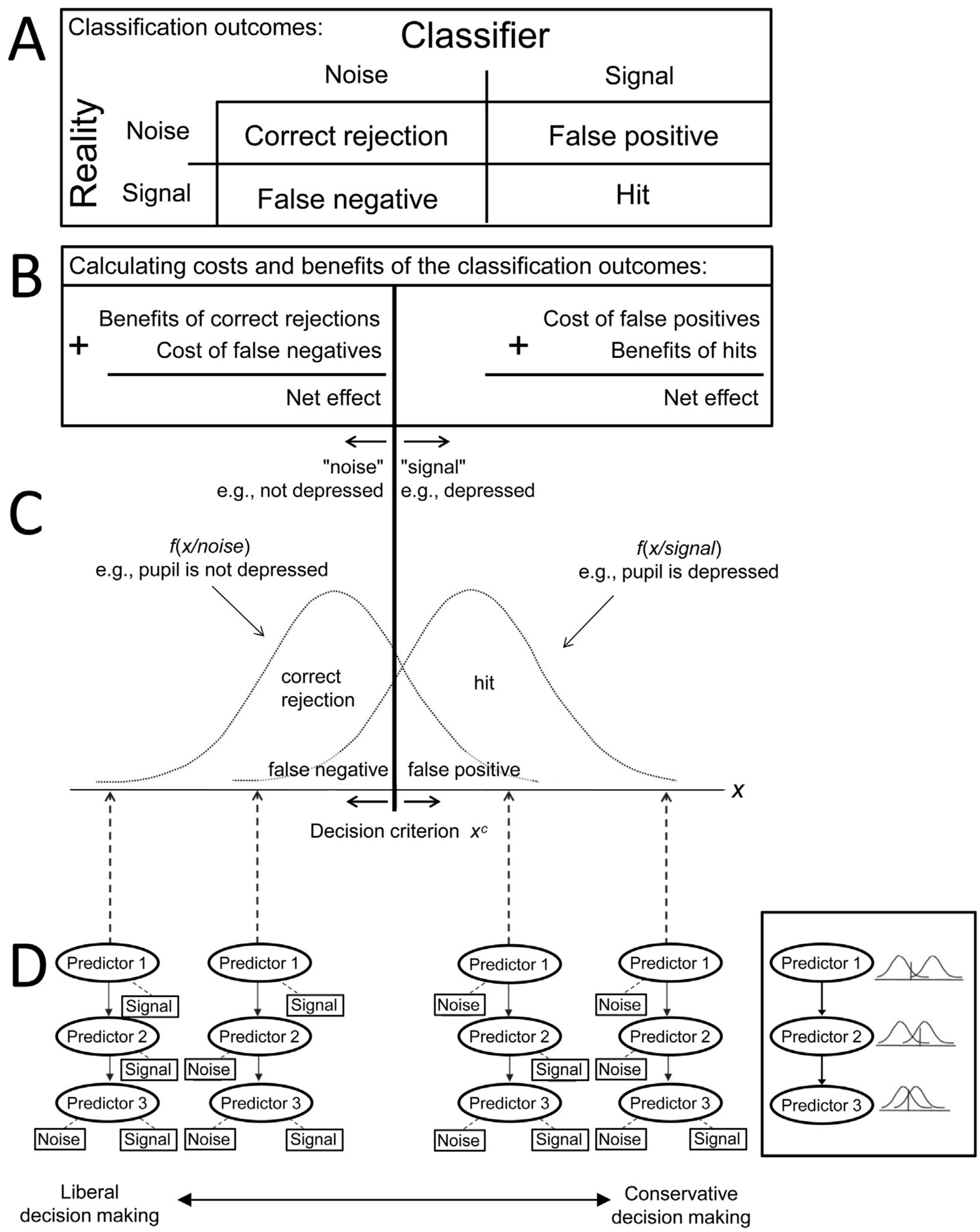

Figure 5. A signal detection analysis shows how fast-and-frugal trees can be selected based on the cost–benefit structure of the situation. Panel A shows the four different classification outcomes. Panel B shows how the benefits and costs of the four outcomes (from Panel A) are related to the decision criterion x^c (in Panel C). Panel C illustrates how the four outcomes depend on the underlying signal and noise distributions, as well as on what decision criterion x^c is chosen. For instance, the larger the costs of false negatives compared to those of false positives, the further should the decision criterion move to the left, and vice versa. Panel D illustrates how different decision criteria map onto the exit structures of fast-and-frugal trees.
Figure adapted from Luan et al. (2011).

correct rejections (classifying noise as noise). These outcomes lead to different costs and benefits (represented in Panel B of Figure 5). Hits lead to depression treatment that is potentially successful; false positives lead to unnecessary treatment and potentially to social stigmatization of the diagnosed pupil; false negatives prevent pupils from receiving necessary treatment; correct rejections avoid unnecessary treatment. In consideration of the differential costs for these outcomes, researchers can not only set the decision criterion but also select the corresponding fast-and-frugal tree. Panel D of Figure 5 shows how differently fast-and-frugal trees can be described in terms of the decision criterion, x^c, and how this allows each tree to be located on a spectrum from liberal (classifying many pupils as depressed) to conservative (classifying only few pupils as depressed) decision making (Luan, Schooler, & Gigerenzer, 2011).

When researchers construct a fast-and-frugal tree to describe and understand how people actually make decisions, they work from Panel D to Panel A of Figure 5. Instead of starting off with the cost structure and the determination of the decision criterion to ultimately select the corresponding tree, they start with the tree that describes how decisions are made. This tree, in turn, allows them to reconstruct the underlying decision criterion and to analyze to what extent this criterion corresponds to the cost structure. In some cases, decision makers are found to rely on decision trees that are well adapted to their personal cost–benefit structure but that produce high costs for those on whose behalf they are deciding. For instance, especially in the US, physicians overdiagnose and overtreat patients (Gigerenzer & Muir Gray, 2011), thereby avoiding costs from potential lawsuits that would fall on themselves but imposing costs on their patients (e.g., from harms and side effects of overtreatment) and on society, which ultimately pays for these superfluous treatments. Or managers make decisions in ways that are easy to justify to others rather than based on what they believe is best for their organization (Gigerenzer, 2014). Such defensive decision making can be uncovered by reverse-engineering the fast-and-frugal trees these decision makers relied on. What is more, by constructing better trees that reflect the real cost structures for patients, organizations, and society at large, researchers can provide simple and accessible tools that steer decision-makers to take into account costs for all relevant stakeholder groups and thus to overcome such defensive decision making. In sum, Figure 5 illustrates how fast-and-frugal trees can be adapted to the cost–benefit structure of the environment in which the decisions are taken. Using signal detection theory as the connecting link between the cost–benefit structure and the fast-and-frugal trees makes these trees particularly accessible for researchers who aim at aiding, improving, and describing applied decision making. We have made this experience ourselves, for instance, when teaching executives, lawyers, and doctors on how to build decision trees, using similar graphical displays of signal and noise distributions.

Speed

Relative simplicity makes decision strategies not only more accessible but also potentially more suitable for use under time pressure. The gaze heuristic used during the emergency plane landing reported above is just one example. After the airplane crashes of September 11, 2001, fast decision making was necessary to determine whether an injured person required immediate treatment or whether treatment could be delayed and priority be given to other victims. Figure 6 shows the fast-and-frugal tree that enabled paramedics to make such decisions rapidly (Cook, 2001; Luan et al., 2011).

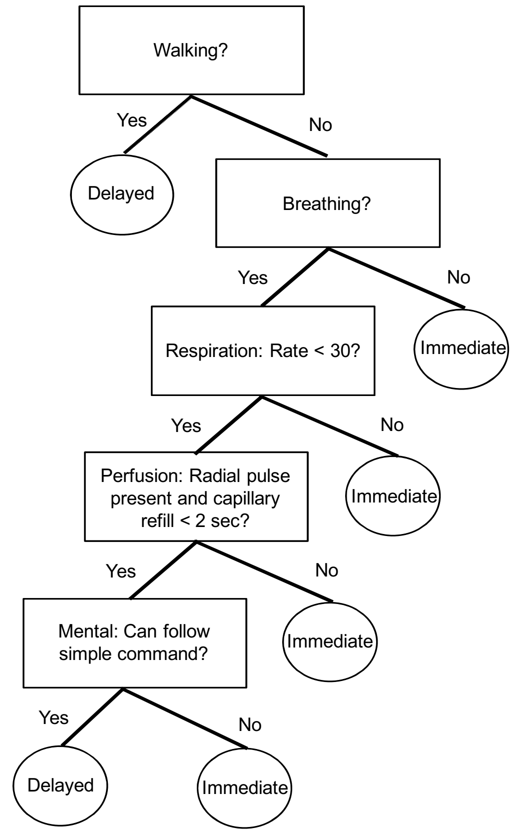

Figure 6. A fast-and-frugal tree for emergency treatment allocation (START). This tree classifies people with injuries, such as victims of terrorist attacks into two groups: those who warrant urgent treatment and those whose treatment can be delayed (Super, 1984).
Figure adapted from Luan et al. (2011).

To allow for quick decisions, heuristics typically reduce the amount of information decision makers need to consult before making a decision. Instead of integrating numerous predictor variables in computationally complex ways, trying to weigh them optimally, many heuristics ignore all but a few predictors. The degree of *frugality* of a heuristic (for a given task) can be measured by the average number of predictors it requires; more frugal heuristics take fewer predictors into account. The bias–variance trade-off implies that higher frugality does not necessarily lead to lower accuracy, depending both on how predictors are combined and on the statistical structure of the task environment. In one of the early studies of the fast-and-frugal heuristics program, Czerlinski, Gigerenzer, and Goldstein (1999) analyzed 20 data sets involving psychological, biological, sociological, and economic decision tasks and showed that take-the-best outperformed on average multiple regression in correct predictions and also considered *the fewest* predictor variables. As Figure 7 illustrates, predictions based on take-the-best

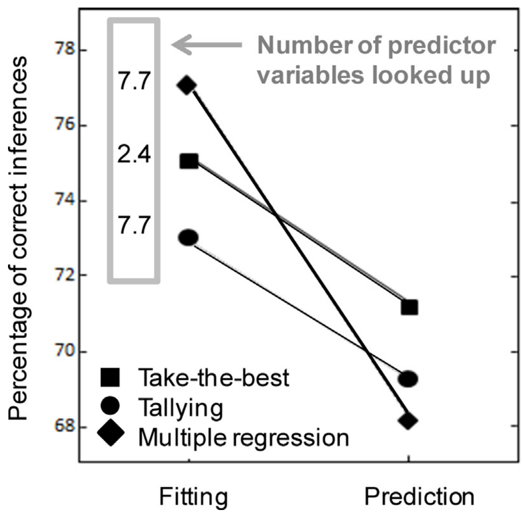

Figure 7. Average number of predictor variables looked up (frugality) by take-the-best, multiple regression, and tallying and average percentage of correct inferences across 20 studies involving psychological, biological, sociological, and economic decision tasks (Czerlinski et al., 1999). In a cross validation, the models' free parameters were estimated in a training data set (fitting) and then used to make predictions in a test data set (prediction). Not surprisingly, all models did better at fitting than at predicting. But in prediction, multiple regression was less accurate than the two heuristics. Tallying is a heuristic that adds up all values of predictors, treating them equally by assigning them unit weights (e.g., $w_i = 1$).
Figure adapted from Marewski, Gaissmaier, and Gigerenzer (2010).

took into account only 2.4 predictor variables on average, compared to 7.7 predictor variables for predictions based on multiple regression. Thus, it was on average more frugal *and* accurate. Since then, these findings have been replicated and extended to different types of model comparisons (see e.g., Brighton, 2006; Gigerenzer & Brighton, 2009; Hogarth & Karelaia, 2007; Katsikopoulos, Schooler, & Hertwig, 2010; Luan, Schooler, & Gigerenzer, 2014).

Transparency

One class of situations in which transparency is advantageous is group decision making. Let us consider the case of a group of skiers or hikers in the mountains facing the danger of potential avalanches. Imagine you and some friends are climbing a snowy mountain in winter on skis. Approaching the summit, you have to cross a steep and exposed slope, potentially prone to avalanches. Before setting foot on it, you stop and ask: "Is this slope safe?" How should you and your fellow skiers decide whether or not this is likely the case? Although there are several decision aids for such a task (Uttl, McDouall, Mitchell, & White, 2012), all of the more accurate ones share a common structure. As Uttl et al. (2012, p. 835) summarize: "In essence, each of these tools can be reduced to a simple checklist where a user determines the presence or absence of various avalanche conditions, terrain characteristics, and human factors; adds up all the points; and uses recommended cut-offs to determine whether or not to travel across a particular slope is not recommended [..]". Consequently, these decision aids can be represented as a tallying heuristic, which works by counting how many predictor variables are detected when hiking (e.g., whether there is a trap such as a gully or a cliff). The tally (i.e., the count) of detected alert signals is then compared to a threshold, which could depend on the general avalanche risk on that day and on the risk preferences of the group:

> Avoid a slope when more predictors are present than the threshold allows.

Such a decision strategy is not only simple and accurate; it also helps against possible pitfalls when making decisions together in a group. For instance, groups often fail to share information that is distributed among group members (e.g., Stasser & Titus, 1985). To counteract this, avalanche decision aids based on a tallying heuristic help structure the discussion by evaluating the clues one by one. Moreover, groups often tend to postpone or defer choice (cf. White, Hafenbrädl, Hoffrage, Reisen, & Woike, 2011). By providing an unambiguous decision rule, tallying heuristics can help groups overcome this inertia.

Cost Effectiveness

Have you ever felt dizzy or vertigo? Most people have, and often those disturbing sensations disappear on their own – sometimes also with the help of sleep or a glass of water. While being harmless most of the time, these common symptoms can also hint at a dangerous brainstem or cerebellar stroke. In the US, annually about 2.6 million people come to the emergency room with these symptoms. For the medical personnel, these visits can be understood as a signal detection problem, similar to the one in Figure 5: whether the patient belongs to the vast distribution of non-problematic cases (i.e., the "noise" in Figure 5C) or there is a serious health risk (i.e., the "signal" in Figure 5C). One tool that can help the medical personnel make the correct diagnosis is an MRI. The alternative is a simple bedside exam, a tallying rule that announces "Alarm!" if at least one of three tests indicates a stroke (Kattah, Talkad, Wang, Hsieh, & Newman-Toker, 2009). As mentioned above, tallying simply counts the predictors and compares the result to a predefined threshold (in this case the threshold is one).

How effective is the bedside tallying heuristic compared to a high-tech MRI? As mentioned above, tallying ignores information about the relative importance of the predictors by treating all of them equally and simply counting them. Good diagnostic tools have a high sensitivity (hit rate) and a low false positive rate. The sensitivity of the bedside tallying heuristic is higher than that of the MRI; that is, it detects strokes more often than the MRI does, thereby helping to reduce the frequency of potentially life-threatening diagnostic errors (i.e., not diagnosing a stroke when there is one). The heuristic's false positive rate is only slightly higher than that of the MRI. This can lead to a few more patients being accidentally diagnosed with a stroke, which is a less serious mistake than overlooking one. Moreover, the bedside exam is also less cost-intensive (an MRI costs between \$500 and \$2000), takes little time, and can be conducted almost anywhere, including in very poor countries where MRIs are unavailable (Gigerenzer & Gaissmaier, 2011; Marewski & Gigerenzer, 2012).

Understanding When and Why People Make Mistakes

The fast-and-frugal heuristics framework allows the conditions under which a heuristic can lead one astray to be formally specified. For instance, Figure 5 above illustrates when different trees will result in larger false-positive rates, and Figure 1 indicates when models will overfit the data. Figure 2, in turn, facilitates understanding when relying on the recognition heuristic is not ecologically rational – namely when there are zero correlations between the criterion, the mediator, and recognition.

Another possible instance of a heuristic leading to imprudent decisions occurred after the horrifying airplane crashes on September 11, 2001, when many people in the US decided to travel by car rather than by plane. As a result, the number of road traffic accidents increased in the aftermath of the airplane crashes – to the extent that the number of extra casualties on the road exceeded the number of casualties on board the four fatal flights on September 11 (Gigerenzer, 2006; Gaissmaier & Gigerenzer, 2012). This deadly avoidance behavior may have resulted from the *dread risk rule* (Gigerenzer, 2014; see also Slovic, 1987):

> If many people die at one point in time, react with fear and avoid that situation.

Although situations in which this heuristic may be ecologically rational readily come to mind, the dread risk rule may also underlie both illusions of relative safety and what appear to be irrational fears. Many of us are afraid of plane crashes, terrorist attacks, and nuclear power plant accidents – all of which represent low-probability but potentially disastrous single events in Western countries – but do not worry much about the greater likelihood of dying in a car accident or developing diseases due to pollution from coal plants (Gigerenzer, 2014).

The study of ecological rationality highlights an important point: There is no such thing as one optimal tool for all situations; the performance of *all* models of decision-making – be they heuristics or Bayesian, expected utility, or other 'optimization' tools – depends on the task environment to which they are applied. Leibnizian dreams (1677/1952) of a universal calculus collapse in worlds of Knightian uncertainties. This is why the conceptual lens of fast-and-frugal heuristics directs researchers to specify *when* and *why* a given heuristic results in adaptive behavior – the boundary conditions of ecological rationality.[2]

Focus on Decision Processes also Enables Improving Decision Making Under Risk

By using the conceptual lens of fast-and-frugal heuristics as a starting point, emphasis is placed on precisely specifying the *process* of how people make decisions. Instead of treating this process as a black-box and focusing on predicting outcomes of people's decisions (i.e., what option they choose), researchers within the fast-and-frugal heuristics framework investigate how people search through information, when they stop, and how they ultimately make their decision (e.g., Rieskamp & Hoffrage, 1999). These processes are, in turn, cast into computational or mathematical models (Marewski & Olsson, 2009). The trees shown in Figures 3 and 6 above are examples of such process models. These process models are the connecting links between people's choices and the options from which they can choose in their decision environment. Knowing people's choices and the decision environment, researchers who want to describe decision making can compare different process models to evaluate their predictive accuracy. After having identified a process that decision makers should follow, researchers who want to improve or aid decision making can develop prescriptive decision strategies that help people follow that process. And they could alter the decision environment such that people could follow this process more easily.

Indeed, by analyzing decision processes and their interplay with the structure of people's task environments, researchers have identified ways to improve decision making – even in situations of risk rather than uncertainty. Consider a Bayesian analysis of HIV testing. A man who does not engage in risky behavior (he belongs to a group in which the prevalence of HIV is 0.01%) participates in screening for HIV and receives a positive HIV test result. What is the probability that he actually is infected? To answer this question, one needs to know the sensitivity and specificity of the test. A sensitivity of 99.8% means that 99.8% of those who have the disease receive a positive test result. A specificity of 99.99% means that 99.99% of those who do not have the disease receive a negative test result. How should an AIDS counselor determine the probability that the man with a positive test result is indeed infected? This task can be solved by Bayes rule. Yet in a study, most professional AIDS counselors failed to do so, overestimating the probability or even providing illusions of certainty (Gigerenzer, Hoffrage, & Ebert, 1998); a recent study showed no improvement (Prinz, Feufel, Gigerenzer, & Wegwarth, 2015). The same lack of understanding has been reported by legal professionals (Lindsey, Hertwig, & Gigerenzer, 2003) and in management (Hoffrage, Hafenbrädl, & Bouquet, 2015).

By investigating the process of how decision makers solve these tasks, Gigerenzer and Hoffrage (1995) found that many difficulties individuals have with such tasks stem from the format in which information is presented to them. The presentation format can be conceptualized as a window through which individuals see their decision environment. Specifically, when information was presented in terms of probabilities or percentages (base rate, sensitivity, and specificity), professionals and laypeople had difficulties making sense of the information, as though they were seeing it through a foggy window. Presenting the same information in terms of natural frequencies gave them a much clearer view of their decision environment, which in turn enabled them to solve these Bayesian inference tasks significantly better (see also Brase & Hill, 2015; Hafenbrädl & Hoffrage, 2015; Hoffrage, Lindsey, Hertwig, & Gigerenzer, 2000; Hoffrage, Krauss, Martignon, & Gigerenzer, 2015; Johnson & Tubau, 2015). For the HIV testing situation, a natural frequency representation starts with a sample of men and decomposes this sample into its parts without normalizing

[2] For a discussion of such how institutions learn from errors and adapt and improve their simple rules, see Sull and Eisenhardt's (2015) selection of cases.

(as relative frequencies or probabilities do). For instance, out of 10,000 men in the same risk group, only 1 is expected to have HIV (prevalence of 0.01%), and he is expected to receive a positive test (sensitivity of 99.8%). From the 9,999 who are not infected, 9,998 (99.99%) are expected to receive a negative test result, and 1 (0.01%) to receive a positive test result. In sum, out of the 10,000 men, 2 receive a positive test, but only one of them actually has the disease, resulting in a probability of 50% that a man with a positive test result actually has the disease.

This insight into the difficulty decision makers have in dealing with probabilities and the relative ease they have in dealing with natural frequencies has led researchers to propose or test a variety of potential remedies, including graphical displays of natural frequencies (Garcia-Retamero & Hoffrage, 2013) and curricula on statistical literacy (Gigerenzer, 2002; Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, & Woloshin, 2008). To sum up, even in domains where probabilities are known and decisions could be taken by using optimization techniques such as Bayesian inference tasks, the conceptual lens of fast-and-frugal heuristics provided important and useful insights by leading researchers to focus squarely on the process of how people make decisions.

Conclusion

Does the lens of fast-and-frugal heuristics imply that people always rely on heuristics and that they always should do so? And, in turn, does it suggest that other approaches to applied decision making should be excluded from consideration? We do not think so. If one can find the optimal solution to a problem, one should do it (see Box 1). But that is rarely the case in applied settings, where uncertainty reigns.[3] Herbert Simon (e.g., 1956) set the stage by pointing out that it is often impossible to optimize in the real world and that people have no choice but to satisfice. Nevertheless, researchers in many disciplines have continued to study mostly problems for which an optimal solution can be calculated, thereby ignoring the large world of uncertainty for which optimal solutions are unavailable. The program on fast-and-frugal heuristics provides a genuine alternative that can deal with decision making under uncertainty. This makes the conceptual lens of fast-and-frugal heuristics the ideal starting point for anyone interested in describing and improving real-world decision making. By building on knowledge about how people decide, it is possible to design environments so that people can make better decisions.

Box 1: How to Select a Heuristic from the Adaptive Toolbox?

Whereas researchers should model the ecological rationality of decision strategies to normatively evaluate when each strategy should be used, decision makers often need a fast and simple way of choosing among the various heuristics in their toolbox. Several ways to conceptualize, predict, and improve corresponding strategy selection processes have been suggested (Glöckner & Betsch, 2008; Marewski & Schooler, 2011; Newell & Lee, 2011; Payne et al., 1993; Rieskamp & Otto, 2006; see Marewski & Link, 2014 for a recent overview). Particularly relevant for applied decision makers is Katsikopoulos' (2011) discussion of conditions under which heuristics make better inferences than approaches based on optimization techniques, in which he proposes a simple tree to model when people should rely on optimization procedures and when on heuristics. That being said, the problem of how to model when people should use which strategy is far from resolved and it would be desirable if future research tackled this issue. The same holds for the related questions of how people learn the statistical structures of their environments, and correspondingly which pieces of information (cues) to rely on in which environment (Garcia-Retamero, Takezawa, Woike, & Gigerenzer, 2013; Gigerenzer, Hoffrage, & Goldstein, 2008). This "strategy selection problem" is not unique to fast-and-frugal heuristics. Optimization requires the selection of parameters before a prediction can be made in any given situation. When the conceptual lens of optimization is adopted instead of fast-and-frugal heuristics, the problem of strategy selection is hence merely replaced by the problem of parameter selection, with no gains for the applied decision maker. On the other hand, researchers in *applied* decision making are typically not concerned with drawing from an all-encompassing theory of strategy selection. Instead, many of them focus on describing or improving decision making with respect to a specific task, environment or situation.

[3] As a matter of fact, heuristics are not the only tools for dealing with uncertainty: others include reasoning by analogies, by examples, or by stories (see also Hogarth & Soyer, 2015).

Conflict of Interest Statement

The authors declare that they have no conflict of interest

References

Aikman, D., Galesic, M., Gigerenzer, G., Kapadia, S., Katsikopoulos, K. V., Kothiyal, A., et al. (2014). Taking uncertainty seriously: Simplicity versus complexity in financial regulation. *Bank of England Financial Stability Paper*, *28*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2432137

Alba, J. W., & Chattopadhyay, A. (1985). Effects of context and part – Category cues on recall of competing brands. *Journal of Marketing Research*, *22*, 340–349.

Allison, G. T. (1969). Conceptual models and the Cuban missile crisis. *American Political Science Review*, *63*, 689–718.

Arrow, K. J. (1966). Exposition of the theory of choice under uncertainty. *Synthese*, *16*, 253–269.

Beck, A. T., Ward, C. H., Mendelson, M., Mock, J., & Erbaugh, J. K. (1961). An inventory for measuring depression. *Archives of General Psychiatry*, *4*(6), 561–571.

Becker, G. S. (1993). Nobel lecture: The economic way of looking at behavior. *Journal of Political Economy*, *101*(3), 385–409.

Binmore, K. (2009). *Rational decisions*. Princeton, NJ: Princeton University Press.

Brase, G. L., & Hill, W. T. (2015). Good fences make for good neighbors but bad science: A review of what improves Bayesian reasoning and why. *Frontiers in Psychology*, *6*, 340. http://dx.doi.org/10.3389/fpsyg.2015.00340

Brighton, H. (2006). Robust inference with simple cognitive models. In C. Lebiere, & R. Wray (Eds.), *A.A.A.I. spring symposium: Cognitive science principles meet AI-hard problems* (pp. 17–22). Menlo Park, CA: American Association for Artificial Intelligence.

Brown, R. V. (2015). Decision science as a by-product of decision-aiding: A practitioner's perspective. *Journal of Applied Research in Memory and Cognition*, *4*(3), 212–220.

Chandisarewa, W., Stranix-Chibanda, L., Chirapa, E., Miller, A., Simoyi, M., Mahomva, A., et al. (2007). Routine offer of antenatal HIV testing ("opt-out" approach) to prevent mother-to-child transmission of HIV in urban Zimbabwe. *Bulletin of the World Health Organization*, *85*, 843–850.

Chater, N., & Oaksford, M. (2008). *The probabilistic mind: Prospects for Bayesian cognitive science*. New York, NY: Oxford University Press.

Cook, L. (2001). The World Trade Center attack: The paramedic response: An insider's view. *Critical Care*, *5*, 301–303.

Curkin, S., & Monek, B. (2009). Miracle on the Hudson. *ABC News*,. Retrieved from http://abc7ny.com/archive/6606410/

Czerlinski, J., Gigerenzer, G., & Goldstein, D. G. (1999). How good are simple heuristics? In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 97–118). New York, NY: Oxford University Press.

Davis-Stober, C. P., Dana, J., & Budescu, D. V. (2010). Why recognition is rational: Optimality results on single-variable decision rules. *Judgment and Decision Making*, *5*(4), 216.

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, *22*, 1915–1953.

Drexler, A., Fischer, G., & Schoar, A. (2014). Keeping it simple: Financial literacy and rules of thumb. *American Economic Journal: Applied Economics*, *6*(2), 1–31.

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

First, M. B., Spitzer, R. L., Gibbon, M., & Williams, J. B. (1995). The structured clinical interview for DSM-III-R personality disorders (SCID-II): Part I. Description. *Journal of Personality Disorders*, *9*(2), 83–91.

Gaissmaier, W., & Gigerenzer, G. (2012). 9/11, Act II: A fine-grained analysis of regional variations in traffic fatalities in the aftermath of the terrorist attacks. *Psychological Science*, *23*, 1449–1454.

Gaissmaier, W., & Marewski, J. N. (2011). Forecasting elections with mere recognition from small, lousy samples: A comparison of collective recognition, wisdom of crowds, and representative polls. *Judgment and Decision Making*, *6*, 73–88.

Garcia-Retamero, R., & Hoffrage, U. (2013). Visual representation of statistical information improves diagnostic inferences in doctors and their patients. *Social Science & Medicine*, *83*, 27–33.

Garcia-Retamero, R., Takezawa, M., Woike, J. K., & Gigerenzer, G. (2013). Social learning: A route to good cue orders. In R. Hertwig, U. Hoffrage, & The ABC Research Group (Eds.), *Simple heuristics in a social world*. New York, NY: Oxford University Press.

Garcia-Retamero, R., & Dhami, M. K. (2009). Take-the-best in expert-novice decision strategies for residential burglary. *Psychonomic Bulletin & Review*, *16*, 163–169.

Geman, S., Bienenstock, E., & Doursat, R. (1992). Neural networks and the bias/variance dilemma. *Neural Computation*, *4*, 1–58.

Gigerenzer, G. (1991). From tools to theories: A heuristic of discovery in cognitive psychology. *Psychological Review*, *98*, 254–267.

Gigerenzer, G. (2002). *Reckoning with risk: Learning to live with uncertainty*. UK: Penguin.

Gigerenzer, G. (2006). Out of the frying pan into the fire: Behavioral reactions to terrorist attacks. *Risk Analysis*, *26*, 347–351.

Gigerenzer, G. (2007). *Gut feelings: The intelligence of the unconscious*. New York, NY: Viking.

Gigerenzer, G. (2013). HIV screening: Helping clinicians make sense of test results to patients. *British Medical Journal*, *347*, f5151.

Gigerenzer, G. (2014). *Risk savvy: How to make good decisions*. New York, NY: Penguin.

Gigerenzer, G., & Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science*, *1*, 107–143.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*, 451–482.

Gigerenzer, G., Gaissmaier, W., Kurz-Milcke, E., Schwartz, L. M., & Woloshin, S. (2008). Helping doctors and patients make sense of health statistics. *Psychological Science in the Public Interest*, *8*(2), 53–96.

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669.

Gigerenzer, G., Hertwig, R., & Pachur, T. (2011). Introduction to chapter 33. In G. Gigerenzer, R. Hertwig, & T. Pachur (Eds.), *Heuristics: The foundations of adaptive behavior* (pp. 633–634). New York, NY: Oxford University Press.

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: Frequency formats. *Psychological Review*, *102*, 684–704.

Gigerenzer, G., Hoffrage, U., & Goldstein, D. G. (2008). Fast and frugal heuristics are plausible models of cognition: Reply to Dougherty, Franco-Watkins, and Thomas. *Psychological Review*, *115*(1), 230–239.

Gigerenzer, G., Hoffrage, U., & Ebert, A. (1998). AIDS counselling for low-risk clients. *AIDS Care*, *10*(2), 197–211.

Gigerenzer, G., & Muir Gray, J. A. (2011). Launching the century of the patient. In G. Gigerenzer, & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning health care 2020* (pp. 3–28). Cambridge, MA: MIT Press.

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

Glöckner, A., & Betsch, T. (2008). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(5), 1055.

Gluck, K. A., McNamara, J. M., Brighton, H., Dayan, P., Kareev, Y., Krause, J., et al. (2012). Robustness in a variable environment. In J. R. Stevens, & P Hammerstein (Eds.), In J. Lupp (Ed.), *Strüngmann forum report* (Vol. 11) *Evolution and the mechanisms of decision making*. Cambridge, MA: MIT Press.

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109*, 75–90.

Goldstein, D. G., & Gigerenzer, G. (2009). Fast and frugal forecasting. *International Journal of Forecasting*, *25*(4), 760–772.

Hafenbrädl, S., & Hoffrage, U. (2015). Toward an ecological analysis of Bayesian inferences: How task characteristics influence responses. *Frontiers in Psychology*, *6*, 939. http://dx.doi.org/10.3389/fpsyg.2015.00939

Hafenbrädl, S., Hoffrage, U., & White, C. (2013). The impact of affect on willingness-to-pay and desired-set-size. In C. Pammi, & N. Srinivasan (Eds.), *Decision making: Neural and behavioural approaches, progress in brain research* (Vol. 202). Amsterdam, Netherlands: Elsevier.

Hauser, J. R. (1986). Agendas and consumer choice. *Journal of Marketing Research*, *18*, 199–212.

Hauser, J. R., & Wernerfelt, B. (1990). An evaluation cost model of consideration sets. *Journal of Consumer Research*, *16*, 393–408.

Hertwig, R., Herzog, S. M., Schooler, L. J., & Reimer, T. (2008). Fluency heuristic: A model of how the mind exploits a by-product of information retrieval. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, *34*, 1191–1206.

Hertwig, R., Pachur, T., & Kurzenhäuser, S. (2005). Judgments of risk frequencies: tests of possible cognitive mechanisms. *Journal of Experimental Psychology: Learning Memory, and Cognition*, *31*(4), 621.

Herzog, S. M., & Hertwig, R. (2011). The wisdom of ignorant crowds: Predicting sport outcomes by mere recognition. *Judgment and Decision Making*, *6*, 58–72.

Herzog, S. M., & Hertwig, R. (2013). The ecological validity of fluency. In C. Unkelbach, & R. Greifeneder (Eds.), *The experience of thinking: How the fluency of mental processes influences cognition and behavior* (pp. 190–219). New York: Psychology Press.

Hoffrage, U., Hafenbrädl, S., & Bouquet, C. (2015). Natural frequencies facilitate diagnostic inferences of managers. *Frontiers in Psychology*, *6*, 642. http://dx.doi.org/10.3389/fpsyg.2015.00642

Hoffrage, U., Krauss, S., Martignon, L., & Gigerenzer, G. (2015). Natural frequencies improve Bayesian reasoning in simple and complex inference tasks. *Frontiers in Psychology*, *6*, 1473. http://dx.doi.org/10.3389/fpsyg.2015.01473

Hoffrage, U., Lindsey, S., Hertwig, R., & Gigerenzer, G. (2000). Communicating statistical information. *Science*, *290*, 2261–2262.

Hoffrage, U., & Marewski, J. N. (2015). Unveiling the lady in black: Modeling and aiding intuition. *Journal of Applied Research in Memory and Cognition*, *4*(3), 145–163.

Hogarth, R. M., & Karelaia, N. (2007). Heuristic and linear models of judgment: Matching rules and environments. *Psychological Review*, *114*(3), 733.

Hogarth, R. M., & Soyer, E. (2015). Providing information for decision making: Contrasting description and simulation. *Journal of Applied Research in Memory and Cognition*, *4*, 221–228.

Howard, J. A., & Sheth, J. N. (1969). *The theory of buyer behavior*. New York, NY: Wiley.

Jenny, M. A., Pachur, T., Lloyd Williams, S., Becker, E., & Margraf, J. (2013). Simple rules for detecting depression. *Journal of Applied Research in Memory and Cognition*, *2*(3), 149–157.

Johnson, J. G., & Raab, M. (2003). Take the first: Option-generation and resulting choices. *Organizational Behavior and Human Decision Processes*, *91*, 215–229.

Johnson, E. D., & Tubau, E. (2015). Comprehension and computation in Bayesian problem solving. *Frontiers in Psychology*, *6*, 938. http://dx.doi.org/10.3389/fpsyg.2015.00938

Juran, J. M. (1954). Universals in management planning and controlling. *Management Review*, *43*, 748–761.

Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Straus and Giroux.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. New York, NY: Cambridge University Press.

Katsikopoulos, K. V. (2011). Psychological heuristics for making inferences: Definition, performance, and the emerging theory and practice. *Decision Analysis*, *8*(1), 10–29.

Katsikopoulos, K. V., Schooler, L. J., & Hertwig, R. (2010). The robust beauty of ordinary information. *Psychological Review*, *117*(4), 1259–1266.

Kattah, J. C., Talkad, A. V., Wang, D. Z., Hsieh, Y. H., & Newman-Toker, D. E. (2009). HINTS to diagnose stroke in the acute vestibular syndrome. *Stroke*, *40*, 3504–3510.

Klein, G. (2015). A naturalistic decision making perspective on studying intuitive decision making. *Journal of Applied Research in Memory and Cognition*, *4*(3), 164–168.

Knight, F. H. (1921). *Risk, uncertainty, and profit*. New York, NY: Houghton Mifflin.

Laskey, K., & Martignon, L. (2014). Comparing fast and frugal trees and Bayesian networks for risk assessment. In K. Makar, B. de Sousa, & R. Gould (Eds.), *Sustainability in statistics education. Proceedings of the Ninth International Conference on Teaching Statistics*. Flagstaff, AR: International Statistical Institute and International Association for Statistical Education.

Leibniz, G. W. (1677/1952). Toward a universal characteristic. In G. W. Leibniz (Ed.), *Selections* (pp. 17–25). New York: Scribner's Sons.

Lindsey, S., Hertwig, R., & Gigerenzer, G. (2003). Communicating statistical DNA evidence. *Jurimetrics*, 147–163.

Luan, S., Schooler, L. J., & Gigerenzer, G. (2011). A signal-detection analysis of fast-and-frugal trees. *Psychological Review*, *118*, 316–338.

Luan, S., Schooler, L. J., & Gigerenzer, G. (2014). From perception to preference and on to inference: An approach-avoidance analysis of thresholds. *Psychological Review*, *121*, 501–525.

Marewski, J. N., Gaissmaier, W., & Gigerenzer, G. (2010). Good judgments do not require complex cognition. *Cognitive Processing*, *11*(2), 103–121.

Marewski, J. N., Gaissmaier, W., Schooler, L. J., Goldstein, D. G., & Gigerenzer, G. (2010). From recognition to decisions: Extending and testing recognition-based models for multialternative inference. *Psychonomic Bulletin & Review*, *17*(3), 287–309.

Marewski, J. N., & Gigerenzer, G. (2012). Heuristic decision making in medicine. *Dialogues in Clinical Neuroscience*, *14*(1), 77–89.

Marewski, J. N., & Link, D. (2014). Strategy selection: An introduction to the modeling challenge. *Wiley Interdisciplinary Reviews: Cognitive Science*, *5*(1), 39–59.

Marewski, J. N., & Olsson, H. (2009). Beyond the null ritual: Formal modeling of psychological processes. *Zeitschrift für Psychologie*, *217*(1), 49–60.

Marewski, J. N., & Schooler, L. J. (2011). Cognitive niches: An ecological model of strategy selection. *Psychological Review*, *118*, 393–437.

Martignon, L., & Hoffrage, U. (1999). Why does one-reason decision making work? A case study in ecological rationality. In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 119–140). New York, NY: Oxford University Press.

Martignon, L., Katsikopoulos, K. V., & Woike, J. K. (2008). Categorization with limited resources: A family of simple heuristics. *Journal of Mathematical Psychology*, *52*(6), 352–361.

Martignon, L. F., Katsikopoulos, K. V., & Woike, J. K. (2012). Naive, fast, and frugal trees for classification. In P. M. Todd, G. Gigerenzer, & The ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world* (pp. 360–378). New York: Oxford University Press.

Martignon, L., Vitouch, O., Takezawa, M., & Forster, M. (2003). Naive and yet enlightened: From natural frequencies to fast and frugal trees. In D. Hardman, & L. Macchi (Eds.), *Thinking: Psychological perspectives on reasoning, judgment, and decision making* (pp. 189–211). Chichester, UK: Wiley.

Newell, B. R., & Lee, M. D. (2011). The right tool for the job? Comparing an evidence accumulation and a naive strategy selection model of decision making. *Journal of Behavioral Decision Making*, *24*(5), 456–481.

Pachur, T., & Marinello, G. (2013). Expert intuitions: How to model the decision strategies of airport customs officers*? Acta Psychologica*, *144*, 97–103.

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

Pitt, M. A., & Myung, I. J. (2002). When a good fit can be bad. *Trends in Cognitive Sciences*, *6*(10), 421–425.

Pitt, M. A., Myung, I. J., & Zhang, S. (2002). Toward a method of selecting among computational models of cognition. *Psychological Review*, *109*, 472–491.

Prinz, R., Feufel, M., Gigerenzer, G., & Wegwarth, O. (2015). What counselors tell low-risk clients about HIV test performance. *Current HIV Research*, *13*, 369–380.

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics and how can we tell? In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 119–140). New York, NY: Oxford University Press.

Rieskamp, J., & Otto, P. E. (2006). SSL: A theory of how people learn to select strategies. *Journal of Experimental Psychology: General*, *135*, 207–236.

Rose, C. (2009, February). *The Charlie Rose show [television broadcast]*. New York, NY: PBS.

Savage, L. J. (1954). *The foundation of statistics*. New York, NY: Wiley.

Scheibehenne, B., & Bröder, A. (2007). Predicting Wimbledon 2005 tennis results by mere player name recognition. *International Journal of Forecasting*, *23*(3), 415–426.

Schmittlein, D. C., & Peterson, R. A. (1994). Customer base analysis: An industrial purchase process application. *Marketing Science*, *13*, 41–67.

Schooler, L. J., & Hertwig, R. (2005). How forgetting aids heuristic inference. *Psychological Review*, *112*(3), 610.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*, 129–138.

Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology*, *41*, 1–20.

Slovic, P. (1987). Perception of risk. *Science*, *236*(4799), 280–285.

Stasser, G., & Titus, W. (1985). Pooling of unshared information in group decision making: Biased information sampling during discussion. *Journal of Personality and Social Psychology*, *48*(6), 1467.

Super, G. (1984). *START: A triage training module*. Newport Beach, CA: Hoag Memorial Hospital Presbyterian.

Sull, D., & Eisenhardt, K. M. (2015). *Simple rules: How to thrive in a complex world*. London: John Murray.

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

UNAIDS WHO. (2014). *Fact sheet 2014*. http://www.unaids.org/sites/default/files/en/media/unaids/contentassets/documents/factsheet/2014/20140716_FactSheet_en.pdf

Uttl, B., McDouall, J., Mitchell, C., & White, C. A. (2012). Avalanche accident risk reduction tools in a North American context. In *International Snow Science Workshop* (pp. 834–839). Retrieved from. http://arc.lib.montana.edu/snow-science/objects/issw-2012-834-839.pdf

Verhoef, P. C., Spring, P. N., Hoekstra, J. C., & Leeflang, P. S. H. (2002). The commercial use of segmentation and predictive modeling techniques for database marketing in the Netherlands. *Decision Support Systems*, *34*, 471–481.

von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior* (2nd ed.). Princeton, NJ: Princeton University Press.

Walsh, M. M., Einstein, E. H., & Gluck, K. A. (2013). A quantification of robustness. *Journal of Applied Research in Memory and Cognition*, *2*(3), 137–148.

Walsh, M. M., & Gluck, K. A. (2015). Mechanisms for robust cognition. *Cognitive Science*, *39*(6), 1131–1171.

White, C. M., Hafenbrädl, S., Hoffrage, U., Reisen, N., & Woike, J. K. (2011). Are groups more likely to defer choice than their members? *Judgment and Decision Making*, *6*(3), 239–251.

White, C. M., Hoffrage, U., & Reisen, N. (2015). Choice deferral can arise from absolute evaluations or relative comparisons. *Journal of Experimental Psychology: Applied*, *21*(2), 140.

Wübben, M., & Wangenheim, F. V. (2008). Instant customer base analysis: Managerial heuristics often “get it right”. *Journal of Marketing*, *72*, 82–93.

Received 13 August 2013;
received in revised form 18 February 2016;
accepted 18 April 2016
Available online 22 June 2016