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Smart Heuristics for Individuals, Teams, and Organizations

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Abstract

Heuristics are fast, frugal, and accurate strategies that enable rather than limit decision making under uncertainty. Uncertainty, as opposed to calculable risk, is characteristic of most organizational contexts. We review existing research and offer a descriptive and prescriptive theoretical framework to integrate the current patchwork of heuristics scattered across various areas of organizational studies. Research on the adaptive toolbox is descriptive, identifying the repertoire of heuristics on which individuals, teams, and organizations rely. Research on ecological rationality is prescriptive, specifying the conditions under which a given heuristic performs well, that is, when it is smart. Our review finds a relatively small but rapidly developing field. We identify promising future research directions, including research on how culture shapes the use of heuristics and how heuristics shape organizational culture. We also outline an educational program for managers and leaders that follows the general approach of "Don't avoid heuristics—learn how to use them."

INTRODUCTION

How can one hire the best employees? Firms often consider candidates' education, personality, and prior work experience. According to Tesla chief executive officer (CEO) Elon Musk, these criteria are not what counts. Instead, Musk looks for "evidence of exceptional ability" (Popomaronis 2021). To find this, he asks each candidate: "Tell me about some of the most difficult problems you worked on and how you solved them." The idea is that people who have shown exceptional ability in the past are likely to continue showing it in the future. To determine whether candidates are telling the truth, Musk insists on hearing precisely how they solved a problem because only those who actually did can know the finer details.

Heuristic: a procedure for decision making under uncertainty; ignores information to make decisions more quickly, frugally, and/or accurately than complex procedures

Uncertainty: situations in which perfect foresight of all future events, their consequences, and probabilities is impossible (e.g., hiring, project selection); also known as VUCA environments

Smart heuristic: a heuristic used in situations in which it is ecologically rational

Adaptive toolbox: the repertoire of heuristics that an individual, team, or organization has at its disposal for making decisions

Ecological rationality: the study of the environmental conditions under which a given strategy performs better than other strategies

Musk's approach to hiring is fast and frugal and of a heuristic nature. It is fast because it dispenses with dozens of interviews, lengthy questionnaires, or assessment centers. It is frugal because it relies instead on a single reason. Musk is no exception. Environments subject to uncertainty—in leadership theories known as VUCA (volatility, uncertainty, complexity, and ambiguity)—are prime conditions for firms and leaders to develop and use heuristics. "A heuristic is a procedure for decision making under uncertainty. It ignores information to make decisions faster, more frugally, and/or more accurately than complex procedures" (Gigerenzer & Gaissmaier 2011, p. 454).

Herbert A. Simon (1947, 1955), the only person to date to have received both the Nobel Memorial Prize in Economics and the Turing Award, placed decision making at the center of organizational scholarship and promoted the systematic study of heuristics. Yet a glance into recent reviews of the field reveals a striking departure: Heuristics are either not mentioned at all or portrayed as inferior to so-called rational strategies such as expected utility maximization (Larrick 2016, Oswald et al. 2020), which are unfeasible in VUCA environments. Although organizations are the primary example for the use of heuristics in Simon's work, organizational psychology has paid little attention to how decisions are actually made. It is our hope to change that.

Scope and Purpose of Review

We review a field in an early but rapidly developing stage: the study of smart heuristics in organizations (Artinger et al. 2015, Eisenhardt & Sull 2015, Loock & Hinnen 2015). We do not aim for an exhaustive review; rather, we organize our review within the theoretical framework of the adaptive toolbox and ecological rationality (Gigerenzer et al. 2011). This framework provides a foundation to ask specific research questions; in an emerging field, it is more important to pose the right questions than to find the right answers to the wrong questions (known as Type III errors). The heuristics we include in this review are known as fast-and-frugal heuristics (Gigerenzer et al. 1999) or simple rules (Bingham & Eisenhardt 2011). All of these heuristics specify a course of action, such as what information to search, when to stop search, and how to make the final decision, and are effective under specific ecological conditions.

The scope of this review is both descriptive and prescriptive. Research on the adaptive toolbox describes the repertoire of heuristics for individuals, teams, or organizations. Research on ecological rationality investigates under what conditions a heuristic is likely to lead to successful decisions, and thus prescribes what heuristics should be used in what situations (Todd et al. 2012).

We do not deal here with what have been labeled heuristics that do not specify a course of action and that are typically invoked as post hoc explanations when decisions are proved wrong. We found this negative use to be the most frequent one in organizational research. For instance, concepts such as availability, representativeness, and System 1 link heuristics with biases (Kahneman 2011) but without specifying positive guidelines for behavior, such as whom to hire, fire, or promote. To signal the functional nature of heuristics, we chose the qualifier "smart." That does not mean that all uses of heuristics are smart but rather that it is possible to ascertain the conditions in which the heuristics we review are functional. Nor do we cover research on human behavior in organizations in general; instead, we focus only on the research that investigates heuristics.

In this review, we address two general issues: (*a*) why organizational psychology should look (again) at heuristics, but from the perspective of ecological rationality, and (*b*) how to move from a miscellany of rules to more theoretical research on the adaptive toolbox of heuristics.

Satisficing: a class of heuristics that sets an aspiration level and chooses the first item that meets it; the level is adaptable

Heuristics: A Brief History

The term heuristic is of Greek origin and means "serving to find out or discover." Max Wertheimer, Karl Duncker, and other Gestalt psychologists used it in this sense and spoke of heuristic methods such as "looking around" to guide search for information. Albert Einstein included the term in the title of his Nobel Prize–winning 1905 paper on quantum physics to signal that the view he presented was an incomplete yet highly useful route to discovering something closer to the truth (Holton 1988). The mathematician George Pólya (1945) argued that science requires both analytical and heuristic tools; for instance, analysis is necessary to check a proof, whereas heuristics are needed to find the proof in the first place.

Together with Allen Newell, a student of Pólya's, Simon adopted this idea to make computers intelligent. The result was the original program of artificial intelligence (AI), which consisted of studying the heuristics experts use consciously or unconsciously and translating them into computer algorithms. Here, the human was the teacher and the computer the pupil. The *I* in AI originally referred to human intelligence or, more precisely, human heuristics, because heuristics can solve problems that logic and probability cannot; this defined Simon's vision of psychological AI. Despite their remarkable performance and recent popularity (Oswald et al. 2020), machine learning systems (which are not inspired by psychology) have not yet been able to create what could be called human intelligence, and psychological AI is currently being reconsidered as a route to true machine intelligence (Marcus & Davis 2019).

Simon (1955) also formulated one of the first algorithmic models of heuristics, known as satisficing. Satisficing can lead to good decisions in situations in which optimizing is impossible. This view of heuristics as useful tools was, however, turned upside down in the 1970s, when researchers started to associate heuristics with biases and presented probability theory as the universal tool for rational decisions (Kahneman 2011, Tversky & Kahneman 1974). The influence of this heuristics-and-biases program may be one of the reasons why the positive features of heuristics have remained underresearched and underestimated in organizational psychology (Gilbert-Saad et al. 2018). Beginning in the 1990s, the program of fast-and-frugal heuristics took up Simon's original, unfinished work and expanded it by developing algorithmic models of heuristics and introducing the concept of ecological rationality, which studies when a heuristic is successful or not (Gigerenzer & Selten 2001, Gigerenzer et al. 1999). These two features, algorithmic models and ecological rationality, contribute to improving and expanding the earlier heuristics-and-biases program: They enable the study of concrete rules that help organizations make better decisions under uncertainty. The two programs should be seen not as antagonistic but rather as natural steps toward progress.

WHY DO WE NEED HEURISTICS?

It is sometimes said that heuristics save effort but lead to less accurate judgments and decisions than do more effortful procedures. In VUCA environments, this claim is not correct.

Uncertainty, Not Risk

Risk: a situation in which all possible events, probabilities, and consequences are known and optimal action can be calculated (e.g., lotteries, roulette)

Accuracy–effort trade-off: the claim that heuristics must always sacrifice accuracy for less effort; true in situations of risk but false under uncertainty

Less-is-more: when using less information or computation leads to more accurate decisions; no accuracy–effort trade-off

Intuition: a judgment based on extensive experience in which one is not fully aware of the underlying reasons; sometimes intuition is the unconscious use of heuristics

At a most general level, heuristics are tools for dealing with uncertain situations, such as hiring and firing, negotiation, and leadership. Probability theory, in contrast, is tailored to situations of risk (Knight 1921). In a situation of risk, an agent has perfect knowledge of all relevant future states of the world and their probabilities and consequences. An example is the game of roulette, which has exactly 37 possible future states (the numbers 0 to 36), for which the probabilities and outcomes (payoffs) are known. In the social games that organizations play, this certainty does not exist. Uncertainty is created by many factors, including the unpredictable behavior of people; changes in technology and politics; and unforeseeable personal, financial, or global crises.

Leonard J. Savage (1954), known as the father of Bayesian decision theory, made it clear that expected utility maximization applies to small worlds of risk only and that it would be "ridiculous" to apply it in situations of uncertainty, be they as mundane as "planning a picnic" (p. 16). Similarly, when young Simon tried to apply rational choice theory to budget decision problems while working for Milwaukee's recreation department, he learned that managers did not compare the marginal utility of a proposed expenditure with its marginal costs but instead relied on rules of thumb. He concluded that in organizations, the framework of utility maximization "was hopeless" (Simon 1988, p. 286). Nevertheless, one still encounters today statements assuming that when managers use heuristics, they at best approximate the optimal solutions or make suboptimal decisions. Yet in situations of uncertainty, optimization is a delusion: By definition, the optimal decision cannot be determined. The general point is that probability theory and optimization models are perfect tools for risk and that heuristics are the better tools for uncertainty.

Less-Is-More

A widespread, albeit incorrect, account of why people use heuristics is the accuracy–effort trade-off: Using heuristics reduces effort but decreases accuracy (Shah & Oppenheimer 2008). Although this trade-off is a general characteristic of situations of risk, it does not apply to uncertainty, under which heuristics can both save effort and lead to more accurate decisions than would more effortful strategies. This striking benefit is called the less-is-more effect. Consider companies that need to predict which previous customers will continue buying their products. Experienced managers rely on the hiatus heuristic: If a customer has not purchased within x months, the customer is classified as inactive, otherwise as active. In retail companies and airlines, the hiatus is often $x = 9$ months. A study of 35 companies showed that this heuristic predicts future purchases more accurately than complex marketing and machine learning models do (Artinger et al. 2018, Wübben & Wangenheim 2008). Managers use the hiatus heuristic not because of personal biases or limited mental capacity but because it is effective. Here, less complexity means more accuracy.

Note that less-is-more does not imply ignoring all features; rather, it means that using only one or a few critical features, such as the hiatus, is effective. Under uncertainty, there is typically an inverse-U-shaped function between the number of features used and accuracy (Goldstein & Gigerenzer 2002).

Fast Decisions

Because heuristics enable quick decision making, they have become associated with making errors, resulting in a supposed accuracy–speed trade-off (Kahneman 2011). As the hiatus heuristic illustrates, however, that is not generally true. A large body of research on sports shows that experts, unlike novices, often perform better when they have limited time (Beilock et al. 2004). The unconscious use of heuristics by experts is one facet of intuition (see the sidebar titled Intuition in Organizations). Similarly, the heuristics used by senior managers to decide in which project

INTUITION IN ORGANIZATIONS

An intuition, or gut feeling, is a judgment based on years of experience for which one is not fully aware of the underlying reasons; that is, one cannot explain why it was made. In some cases, intuitions can be equated with the unconscious use of heuristics (Gigerenzer 2007, 2014). Studies of experts show that an option that intuitively comes to mind first is likely the best, and further deliberation tends to generate inferior options (Johnson & Raab 2003). Experienced managers also rely on intuition. In confidential interviews with mid- to high-level managers from an international technology services provider, the majority (24 of 32) said that 50% or more of their professional decisions were—after consulting all the data—ultimately based on gut feelings. At the top level of management of an international car manufacturer, consisting mostly of engineers, everyone (50 out of 50) said the same (Gigerenzer 2014). Yet the very same executives would never admit to this practice in public for fear of negative consequences from stakeholders (unlike in family or owner-held businesses). Instead, executives tend to hire consulting firms to justify the gut feeling after the fact, which is then presented to the public as a deliberative decision derived from data alone. Fear of negative consequences of admitting to decisions based on gut feelings leads to a waste of intelligence, resources, and time.

to invest were as accurate as when the managers relied on slower analytic methods (West et al. 2020). And firms making faster strategic decisions often showed both greater profits and more rapid growth (Baum & Wally 2003).

Transparency

Heuristics can be easily understood, executed, and taught. Black box AI systems, in contrast, are opaque because they are proprietary or too complicated to be comprehensible. As in the case of effort and speed, another common misconception is that the more transparent an algorithm is, the less accurate it must be. Under uncertainty, simple heuristics can often predict as accurately as or better than commercial black box software, but in a transparent way (Katsikopoulos et al. 2020). Moreover, transparency can lead to greater trust in leadership (Norman et al. 2010) and make inadvertent biases, such as adverse impact in hiring, more readily identifiable and thus fixable.

THE ADAPTIVE TOOLBOX

In this section we describe specific heuristics and provide an overarching framework that helps to construct, modify, and classify these heuristics.

One-Reason Decision Making

In one-reason decision making, a decision maker relies on a single important cue or feature. There are two classes of such heuristics (Gigerenzer & Gaissmaier 2011). In the first class, a single powerful cue is identified, such as exceptional ability or general intelligence of a job applicant, and the rest, such as academic grades, are ignored. We refer to this class as one-clever-cue heuristics. Musk's heuristic (i.e., hire the person if evidence for exceptional ability is present, otherwise don't hire) is an example. This class of heuristic can be used to make final yes–no decisions but also to narrow down the number of alternatives to a smaller consideration set (Hauser 2014).

One-reason decision making: a class of heuristics that bases decisions on a single reason, including one-clever-cue and sequential search heuristics

The second class, sequential search heuristics, builds on the first cue and adds further ones. In each case, however, the decision is always based on a single cue and no weighting and adding of multiple cues occurs. These heuristics are lexicographic, making no trade-offs between cues,

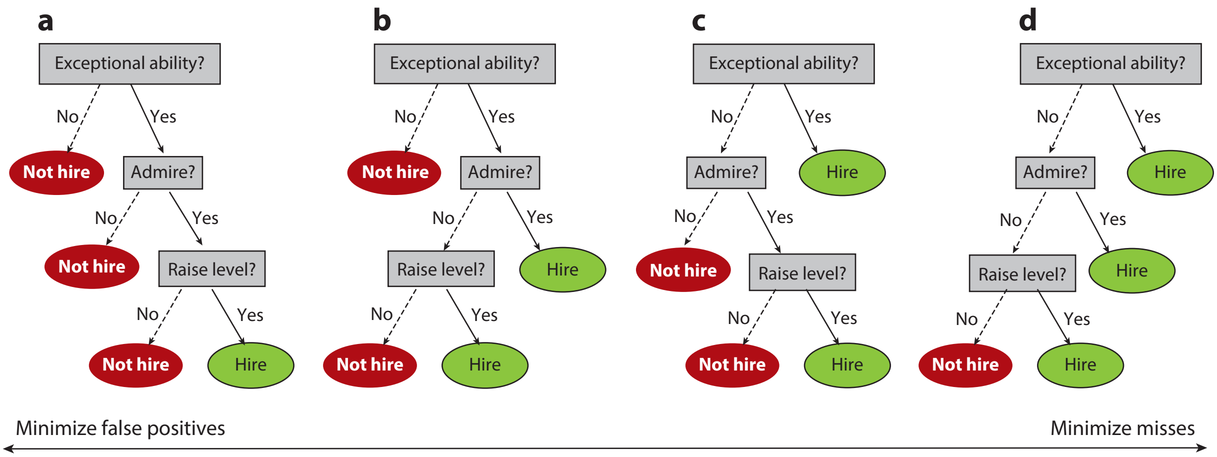

Figure 1

Four possible fast-and-frugal trees with the same three cues and cue orders. The leftmost tree (*a*) represents Jeff Bezos's hiring strategy and illustrates how a one-clever-cue heuristic (here, Musk's exceptional ability heuristic) can be expanded to form a fast-and-frugal tree. This tree minimizes false positives. In contrast, the rightmost tree (*d*) minimizes misses. The two middle trees (*b*, *c*) balance the two errors accordingly.

which stands in contrast to virtually all regression and Bayesian models. Lexicographic decision making has been reported in many contexts, from consumers' choice of smartphones on the internet (Hauser 2014) to senior managers' investment decisions about innovative projects in the advertising, digital, software, and publishing industries (West et al. 2020). Here, we describe two types of sequential search heuristics.

Fast-and-frugal trees. When Amazon was still a small company and CEO Jeff Bezos made hiring decisions himself, he, like Musk, looked for exceptional ability. But in his case, he required two additional features before accepting a candidate (Popomaronis 2020). We have reconstructed his strategy in the form of a fast-and-frugal tree (see **Figure 1*a***). The first feature was exceptional ability; if Bezos judged it to be absent, the applicant was not hired. Otherwise, he asked himself a second question, Would you admire this person?, as Bezos believes that colleagues he admires are those from whom he can learn. A no was sufficient reason for elimination. If the answer was yes, he asked himself a third question, Will this person raise the average level of effectiveness of the group they're entering? That would ensure that the bar in the company goes up continuously. Only in the event of another positive answer was the candidate hired.

Fast-and-frugal tree: a decision tree with n cues and $n + 1$ exits (one exit for each cue except two for the last cue)

Building blocks: basic components of heuristics, such as search, stopping, and decision rules; can be recombined to generate new heuristics

In general, in the case of binary decisions, a fast-and-frugal tree is an incomplete tree with n questions (or cues) and $n + 1$ exits. It has three building blocks:

- Search rule: Search through cues beginning from the top.
- Stopping rule: Stop search if a cue leads to an exit.
- Decision rule: Act according to what the exit specifies.

Figure 1 illustrates how features or cues can be combined into a fast-and-frugal tree, which can be further designed to minimize either false positives or misses. Every hiring decision, like any other classification, can lead to two kinds of errors: a false positive (an offer to the wrong person) or a miss (no offer to the right person). The tree depicted in **Figure 1*a*** minimizes false positives because it is conservative and specifies making an offer only if a candidate passes all three questions. To reduce misses instead of false positives, one can alter the structure of the first two exits of the tree. **Figure 1** shows all four possible fast-and-frugal trees for this particular hiring decision, each containing the same three cues and the same order of cues. The further the tree is to the right, the fewer cases of misses and the more cases of false positives there will be.

The tree depicted in **Figure 1*d*** allows for hiring after a positive answer to at least one question and thus minimizes misses. It can also be represented as a disjunctive rule that accepts a candidate if at least one of n features is met, whereas the tree depicted in **Figure 1*a*** is a conjunctive rule that requires all n features to be met. The trees depicted in **Figure 1*b*,*c*** are the interesting cases, in which the order of cues matters for decision accuracy (it does not matter for the two other trees, although it can affect the speed of decision making). The four trees correspond to four settings of the decision criterion in signal detection theory (Luan et al. 2011). But unlike signal detection theory, the trees require no assumptions about distributions and can easily handle more than one cue. The construction of fast-and-frugal trees is described in detail in Katsikopoulos et al. (2020).

Take-the-best: a heuristic for two alternative choices that searches through binary cues in the order of their validity; search stops when cue values differ

Delta-inference: similar to take-the-best, but for continuous cues; search stops when values of alternatives on a cue differ by at least Δ

Equality heuristic: a class of heuristics that weights all cues equally or invests in all alternatives equally (e.g., tallying and 1/*N*)

Take-the-best and delta-inference. Now consider a different task: to select one out of two alternatives, such as a final job candidate or project proposal. To solve such tasks, take-the-best (Gigerenzer & Goldstein 1996) and delta-inference (Luan et al. 2014) follow the same principles as fast-and-frugal trees. The heuristics search cues by their validity (the correlation with the criterion, such as job performance) and start with the most valid (best) cue, choosing the alternative that is better on that cue (take-the-best uses binary cues with values 0 and 1, and delta-inference generalizes take-the-best to continuous cues, such as IQ score). Only if the alternatives are tied is the next cue considered.

Equality

One-reason decision making is ecologically rational in situations in which a strong, dominant cue exists. In situations characterized by cues with similar strengths, dominance should be replaced by equality. We describe two classes of equality heuristics, the first treating cues equally (tallying) and the other treating alternatives equally (1/*N*).

Tallying. Whereas sequential search heuristics are based on the principle of ordering, tallying is based on counting. Consider classifying a person or a project into two categories, A and B, such as accept or reject, on the basis of n binary cues. Tallying defines a number k ($1 < k \leq n$) of positive cue values a candidate must have in order to be classified as A. For instance, if there are $n = 7$ features and $k = 5$, then all candidates with at least 5 positive values are accepted. Tallying rules have successfully predicted the popular vote winners in US presidential elections and outperformed poll prediction markets and big data analytics (Lichtman 2016). Czerlinski et al. (1999) found that across 20 tasks for predicting psychological, economic, and other outcomes, tallying led to more accurate results than did multiple regression. In the next section, we specify a condition (dominant cues) under which tallying and other equality heuristics fail.

1/N. Equality is an issue when allocating resources to N alternatives. Instead of weighting, the 1/*N* rule invests or shares resources equally: Allocate resources equally to each of N alternatives (Messick 1993). The rule can generate a sense of fairness, for example, when parents allocate equal time and attention to each of their children, or supervisors to their employees. It can also create robust financial diversification by investing equal amounts into N assets. 1/*N* performs on par with or better than Harry Markowitz's Nobel Prize–winning mean-variance portfolio

(Markowitz 1952) and other highly sophisticated investment models, with considerably less time and effort (DeMiguel et al. 2009).

Social heuristics: a class of heuristics that relies exclusively on social input, such as word-of-mouth and imitating-the-best

Satisficing

Kurt Lewin (1935), who promoted the concept of aspiration, maintained that successful people are those who set attainable goals. An aspiration is a goal, and an aspiration level is a goal value. The basic version of the satisficing heuristic sets an aspiration level α and chooses the first alternative (e.g., an applicant or project) that satisfies it (Simon 1955). In situations in which the proper α is unclear, the basic version of the heuristic can be extended to satisficing with aspiration-level adaptation. Satisficing is used for pricing products, accepting or rejecting offers, and deciding in which project to invest, among others (Artinger et al. 2021). An analysis of 628 German used-car dealers showed that 97% of them relied on satisficing with or without aspiration-level adaptation. The most frequent strategy was to begin with an above-average price, wait for approximately 4 weeks before lowering the price, and repeat the procedure until the car is sold (Artinger & Gigerenzer 2017).

Social Heuristics

All the above heuristics can be used for decisions concerning both social and nonsocial choices. We restrict the term social heuristics to the use of genuinely social information provided by others (Hertwig et al. 2013). Social heuristics facilitate decision making under ignorance, that is, in the absence of knowledge about valid cues or aspiration levels.

Imitation. Imitation, one of the most powerful social heuristics, is an enabler of human culture (Boyd & Richerson 2005). Instead of searching for information individually, one copies the decision already made by someone else, such as an expert or a competitor. Within an organization, imitation can lead to shared practices, common values, and group conformity. Also, companies tend to imitate other companies' successful products, processes, and technologies to increase competitiveness, as witnessed by copyright laws and patent court cases.

Wisdom-of-crowds. To estimate an unknown quantity, one can simply rely on the aggregated estimate of a reference group (Surowiecki 2005). The rationale of this wisdom-of-crowds heuristic is based on the law of large numbers, which requires independent estimates and the absence of a systematic bias in the crowd. Under these conditions, the average estimate can be expected to approach the true value as the number of members in the crowd increases—but not otherwise.

Word-of-mouth. The word-of-mouth heuristic makes choices on the basis of others' recommendations. For instance, instead of advertising job positions, companies often ask current employees for recommendations. Relying on word-of-mouth can change the culture and efficiency of an organization. Those who are asked feel trusted and likely recommend people of high ability and motivation because their own reputation is at stake (Beaman & Magruder 2012). Word-of-mouth in social media and beyond also has a strong impact on consumer behavior (Berger 2014).

CONDITIONS UNDER WHICH HEURISTICS ARE SMART

One might ask, How can heuristics that base decisions on a single cue (and ignore the rest) ever lead to superior decisions? The conditions under which a heuristic can be expected to generate results comparable to or better than those of more complex strategies—i.e., is smart—constitute the subject of the study of ecological rationality. Specific results about the ecological rationality of heuristics have been reviewed by Katsikopoulos (2011), Şimşek (2013), and Todd et al. (2012). Here, we focus on two general results: the existence of dominant cues and the bias–variance dilemma.

Bias–variance dilemma: the trade-off between the bias and the variance, which constitutes the total error of a prediction model

Dominant cue condition: a situation with a powerful cue that allows all other cues to be ignored without loss of accuracy

Dominant Cues

In general, one-reason decision making is ecologically rational in situations in which a dominant cue exists (and is used), in which cues are highly correlated, or in which both apply. To simplify, consider a situation in which n binary cues with values $+1$ or -1 are available to make a binary decision, such as hire or not hire. The weights of these cues are $w_1, \ldots, w_n$, all of which are positive and in which the weight of each subsequent cue reflects its additional contribution (incremental validity) to the higher-ranked cues. A linear rule that uses all cues has the form

$$y = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n.$$

This rule yields the decision "hire" if $y > 0$, otherwise "not hire." Linear rules, such as multiple regression, are standard decision tools that we use for reference here. Now consider a one-clever-cue heuristic using only the most valid cue. If the following condition holds, the heuristic can never be outperformed by a linear model that adds and weights all n cues because the weight of the most valid cue (the first cue) is larger than the sum of all other cues (Artinger et al. 2018, Gigerenzer 2021).

Dominant cue condition. The weights $w_1, w_2, \ldots w_n$ form a dominant cue structure if they satisfy the condition

$$w_1 > \sum_{i=2}^{n} w_i.$$

The dominant cue condition also applies to social heuristics that rely on one good reason, such as imitation or word-of-mouth. If the behavior of others, or word-of-mouth, is the most powerful cue and it also satisfies the dominant cue condition, then no linear model that integrates all n cues can lead to a better decision.

For sequential search heuristics, such as take-the-best, the corresponding condition is stronger: Dominance needs to hold for each cue, such that the weight of the second cue must also be larger than the sum of all lower-ranked cues, and so on. An example is a task with cue weights 1, 1/2, 1/4, 1/8, and 1/16 (Martignon & Hoffrage 2002). **Figure 2*a*** shows the weights of five cues that satisfy both the dominant cue condition and the stronger condition.

In contrast, when all cues have the same weight (**Figure 2*b***), it is easy to see that one-reason decision making is doomed to fail but that tallying leads to the same result as linear models. Similarly, $1/N$ works best when the weights of the N alternatives are roughly equal. Dominant cues are likely in situations in which cues highly correlate with each other and the additional contribution of new cues is therefore marginal. Equal weights are likely when cues are independent. Likewise, relying on the wisdom of crowds is ecologically rational in situations in which individual votes are independent and contribute equally to the aggregate judgment, as in **Figure 2*b***. The dominant cue condition makes relying on one-reason heuristics ecologically rational, whereas the equal cue condition makes the use of equality heuristics ecologically rational.

The contrast between the dominant cue condition and the equal cue condition can serve as a general scheme for evaluating the ecological rationality of rules. Consider the practice of evaluating the quality of research findings solely by statistical significance, that is, whether $p < 0.05$. This

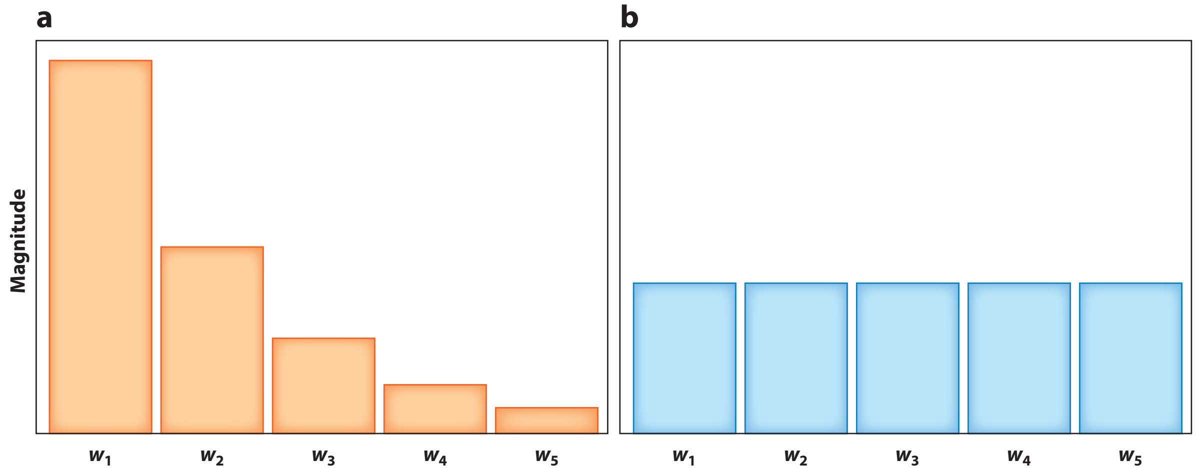

Figure 2

Illustrations of (*a*) a condition for the ecological rationality of one-reason heuristics (dominant cue condition) and (*b*) a condition for the ecological rationality of equality heuristics (equal cue condition). Adapted from Gigerenzer et al. (1999).

one-reason rule is mistaken because the *p*-value is not a dominant cue. Instead, the quality depends on effect size, sample size, replicability, reliability, and a host of other factors that are not covered by the *p*-value. Evaluating research resembles the situation in **Figure 2*b*** and needs multiple cues, not a single one.

Bias–Variance Dilemma

The failure of a project or a hire is sometimes attributed to biases of people who had predicted that the project or hire would be a success. They may have been overly optimistic or impressed by invalid credentials. In prediction, however, there are two errors: bias and variance. Consider the prediction of an unknown true value μ of a candidate by random samples of observations. Each of S samples ($s = 1, \ldots, S$) generates an estimate x_s. The variability of these estimates x_s around their mean $\bar{x}$ is called variance, and the difference between $\bar{x}$ and μ is called bias (Gigerenzer & Brighton 2009). Thus, the prediction error (the sum of squared error) can be captured in the equation

$$\text{prediction error} = \text{bias}^2 + \text{variance} + \varepsilon,$$

where bias $= \bar{x} - \mu$, variance $= \frac{1}{S}\,\Sigma(x_s - \bar{x})^2$, and ε is unsystematic noise (mean at zero and uncorrelated with bias). The decomposition of prediction error into bias and variance reveals a dilemma: Lowering bias typically increases variance, and vice versa.

Figure 3 illustrates bias and variance using a dart analogy. Each estimate x_s is represented by a dart. Player A has a systematic bias but a small variance, whereas Player B has no bias but a large variance. To evaluate a prediction, these two sources of error (ignoring noise) need to be considered. Variance increases with an increasing number of parameters to be estimated and a decreasing sample size on which each estimate x_s is based. One-clever-cue heuristics have only one or even zero parameters to be estimated (e.g., when the hiatus needs to be estimated from data or a known hiatus is available, respectively), meaning that little or no error by variance occurs when using them. In general, compared with using highly parameterized models such as regression and Bayesian models, using heuristics can decrease prediction error because of small variance. If a heuristic has the same bias as a more complex model, such as when the dominant cue condition

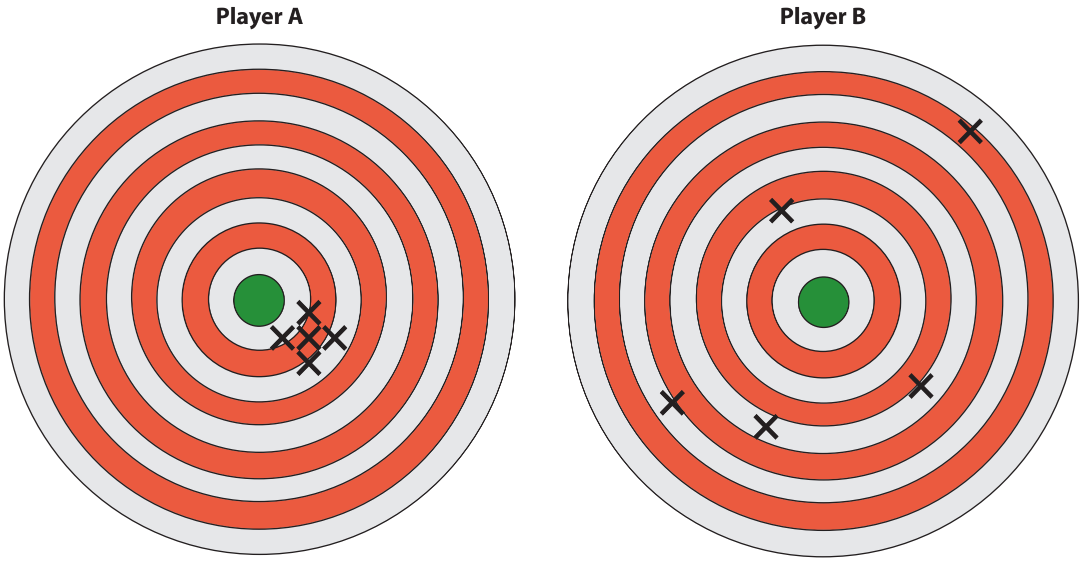

Figure 3

A dartboard illustration of the bias–variance dilemma. (*Left*) Player A's darts show a bias, as they are too far to the right and to the bottom of the bull's-eye, but only a small variance; that is, the darts are close together. (*Right*) Player B's darts show no bias (the average position of all darts is in the bull's-eye) but a large variance.

holds, but produces less error from variance, then it can be intuitively seen how the heuristic can make better predictions. For example, complex personnel selection algorithms using machine learning and scraping large amounts of data from applicants' social media accounts may have a lot of variance due to the large number of parameters. In contrast, one-clever-cue heuristics such as hiring on the basis of general mental or exceptional ability would have little variance, even as they may have some bias.

In sum, just like all decision strategies, heuristics are not good or bad, rational or irrational; rather, they need to be evaluated against the structure of the environment—hence, the study of ecological rationality.

RESEARCH ON SMART HEURISTICS IN ORGANIZATIONAL BEHAVIOR

In this section, we provide a selected review of the emerging research on smart heuristics in different areas of organizational psychology and behavior.

Strategic Decision Making

Business strategies in the form of principles, doctrines, routines, and rules are results of accumulated organizational learning and are heuristic in nature. The simple rules studied extensively by Eisenhardt and colleagues are good examples. In their early work, Eisenhardt & Sull (2001) analyzed how firms strategized in the increasingly unpredictable and fast-growing digital business world. They found that the successful firms often relied on simple rules as their core strategies. For example, Cisco employed the 75–75% rule, that companies to be acquired must have no more than 75 employees, approximately 75% of whom must be engineers. Intel used the rule of allocating manufacturing capacity on the basis of products' gross margins to maintain competitiveness in the highly volatile chip business. Eisenhardt & Sull (2001) argued that simple rules work for firms in the new economy because "when business became complicated, strategy should be simple" (p. 116).

Adaptive toolbox for strategic decisions. This formed the central argument in Eisenhardt's work on strategies. Bingham & Eisenhardt (2011) interviewed executives and closely observed the operations of six information technology firms. They found that these firms' experience led to a collection of simple-rule heuristics: selection heuristics that guide which products or market opportunities to pursue (e.g., enter only English-speaking countries), procedural heuristics that specify actions on an opportunity (e.g., use acquisitions to enter new markets), priority heuristics that rank opportunities (e.g., place highest priorities on government accounts), temporal heuristics related to timing of opportunities or actions (e.g., market products first in the United States, then in Japan, and then in China), and exit heuristics that specify when to stop particular actions (e.g., the hiatus heuristic).

Bingham & Eisenhardt (2011) also found that the development of the adaptive toolbox by an organization is often circular, starting with an elaboration process that successively increases the number and details of the heuristics and ending with a simplification process that prunes details and retains only a small number of heuristics. This shows that, despite their apparent simplicity, smart heuristics are results of careful analysis and continued refinements. Therefore, they "may be a more rational strategy than analytically complex and information-intensive approaches in unpredictable markets" (Bingham & Eisenhardt 2011, p. 1461). We fully endorse this conclusion. The qualitative methods, including interviews, observations, and case studies, applied masterfully in Eisenhardt's work complement the modeling and experimental methods frequently applied in studies of fast-and-frugal heuristics and ecological rationality, and appear to be essential tools for uncovering the specific heuristics used by various organizations.

The effects of ecological factors on the performance of heuristics are discussed occasionally (Davis et al. 2009). Recall Cisco's 75–75% rule for acquisition. It worked well for Cisco at the beginning. However, with changes in the business environment and the company's focus, it was replaced by a tallying rule: An acquisition was given a green light if the target fulfilled five out of five criteria, such as the potential for short-term wins, geographical proximity to Cisco, and cultural compatibility with Cisco; a yellow light if only four criteria were met; and a red light if three or fewer criteria were met. Such an adaptation fits well with the concept of ecological rationality.

There is much work besides Eisenhardt's on the topic. Haksöz et al. (2018) presented a fast-and-frugal tree that manages risks in supply chains. MacGillivray (2014) prescribed three heuristics for crisis management after studying three water contamination events. Pieper et al. (2015) studied multifamily firms and recorded heuristics used by such firms to maintain sustainability. Davies et al. (2016) derived five heuristics in project management on the basis of a case study of London Heathrow terminal construction. West et al. (2014) found through interviews with executives that heuristics such as satisficing, imitation, and default were widely used in budgeting decisions. Finally, drawing on both the simple-rule and the fast-and-frugal heuristics research, Challagalla et al. (2014) proposed a market doctrine approach to understand firms' marketing decisions. For example, two doctrines from Apple are "only enter markets where we can be the best" and "focus on few products and models." Such doctrines are simple to understand and easy to remember. By providing high-level guidance to the decision makers of the firm while not specifying execution details, these doctrines can also strike a good balance between consistency and flexibility, two often conflicting characteristics.

Strategic imitation. For firms competing in a new market, copying ideas from rivals is a way to improve products and survive in the market (McDonald & Eisenhardt 2020). For example, in the early years, the founders of Google struggled to monetize their search engine. The situation changed after they imitated the business plan of GoTo.com, a rival search engine company. Facebook in turn later copied Google's business plan entailing surveillance capitalism. Haunschild & Miner (1997) identified three types of strategic imitation: frequency, in which the most widespread practices are copied; trait, in which practices of firms with certain features are copied (e.g., practices by industry-leading firms); and outcome, in which the most impactful practices are copied.

Sharapov & Ross (2021) addressed the question of ecological rationality using computer simulation and data from a sport contest to study the conditions under which firms should imitate each other. They reported that when environmental changes are infrequent and minor, leading firms should imitate their neighbors (i.e., firms that share similar attributes) to maintain the lead. However, when environmental changes are frequent and substantial, leading firms should imitate their closest challenger (i.e., firms that are in second place in their market).

Conclusion. In sum, heuristics in strategic decision making are the results of refined learning, often highly specific, and critical to a firm's success in a business world that has become increasingly uncertain and unpredictable.

Leadership

Leadership is often investigated in terms of personality traits, leadership styles, and their combinations. But studying traits and styles does not explain how leaders make decisions. We argue that effective leaders draw on their adaptive toolbox of heuristics to make decisions under different contingencies, consistent with the principle of ecological rationality.

Leaders' adaptive toolbox. As Gigerenzer (2014, p. 117) argued, "good leadership consists of a toolbox full of rules of thumb and the intuitive ability to quickly see which rule is appropriate in which context." Various heuristics can be found in the literature on leadership. Interviews with CEOs from large US companies reveal heuristics such as "hire well and let them do their jobs," "promote from within," "first listen, then speak," and "encourage people to take risks and empower them to make decisions and take ownership" (Gigerenzer 2014, Walumbwa et al. 2014). These heuristics are often a result of decades of experience and are valuable components of leaders' adaptive toolbox.

Contingency theories. Although little is known about the conditions under which the above heuristics work well, contingency theories have a long history in leadership research: Effective leadership depends on situational factors such as leader–member relations, position power, and task structure (Fiedler 1964). These factors influence whether task-oriented or relationship-oriented leadership styles should be used. For example, Vroom & Jago (2007) proposed that the extent of involving subordinates in decision making (five styles, from autocratic leader decision to group decision) should be based on eight situational contingencies, such as whether the technical quality of the decision is important and whether the problem is well structured. This decision is modeled by a fairly complex decision tree. Despite some empirical support, it has been questioned whether leaders would engage in such complex deliberations when choosing a leadership style (Day 2012), and research on contingency theories has waned. The ecological rationality paradigm, with its associated rigorous methodology, could provide a fresh impetus to a contingency approach to leadership that is theoretically rich and practically relevant.

Fairness heuristic theory. How do followers decide whether a leader is trustworthy? Fairness heuristic theory posits that under conditions of uncertainty, leaders' procedural fairness is a valid cue to reduce employees' uncertainty about future treatment and outcomes (Proudfoot & Lind 2015). Employees appear to rely on overall fairness perceptions to judge leaders' trustworthiness, particularly when uncertainty is high (Jones & Martens 2009). Other one-clever-cue heuristics have also been proposed. Moorman & Grover (2009) argued that "followers use attributions of leader integrity as a heuristic for how the leader will behave in the future" (p. 102). Similarly, Janson et al. (2008) argued that leader prototypicality and leader self-sacrifice may be cues followers use to decide whether to trust a leader.

Conclusion. What makes an effective leader? Much leadership research has examined leader traits, leadership styles, and leader–follower relationships (Day 2012). The framework of fast-and-frugal heuristics provides a different perspective: How do leaders decide? What is in the adaptive toolbox of leaders? In which situation do leaders choose which heuristic?

Teamwork

A team is "a set of two or more individuals that adaptively and dynamically interacts through specified roles as they work towards shared and valued goals" (Salas et al. 2017, p. 3). In modern organizations, it is teams, not individuals, that make most of the decisions. Therefore, how team members cooperate, collaborate, and work as a whole is vital to an organization's success (Kozlowski & Ilgen 2006).

Teams' adaptive toolbox. Practitioner-oriented writings are replete with simple rules for teams. Many of these rules, such as "have a devil's advocate," "protect your deviant," "keep teams small," or "provide early wins," are based on research evidence (Hackman 2002, Salas et al. 2017). Others are based on practical experience. For example, Joel Spolsky, founder of several technology companies, developed a "rule of five" heuristic for team task management (Moon 2020). Specifically, he wanted to hear from each of his teams on five things in their meetings: two tasks they are currently working on, two tasks they plan to do next, and one task that people might expect them to be working on but they are not actually planning on doing. This heuristic helps teams prioritize tasks properly, remain focused, and communicate better.

Page (2007) argued that diverse teams are better at solving problems not only because diverse team members have different perspectives but also because they bring different heuristics to the team, thereby enlarging a team's toolbox of heuristics. Furthermore, the combination of heuristics can lead to superadditivity—a key reason for the potential of diverse teams—such that two heuristics brought by two team members of the team add up to three: the first, the second, and a combination of the two heuristics.

Team size. Jeff Bezos is credited with having coined the two-pizza rule: Teams should not exist if they cannot feed themselves with two pizzas (Spalding 2015). In a study of 329 teams in for-profit and nonprofit organizations, Wheelan (2009) found that teams consisting of three to eight members were more productive and more cohesive than teams with more than eight members. These rules approximately match the magical number 7 ± 2 of the memory capacity of human information processing (Miller 1956). Some of the most powerful teams in the world are committees of single-digit size, such as the US Supreme Court, the executive boards of *Fortune* 100 companies, the Central Political Bureau (Politburo) of the Communist Party of China, and the review committees of the National Science Foundation for grant applications.

ARE MORE INTERVIEWERS ALWAYS BETTER?

Multiple managers often interview job candidates and then vote independently, with the majority rule determining who gets an offer. For such situations, Fifić & Gigerenzer (2014) showed the surprising result that if the interviewer with the best track record conducts the first interview, adding a second interviewer never increases accuracy. For instance, if the best interviewer has a hit rate h_{best} of 80%, meaning that they correctly identify 8 of the 10 top candidates in the pool but miss 2, adding a second interviewer with a hit rate of 60% and applying the majority rule results in an expected collective hit rate of only 70%. One might need an additional 6 or more interviewers (with hit rates between h_{best} and 1/2 h_{best}) to improve upon having the best interviewer alone. The policy implication is to invest in training an excellent interviewer in each domain, increase their hit rate, and let them alone make the choice. Furthermore, the policy advises against outsourcing hiring decisions to assessment centers or black box algorithms that lack the internal knowledge that a well-trained interviewer can acquire firsthand.

Mannes et al. (2014) compared forecasting accuracies of whole crowds of forecasters (medium size: 35 members) with those of the best member of the whole crowd and those of a select crowd comprising only the top-performing *k* members. Tasks included predicting economic indicators such as the consumer price index, the nominal gross domestic product, and the interest rate on the 10-year Treasury note. In general, a small select crowd of five to nine members made the most accurate forecasts.

Nevertheless, the statement that the ideal team size should be approximately seven overlooks the question of ecological rationality. There is no best team size independent of the structure of the task and the distribution of the members. In fact, in a common hiring situation, it can be proved that relying on the best interviewer alone is always better than adding a second to form a team (see the sidebar titled Are More Interviewers Always Better?).

Conclusion. Overall, despite a substantial number of studies and a plethora of anecdotal and evidence-based simple rules, team heuristics are not featured prominently in current models of teamwork. These models focus instead on constructs such as team climate, memory, affect, cohesion, and conflict as antecedents of team effectiveness and satisfaction (Kozlowski & Ilgen 2006). Although these constructs are important, studying them does not reveal how teams decide on a course of action. We believe that the study of team heuristics would provide not only valuable opportunities to better understand teamwork but also innovative ways to improve teamwork quality.

Negotiation and Conflict Management

Negotiation is a process through which two or more parties resolve conflicts by jointly agreeing on how to allocate scarce resources (Brett 2007). Heuristics feature prominently in the negotiation and conflict management literature, albeit largely in the tradition of heuristics-and-biases. For instance, Caputo (2013) reviewed research on cognitive biases in negotiations such as anchoring, framing, fixed-pie bias, and incompatibility bias. On this basis, common prescriptive advice focuses on "how negotiators can exploit heuristic reasoning on the part of others for personal gain" (Korobkin & Guthrie 2003, p. 798).

Imitation. This negative view of heuristics is particularly striking given that one of the best-known heuristics, tit-for-tat, originated in this field. Tit-for-tat relies on only two principles: be kind first and then imitate the other side's actions (Rapoport & Chammah 1965). Despite—or perhaps thanks to—its unmatched simplicity, tit-for-tat won several computer tournaments on the iterated Prisoner's Dilemma (Axelrod 1984). Studies of the ecological rationality of tit-for-tat have revealed conditions under which it is less successful, such as when other parties make mistakes, and how adapting its building blocks (such as tit-for-two-tats) or switching to win-stay, lose-shift can solve this problem (Nowak & Sigmund 1993). Moreover, Duersch et al. (2012) showed for many classes of symmetric two-player games that imitating the opponent's behavior if it was successful in the previous encounter is an unbeatable strategy. Exceptions are games of the Rock-Paper-Scissors variety, which define a limit to the ecological rationality of imitate-the-best.

Maddux et al. (2008) reported that negotiators who mimicked their counterparts' mannerisms increased the likelihood of uncovering compatible interests and striking a deal, with trust as a mediating mechanism. Similarly, Swaab et al. (2011) showed that linguistic mimicry improves outcomes in virtual negotiations, albeit only when the mimicking occurs at the beginning of the negotiation, not at the end, illustrating an ecological boundary condition based on the importance of first impressions.

Equality. Dividing a fixed pie into equal pieces (1/*N*) and meeting-in-the-middle are key heuristics in negotiation. Giving and taking equally over time is known as reciprocity, which forms the basis of social exchange and trust (Cosmides & Tooby 1992). In a comprehensive review, Druckman & Wagner (2016) show that sticking to the principle of equality can enhance perceptions of distributive justice during negotiation, which not only facilitates successful outcomes but also helps nurture enduring relationships between the negotiating parties. However, in win-win integrative—compared with fixed-sum distributive—negotiations, using the meeting-in-the-middle heuristic may leave money on the table, and negotiators could fare better by trading off their differences using integrative heuristics such as logrolling, in which each negotiator gives their counterpart something they value less and their counterpart values more (e.g., a price-conscious buyer receives a lower price from a volume-conscious seller in exchange for ordering a larger amount; Brett 2007).

Personnel Selection

Hiring decisions are among the most important decisions made in an organization (Guion 2011, Sackett & Lievens 2008). Organizations spend large amounts of their budgets on hiring but paradoxically invest little to find out whether their hiring process is effective (Cappelli 2019). Meanwhile, more than a century of selection research has investigated the validities of different selection methods (cues), such as structured interviews, general mental ability, and personality traits, in predicting future job performance (Schmidt & Hunter 1998). Although much research on cue validities (i.e., what cues to use) exists, research examining and comparing specific models of cue integration (i.e., how cues are used) is rare, apart from broad comparisons such as of holistic versus mechanical decision strategies.

Some studies report that the mechanical combination of features or scores is superior to practitioners' holistic (clinical) judgement (Kuncel et al. 2013). These mechanical strategies are typically linear, which enables the researcher to define conditions under which the mechanical use of one-reason heuristics will lead to better selection accuracy than the mechanical use of linear strategies, and those under which this will not. Note that precisely defined heuristics should not be confused with nontransparent holistic judgments.

One-clever-cue heuristics. Decades of research have concluded that general mental ability, performance in structured interviews, and work samples are the most valid predictors of future job performance (Schmidt & Hunter 1998). Moreover, the three cues are substantially correlated, implying a high degree of redundancy. This suggests that companies can select employees using one of these three cues, depending on availability and cost, in a one-clever-cue heuristic, similar to Musk's exceptional ability rule.

Fast-and-frugal trees. Many organizations adopt multi-hurdle approaches in personnel selection, screening out a proportion of applicants at each step and accepting only those who pass the final step (Ock & Oswald 2018). This organizational procedure corresponds to a fast-and-frugal tree, specifically, the tree in **Figure 1*a***, that accepts only applicants who pass all steps. No studies appear to have tested the effectiveness of specific fast-and-frugal trees, including the one by Bezos, on making hiring decisions. Nevertheless, research in other domains (Katsikopoulos et al. 2020) suggests that fast-and-frugal trees might work well for personnel selection, given the high uncertainty these decisions entail.

Delta-inference. For applicants to an airline company, Luan et al. (2019) found that delta-inference (which searches through cues in order of their validity and stops search when the first cue discriminates between the two alternatives) could predict future job performance (3 months later) with higher accuracy than more complex models, including logistic regression and three machine learning algorithms, despite using considerably less information. Consistent with the dominant cue condition, the higher the best cue's quality is relative to that of other cues in hiring, the more accurately delta-inference predicted future job performance. In a subsequent experiment with management students, the more strongly students believed that there was a dominant cue and the more experienced they were, the more frequently they relied on delta-inference when selecting job candidates. This finding suggests that the more experienced managers are, the more they take into account the ecological rationality of heuristics.

Imitation. In a study of how *Fortune* 500 firms hired their top management members, Williamson & Cable (2003) reported that firms tended to hire executives from sources (e.g., General Motors) that in the past had sent many executives to other *Fortune* 500 firms. In other words, firms imitated other firms regarding where to find and hire talent. This form of imitation appears to be a common technique for firms to reduce the substantial uncertainty in top management hires and is similar to the frequency imitation identified by Haunschild & Miner (1997).

Word-of-mouth. After analyzing 20 years of labor and social security records in the Munich metropolitan area, Dustmann et al. (2016) concluded that workers hired through referrals were better matched to firms' needs and also less likely to leave. Word-of-mouth helps uncover information that is otherwise difficult to find, reducing information deficiencies in the labor market. Beaman & Magruder (2012) reported that when employees were rewarded according to their referrals' performances, they recommended a greater number of high-caliber persons, and that high-ability employees recommended candidates who were more capable and reliable than those recommended by low-ability employees. Yet employee referral can also have unintended effects, such as when the Korean owner of a Chicago janitorial and cleaning company hired primarily Koreans recommended by his employees, who were also mostly of Korean descent, and was sued for discrimination (*Equal Employment Opportunity Commission v. Consolidated Service Systems 1993*). Notwithstanding the potentially adverse impact of the heuristic, the US Court of Appeals decided in this case that word-of-mouth hiring was not discriminatory but the cheapest and most effective way to recruit. Thus, relying on referrals can lead to efficient recruitment but also to a lack of diversity and potential discrimination, which is yet another example of how every heuristic—just as any AI algorithm—has its limitations.

Wisdom-of-crowds. Organizations sometimes employ situational judgment tests (SJTs) in personnel selection. SJTs present job applicants with work-related situations and measure their performance (Lievens et al. 2008, McDaniel et al. 2001). The validity of SJTs depends on the wisdom of subject matter experts. Typically, a group of less than 20 experts develops an SJT and its scoring procedure, and some kind of plurality rule, such as simple majority or consensus, is used to aggregate the experts' opinions (Bergman et al. 2006, Gardner & Dunkin 2018). The wisdom of expert crowds is crucial for the ecological rationality of an SJT in personnel selection.

Performance Management

Once hired, organizations make numerous decisions about their employees as part of performance management. These decisions include whom to promote, reward, and fire. We suspect that such decisions are often made with heuristics, even though little research on the topic currently exists.

Fast-and-frugal trees. Luan & Reb (2017) provided managers with cues derived from employees' job performance and found that more than half of their bonus and layoff decisions could be better described by fast-and-frugal trees than by logistic regression models. The proportion was even higher for senior managers, suggesting that more experienced managers use simple heuristics more frequently than do those with less experience (Gigerenzer 2014). The authors also manipulated the proportion of layoff decisions managers had to make (e.g., 10% versus 40% of employees) and found that managers could adaptively adjust the exit structure of the fast-and-frugal trees. In reference to **Figure 1**, when the required proportion increased, the structure of their decision trees moved from that depicted in **Figure 1*d*** to that in **Figure 1*a***.

Stack ranking. Also known as rank and yank or forced distribution, stack ranking was popularized by former General Electric CEO Jack Welch, who introduced the 20/70/10 split, in which the top 20% of employees—as ranked by their managers—were rewarded and the bottom 10% were fired (Cohan 2012). The goal was to reward doers and remove underperformers. The effectiveness of and reactions to such forced distribution ranking rules vary considerably (Blume et al. 2009). The rule worked well when Welch took over General Electric, at a time when the company had much deadwood. However, once its goal is achieved, continuing rank and yank forces managers to fire capable employees, making firms less functional. This may explain why the heuristic did not work well at Microsoft and may even have been part of its decline in the 2000s (Cohan 2012).

TEACHING MANAGERS

Currently, few business schools teach the science and art of heuristic decision making but instead present heuristics as a source of bias and something to avoid. Lejarraga & Pindard-Lejarraga (2020, p. 290) noted that "the dominant view on boundedly rational managers is still embedded in and legitimized by many of the classical lenses taught in business schools (e.g., transaction cost economics or modern portfolio theory), implicitly delegitimizing the simpler decision rules often used by practitioners." Based on these lenses, good decision practices are described using terms such as optimal and optimization, which are meaningless in situations of uncertainty. One can optimize in situations of risk but not under uncertainty, and despite the apparent scientificity of utility maximization theories, they are of limited help in making better decisions in a VUCA world (Bettis 2017). Rational choice theories may also be misconceived as the gold standards of decision making, to be applied in all cultures, contexts, and organizations. Messages conveyed in such teaching facilitate the acceptance of nudging: If decision makers cannot make "rational" decisions, then they should not be trusted and must be nudged for their own good (Thaler & Sunstein 2008). To correct this set of misunderstandings, the business school curriculum needs to change. Such a novel curriculum can be based on ecological rationality. Although the details of teaching need to be developed and refined over time, below are some guidelines. The general approach is, "Don't avoid heuristics—learn how to use them."

- Take uncertainty seriously. Teach the difference between risk and uncertainty and explain that optimization, such as expected utility maximization, is not possible under uncertainty.
- Take heuristics seriously. Teach the basic classes of heuristics, demonstrate their effectiveness, and enrich managers' adaptive toolbox of strategies.
- Analyze ecological rationality. Match task environments with heuristics and other strategies, providing an understanding of the situations in which a particular heuristic is likely to succeed.
- Pay attention to process. Teach the actual process of decision making (e.g., the search, stopping, and decision rules) and the design of the external environment, and focus less on internal psychological constructs.
- More can be less. Teach the conditions under which more effort, more time, and more complex big data models increase costs and lead to less accurate decisions.

Fortunately, teaching heuristics is relatively straightforward because they are transparent and can be easily understood and memorized. It is already happening in many fields. Fast-and-frugal trees have been developed and taught for diagnosis of ischemic heart disease and other medical conditions, and for treatment of catheter-associated infections, which reduced treatment errors (Naik et al. 2017, Wegwarth et al. 2009). Building on medical decision making, Maistry (2019) designed a script-based course on simple rules for insurance underwriters' decisions about whether to insure certain risks. The course improved both decision accuracy and consistency and was most beneficial for underwriters with intermediate experience. These findings suggest that managers can learn smart heuristics through carefully designed training. Katsikopoulos et al. (2020) explain step-by-step how to construct fast-and-frugal trees and tallying heuristics, and describe the conditions under which heuristics can outperform complex machine learning algorithms. The Bank of England collaborates with the Max Planck Institute for Human Development to develop and teach simple heuristics for making the world of finance safer (Aikman et al. 2021).

Bingham & Eisenhardt (2011) found that managers' experience led them to acquire an adaptive toolbox of heuristics that helped them take advantage of internationalization opportunities. This finding indicates that, in addition to explicit training, on-the-job experience also enables managers to learn heuristics. When shared with colleagues and taught to newcomers, these heuristics can become institutional knowledge that benefits—and even shapes the culture of—an organization. Managers and leaders can continuously expand and improve their toolbox, as well as learn when to apply which heuristic. To encourage this, organizations may expose their employees to a variety of tasks and units, thereby allowing them to add and refine their heuristics as they learn from experience and from others. An ecological rationality perspective can also help to understand the benefits of expatriate assignments: Exposure to different cultures enables leaders to add heuristics to their adaptive toolbox, making them more effective decision makers in a broader range of task environments.

FUTURE RESEARCH DIRECTIONS

It is evident from this review that a considerable and increasing amount of research on smart heuristics in organizational psychology and behavior exists. This research provides an important alternative perspective to the association of heuristics with biases that remains prevalent in the field, especially among scholars unfamiliar with recent developments in research on decision making. Our review also found that the existing research is scattered across different areas of organizational scholarship and lacks an underlying theoretical framework. We posit that fast-and-frugal heuristics, the adaptive toolbox, and ecological rationality would provide such a framework.

We end with future research directions (see the Future Issues). These directions apply to various areas of organizational scholarship. For example, studying the adaptive toolbox of leaders may elucidate the day-to-day work of leaders to an equal, and possibly greater, extent than the current emphasis on leadership styles (Day 2012). Examining smart negotiating heuristics can not only counter existing research that construes heuristics as a source of bias but also lend concreteness to notions of negotiation strategies and tactics. Investigating heuristics that teams develop for interacting or for allocating tasks could complement the current emphasis on team processes and emergent states (Kozlowski & Ilgen 2006). To advance understanding of the role of heuristics, a paradigm shift is needed in organizational scholarship: from a negative view of heuristics as biased and second best to a positive view of heuristics as simple yet intelligent strategies that are indispensable for tasks of uncertainty. Here, they can outperform complex strategies when they match characteristics of the task environments.

Origin and Creation of Heuristics

How are smart heuristics created in organizations? Three main sources are trial-and-error learning, social learning, and teaching. Trial-and-error learning requires feedback about success; it often begins with fairly elaborate strategies whose irrelevant details are successively trimmed until one ends up with simple heuristics (Bingham & Eisenhardt 2011). The advantage of trial-and-error learning is that one learns from direct experience, but the disadvantage is that learning this way can be slow and costly. Social learning, in contrast, is fast and may be achieved by imitating the best leader or competitor—a case in which heuristics are used to learn heuristics. Social learning may also mean imitating the majority, such as when a new employee is told "that's how we do it," which may lead to conformity but not necessarily success. The third source is teaching a repertoire of heuristics, as described above. Further research is needed to examine in more depth how (heuristic) learning processes play out in organizations to not only create but also transmit smart heuristics among individuals and teams, and within and between organizations.

How Culture Shapes Use and Effectiveness of Heuristics

The managerial use of heuristics is universal, but this does not mean that specific heuristics are universally effective. Rather, the principle of ecological rationality implies that the effectiveness of a heuristic depends on its match with the cultural environment. In addition, because organizations are social, the effectiveness of a heuristic also depends on how others react to it. For example, whereas using the heuristic of making a first offer early in a negotiation increased joint gains among Japanese negotiators, it reduced joint gains among US negotiators (Adair et al. 2007).

Communal sharing, in which each individual is treated equally, and authority ranking, in which people are placed in a power-differentiating hierarchy, are two of the four fundamental types of cultures distinguished by Fiske (1992). Wellman (2017) showed that these two types are the most common models for leadership in teams and organizations. It might be worth considering the hypothesis that cultures give rise to certain kinds of heuristics, or vice versa. Communal sharing corresponds to equality heuristics and should be more ecologically rational when members do not differ much in task-relevant abilities (corresponding to **Figure 2*b***). Similarly, authority ranking corresponds to one-reason heuristics and should perform better when members vary greatly in ability and when contributions of one or a few dominant members are sufficient (corresponding to **Figure 2*a***).

Overall, culture is an important force shaping the task environment, which in turn determines which heuristics are smart. Unlike the economic notion of rationality as a single, universally applicable process of expected utility maximization, the perspective of smart heuristics thus lends itself naturally to the consideration of culture. A key area of future research would be to examine the origin, use, and ecological rationality of different heuristics in different national and organizational cultures.

How Heuristics Shape Organizational Cultures

The use of fast-and-frugal heuristics seems hardly compatible with the culture of a bureaucratic organization (Weber 1925). It is, however, compatible with the fast-moving organizations of the modern era. Importantly, not only may organizational cultures favor certain decision strategies, but the decision strategies used may also shape organizational culture—a process termed emergence, in which organization-level phenomena such as culture emerge from individual-level decisions (Ployhart & Moliterno 2011). For example, satisficing uses an absolute level of aspiration for promoting or firing. Stack ranking, in contrast, uses relative performance, which can create a culture in which employees perceive other employees as competitors and may incentivize disruptive actions to prevent peers from getting good performance reviews. It also encourages self-presentation to the management and makes employees devote their efforts to reaching the top of the stack instead of focusing on the real task, thereby reducing a firm's competitiveness (Cohan 2012).

When one of the authors was hired by the Max Planck Society as a director to found a research group from scratch, he used several simple heuristics to support a culture conducive to collaboration and innovation (Gigerenzer 2006). These heuristics were heterogeneity (hire for diversity), open doors (make yourself available), social proximity (create opportunities for social interaction through joint tea breaks), spatial proximity (have all members working on the same floor), and temporal proximity (hire the initial team at the same time, so everyone is equal). Of course, this is not to say that these heuristics are always effective. For example, temporal proximity is useful for creating a successful team, but it would be destructive if after a number of years the entire team were to be replaced at one fell swoop with a new set of members.

How Heuristics Mesh with Artificial Intelligence

Heuristics are sometimes seen in opposition to algorithms, but they are not. To clarify their relation, we distinguish two kinds of AI: psychological AI (rule-based algorithms) and deep artificial neural networks. For Simon, a founder of both AI and the study of heuristics, AI meant teaching computers the rules of strategic thinking that human experts use. The AI can then execute these heuristics faster and without errors. In the same way, heuristics such as fast-and-frugal trees can be programmed into software and used to assist decisions such as hiring. This is an instance of psychological AI (Gigerenzer 2022). Deep artificial neural networks, in contrast, have little in common with heuristics (except when rules are built into a network to make it more robust, as in convolutional networks).

One advantage of algorithms that embody heuristics is transparency. Consider black box justice. The proprietary COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) algorithm has been used in US courts for over a million cases (Gigerenzer 2022). On the basis of 137 features, it predicts whether a defendant will commit a misdemeanor or felony within the next 2 years. Yet neither judge nor defendant can understand how the risk score is calculated and whether it discriminates against minorities. Consequently, studies that tried to determine this ended up with contradictory results. By contrast, a transparent heuristic with only three features (age, sex, and prior offenses), created by the machine learning tool CORELS (Certifiable Optimal Rule Lists), is just as accurate and makes it easy to check whether the heuristic discriminates against a group (Gigerenzer 2022). Thus, heuristics can discriminate, just like any decision algorithm, but unlike with complex strategies including neural networks, it is relatively easy to verify whether discrimination occurs.

The study of ecological rationality also helps us understand when big data improves accuracy and when it does not. Like the wisdom-of-crowds heuristic, big data is useful in stable situations, in which the law of large numbers holds, but not necessarily in VUCA environments, where relying on only a few data points can lead to better results. For instance, Google Flu Trends (GFT) tried to predict flu-related doctor visits by analyzing 50 million search terms. The spread of the flu, however, is not a stable situation: The virus changes, as do the reasons why people enter flu-related search terms. In this situation, the recency heuristic, a one-clever-cue heuristic that uses only a single data point (the most recent proportion of flu-related doctor visits), made substantially better predictions, with only half as many errors as GFT (Katsikopoulos et al. 2020). In general, in a stable world, such as the games chess and Go, big data and complex machine learning algorithms are superior to heuristics in accuracy, but in VUCA environments, heuristics can outperform big data analytics. This stable-world principle also indicates how to improve prediction algorithms when they fail (Gigerenzer 2022). For instance, when GFT failed after the swine flu arrived, Google engineers reacted by making the algorithm more complex, instead of simplifying it. In VUCA environments, however, less complexity can be more effective.

CONCLUSION

In this article, we provide a conceptual framework for an emerging field: the study of smart heuristics that individuals, teams, and organizations use in situations of uncertainty. This research is descriptive in that it analyzes the building blocks of heuristics, such as their search, stopping, and decision rules, and depicts various heuristics in the adaptive toolbox. It is also prescriptive by providing guidelines on when one should rely on which heuristics to be ecologically rational.

To develop this field, three methodological principles are helpful. First, translate verbal rules into algorithmic models so that they can be tested. Second, examine competitively which of several models can best explain behavior. And third, test how well models actually predict future behavior rather than simply fitting to known data. Thus far, we have not seen these principles applied consistently in organizational scholarship. Yet we hope this review encourages researchers to take up the challenge.

We are excited about the sheer possibilities for future research against which current research, though considerable, pales. We see the existing studies as potential trailblazers in a quest to unravel the heuristics that individuals, teams, and organizations use. The systematic analysis of smart heuristics will contribute to both understanding and improving decisions in the uncertain world of organizations.

FUTURE ISSUES

1. How do heuristics originate? How do managers learn heuristics? Do they begin with complex procedures until they finally learn to simplify? Are heuristics learned heuristically, for example, through imitation?
2. Do managers in different cultures prefer different kinds of heuristics, such as individual versus social heuristics? If so, do the conditions under which heuristics are ecologically rational vary between cultures?
3. What is the relation between organizational culture and heuristics? How do leadership heuristics shape the social climate in organizations? For instance, does it matter whether heuristics for promotion rely on absolute or relative aspirations?
4. Can we rethink the nature of leadership in terms of an adaptive toolbox rather than leadership traits and styles, and of effective leadership as the ability to draw proper heuristics from the toolbox that match the task at hand?
5. What are the heuristics that lead to better negotiation results, and how can one adapt these to the strategies of the other negotiating party?
6. How can business schools develop and validate efficient programs that teach a portfolio of heuristics and the ability to choose the right heuristic according to the particular situation?
7. Most artificial intelligence algorithms for evaluating job applicants are proprietary and lack transparency, whereas heuristics are transparent and understandable. What effect does transparency have on the perceived fairness of personnel decisions and other types of organizational decisions?
8. Given that no decision algorithm is best under all conditions, strategy comparison is essential. For example, how do Musk's and Bezos's hiring heuristics compare with other strategies (heuristic and otherwise) with respect to effectiveness and adverse impact?

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Errata

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