CHAPTER 5

Heuristics: The Tools of Intuition

> The situation has provided a cue; this cue has given the expert access to information stored in memory, and the information provides the answer. Intuition is nothing more and nothing less than recognition.
>
> *Herbert A. Simon*[1]

> The conventional sources of power include deductive logical thinking, analysis of probabilities, and statistical methods. Yet the sources of power that are needed in natural settings are usually not analytic at all—the power of intuition, mental simulation, metaphor, and storytelling.
>
> *Gary Klein*[2]

To discover how experienced professionals solve real-world problems, Gary Klein and his team of researchers have slept in fire stations, traveled in M-1 tanks and Blackhawk helicopters, and observed high-stake decisions in intensive care units.[3] Firefighters, intelligence analysts, pilots, nurses, and physicians make high-stake decisions under uncertainty. Thanks to extensive training in dealing with stress, these experts have learned skills and tactical concepts that can be routinely exploited under time pressure. Being well prepared allows them to rely on intuition, mental simulation, narratives, and a toolbox of heuristics when facing a decision. Consider firefighter commanders who arrive at the site of a building on fire. The most urgent goal is not to quench the fire, but to save the lives of those still in the building and prevent the fire from spreading to neighboring buildings. What should they do first? Based on years of experience, an option occurs in their mind. These experts, like professional athletes, may follow the option immediately or mentally simulate it first, imagining it being carried out. If this simulation does not lead to the desired goal, then the same

[1] Simon (1992), p. 155. [2] Klein (1998/2017), p. 33.

[3] Klein (2015, 1998/2017); on the relation between Klein's and my work, see Todd & Gigerenzer (2001) and Gigerenzer (2019).

process is repeated with the second option that comes to mind, and so forth.

Intuition and Reason Work Together

When a fire is raging, firefighters do not and cannot compare all possible options, weigh their possible consequences, and choose the one with the highest expected utility. Firefighters make decisions without following rational choice theory and, instead, rely on a combination of intuition and conscious thought. The intuitive part is based on the fluency heuristic, described in Chapter 1 of this book: Choose the first option that comes to mind. But the mental simulation used to explore whether that option can be executed in the given situation requires some degree of conscious thought and illustrates how intuition cooperates with deliberation.

The human brain evolved to detect subtle differences in fluency, a requisite ability for applying the heuristic. Studies reported that people could detect the difference between recognition latencies if these exceeded 100 ms, and that the fluency heuristic predicted individual choices more accurately when the differences increased, up to 82 percent of the time.[4] Nevertheless, not everyone should trust the first option that comes to mind. The fluency heuristic can be extremely effective in particular for persons with long-term experience with the problem at hand. In that event, the first option that comes to mind is likely to be the best one, the second option that comes to mind would be the second-best, and so on (as shown in Figure 1.1). Trying to generate all options and then investigating these would, hence, not only waste time but also increase the possibility of choosing an inferior option.

The fluency heuristic reveals a surprising insight. Options are not compared, as is assumed in the expected utility theory, but are evaluated one-by-one until one is found to be good enough. And if the situation changes because, for example, a fire has suddenly spread, this process is resumed. Relying on the fluency heuristic is ecologically rational for experienced experts, where fluency correlates with the quality of the alternatives. The degree of its ecological rationality can be measured by the correlation between fluency and the quality of the options.[5]

The firefighter example supports the general argument that I make in this book:

[4] Hertwig et al. (2008). [5] Herzog & Hertwig (2013).

- Intuition is based on heuristic processes.
- Intuition and reason work in tandem, rather than in opposition.
- Less time or information can be more effective. For instance, the fluency heuristic works best with limited time so that second-best options do not come to mind.
- Heuristics are ecologically rational, that is, their rationality arises from the match with environmental structures. The rationality of an intuition lies in the ecological rationality of the heuristic on which it is based.
- The intelligence of intuition amounts to the skill of selecting, consciously or intuitively, heuristics that are adapted to the problem at hand.

All in all, I argue that intuition can be understood through the framework of ecological rationality. This can be first understood through a sister term of ecological rationality, *bounded rationality*.

Simon's Revolutionary Program

The concept of bounded rationality goes back to Herbert Simon's University of Chicago dissertation, which would later become his 1947 book *Administrative Behavior*. Simon was not introducing a new theory of rationality, but coined the term as a residual category for everything that was not "fully rational." Full rationality, also called substantive rationality, is defined by the theory of maximizing subjective expected utility and similar optimization models that require perfect knowledge of *all* possible future events and *all* their consequences. Simon's target was the doctrine of optimization, that is, the practice of modeling all decision-making as if it entailed calculating the maximum or minimum of a well-behaved function. Simon was aware that he had identified a problem without resolving it. Late in his life, he wrote in a personal letter:[6]

> I guess a major reason for my using somewhat vague terms – like bounded rationality – is that I did not want to give the impression that I thought I had "solved" the problem of creating an empirically grounded theory of economic phenomena. What I was trying to do was to call attention to the need for such a theory – and the accompanying body of empirical work to establish it – and to provide some examples of a few mechanisms that might

[6] Gigerenzer (2004b).

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> appear in it, which already had some evidential base. There still lies before us an enormous job of studying the actual decision making processes that take place in corporations and other economic settings.

Although Simon had no theory of bounded rationality, he did provide a framework for the study of it. In my reconstruction, Simon's framework is based on three principles. Each of these collides with neoclassical economics and, moreover, with much of behaviorism and cognitive modeling. This framework necessitated reformulating not only the answers but also the very questions asked. For that reason, I refer to it as "revolutionary."

*Principle 1 (*Process*): Model Actual Decision Processes, Not As-If Utility Maximization*

Simon once described his initial experience about how professionals make decisions. While still a student, he attempted to apply the perspective of expected utility maximization, which he had learned in a price theory class at the University of Chicago, to budget decisions in his native Milwaukee's recreation department. To his surprise, the managers did not even try to compare the marginal utility of a proposed expenditure with its marginal costs, but, instead, relied on their intuitions based on heuristics such as adding incremental changes to last year's budget. This experience opened his eyes to how managers actually decide in situations of uncertainty, when perfect foresight of future events and their consequences is impossible. In his own words, the framework of utility maximization for management decisions "was hopeless."[7]

The first principle of Simon's study of bounded rationality is:

Model actual decision processes. Do not construct as-if models of expected utility maximization.

*Principle 2 (*Uncertainty*): Model Decisions Under Uncertainty, Not Only Under Risk*

Simon's budget decisions had to be taken in situations of uncertainty, not of risk. The distinction between these two situations goes back to the economist Frank Knight.[8] The difference between risk and uncertainty can

[7] Simon (1988), p. 286. On as-if models in behavioral economics, see Berg & Gigerenzer (2010).
[8] Knight (1921).

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be explained using Jimmy Savage's concept of a *small world*, which has two properties:[9]

1. **Perfect foresight of all future states:** The agent knows the exhaustive and mutually exclusive set S of future states of the world.
2. **Perfect foresight of all consequences:** The agent knows the exhaustive and mutually exclusive set C of consequences of their actions, given a state.

Savage called the pair Brackets also in italic (S, C) a *small world*. A small world with unknown probabilities is a situation of *ambiguity*; one with known probabilities is a situation of *risk*. For Knight, known probabilities meant long-run frequencies or propensities, not subjective probabilities. Examples for situations of risk are lotteries, slot machines, and roulette. In a game of roulette, all possible future states are known (the numbers 0 to 36), and these are exhaustive (no other numbers can occur) and mutually exclusive (no numbers can occur simultaneously).

Uncertainty, in contrast, refers to situations that are not small worlds, that is, where the *state space* (S, C) is imperfectly known or is unknowable. Here, no probability distribution (with probabilities that add up to one) can be meaningfully constructed over events or consequences, not even subjective probabilities. Also referred to as *radical uncertainty* or *fundamental uncertainty*, these large worlds include budget problems, financial regulation, political resolutions, career planning, predicting mutations of a virus, and most other important real-world decisions.[10] These situations are often called "ill-defined" because the state-space is not fully knowable. Finally, a problem is called *intractable* if the optimal course of action cannot be determined even if it exists, such as in chess and Go.

Savage made it clear that the theory of expected utility maximization applies solely to small worlds and that it would be absurd to apply it in situations of uncertainty, be they as mundane as planning a picnic or as intractable as playing chess.[11] Here, Simon and Savage were of one mind. But how can decision-making be modeled if optimization is out of the question? As Simon noted, there are two research strategies. The first is to convert the original problem into one of risk and then hope that the optimal course of action in the small world will generalize to that problem. This hope can amount to wishful thinking. Consider the game of chess. It is possible to turn the intractable game into a tractable one by reducing the 8×8 board to a 4×4 board and eliminating most of the chess pieces. In

[9] Savage (1954/1972). [10] Kay & King (2020). [11] Savage (1954/1972), p. 16.

this new version, the optimal sequence of moves can be calculated. But this sequence will not help anyone win a real game of chess for the same reasons that expected utility maximization was of little use for Simon's recreation department. The second research strategy is to leave the situation unchanged and, instead, study the heuristics that people actually use to deal with uncertainty or intractability.

Thus, the second principle of the study of bounded rationality is:

Model decision-making under uncertainty, without reducing the situation to one of risk or ambiguity.

*Principle 3 (*Adaptation*): Model the Match of a Process to the Environment*

Evolutionary theory is based on the principles of variability, inheritance, and selection, by means of which organisms adapt to their environment and vice versa. The features of an animal may appear strange if one does not study the environment it is currently or once was inhabiting. The same holds for cognitive processes. Simon used the analogy of a pair of scissors to make this point: One cannot understand the rationality of behavior by looking solely at the mind or at the environment, just as one cannot understand how scissors cut so well by looking at one blade only.[12] However, quite a few psychological theories tend to focus exclusively on the mental blade, such as loss-aversion and risk-aversion, while behavioristic and economic theories tend to have eyes only for the environmental blade, such as incentives.

Thus, the third principle of the study of bounded rationality is:

Model the match of decision processes with environmental structures.

These three principles were far too radical for most of Simon's contemporaries. In his own assessment, his program of bounded rationality was received with "something less than unbounded enthusiasm" and was "largely ignored as irrelevant for economics."[13] Many psychologists and behavioral economists misconstrued Simon's term *bounded rationality* to mean irrationality and interpreted deviations from logical rationality as intuitive errors (see Chapter 3). Simon's revolution did not happen in his lifetime.

Ecological Rationality

Given the semantic confusion surrounding bounded rationality, my research group and I coined the term *ecological rationality* when reviving

[12] Simon (1990), p. 7; Newell & Simon (1972), p. 55. [13] Simon (1997), p. 269.

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and extending Simon's program.[14] This new term signals that rationality is defined by the successful match between a strategy (e.g., a heuristic) and the structure of the environment. Its measuring rod is not adherence to consistency axioms in small worlds, but rather success in large worlds. The ecological rationality program has two goals, one descriptive and one prescriptive. Its descriptive goal is to analyze the repertoire of heuristics that an individual or organization has at its disposal. Known as the *adaptive toolbox*, this repertoire includes the building blocks of heuristics and the core capacities they exploit. This requires the studying and modeling of how managers, physicians, judges, or others actually make decisions under uncertainty, not only under risk or ambiguity. The prescriptive part of the program addresses the question of when one *should* rely on a particular class of heuristics, that is, the conditions under which heuristics are ecologically rational. That question was not part of Simon's original program and answering it requires precise models of heuristics. Meeting the descriptive goal requires observation and experimentation; meeting the prescriptive goal requires mathematical analysis and computer simulation.

Heuristics Can Be Used Intuitively or Deliberately

As pointed out in Chapter 1, every heuristic can be used intuitively, that is, without awareness, or deliberately, that is, consciously. The heuristic process is the same. Consider hiring decisions in organizations, which are decisions made under uncertainty. In the course of personal interviews, an interviewer often has a hunch that a candidate would be an excellent choice or that there is something wrong with a candidate even if they look great on paper. If the reasons for this feeling are not fully conscious, then the judgment is intuitive. To unravel the reasons underlying such intuitions, the ecological rationality program begins by analyzing managers' actual decision processes for hiring.

According to Tesla CEO Elon Musk, for instance, candidates' education, personality, and prior work experience are not what counts. Instead, Musk looks for "evidence of exceptional ability."[15] The idea is that people who have shown exceptional ability in the past are likely to continue showing it in the future. To determine this, Musk reported that he asked

[14] Gigerenzer et al. (1999). As Petracca (2021) argued, Simon's presentation of his concept of bounded rationality to economists (focusing on the cognitive part and neglecting the environmental part) added to the subsequent confusion.

[15] Popomaronis (2021).

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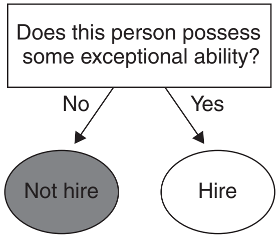

Figure 5.1. A model of Elon Musk's one-good-reason heuristic for hiring.

each candidate: "Tell me about some of the most difficult problems you worked on and how you solved them." To determine whether candidates were telling the truth, he requested precise details on how they solved the problem in question. 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, and assessment centers. It is frugal because it instead relies on a single reason. Musk's process is modeled by the one-good-reason heuristic as in Figure 5.1.

Note that this heuristic can be used consciously or unconsciously: One is either fully or not aware of the criterion that ultimately guides a hiring choice.

Musk is not alone in relying on fast-and-frugal heuristics to select employees. When Amazon was still a small company and CEO Jeff Bezos made hiring decisions himself, he too looked for exceptional ability. For Bezos, however, that alone did not suffice; he required two additional reasons.[16] His strategy can be reconstructed in the form of a fast-and-frugal tree (Figure 5.2). In general, in the case of yes/no decisions, a fast-and-frugal tree is an incomplete tree with n reasons (or cues) and $n + 1$ exits that consists of 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.

As with Musk, the first feature of significance to Bezos was whether someone had exceptional ability; if "no," the applicant was not hired. If

[16] Popomaronis (2020). Many other experts, from Swiss airport customs officers (Pachur & Marinello, 2013) to London magistrates as well as professional burglars (Dhami, 2005) have been reported to rely on similar sequential heuristics, such as fast-and-frugal trees and take-the-best (see Gigerenzer et al., 2022a).

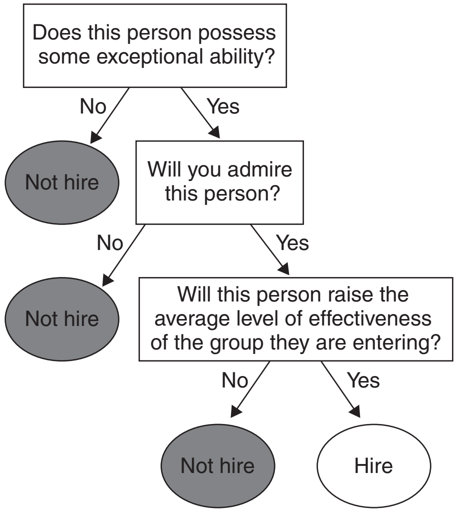

Figure 5.2. A model of Jeff Bezos' sequential decision process for hiring. The process is a fast-and-frugal tree, defined as a tree in which each question can lead to a decision and, thus, has an exit on each question and two on the last one.

"yes," Bezos asked himself a second question, "Would you admire this person?" Bezos believed that those he admired were those he could learn from. A "no" was sufficient for not hiring. If the answer was "yes," he asked a third question, "Will this person raise the average level of effectiveness of the group they're entering?" This feature would ensure that the bar in the company goes up with every hire. Only in the event of three positive answers was the candidate hired.

The two figures show two kinds of decision processes. Which one is better? And in which situation? That can be investigated empirically. Yet, it would be more interesting to find general results, independent of a specific situation and heuristic. The study of the ecological rationality is an analytic discipline for deriving general results, such as in the following two examples. The first concerns the class of one-good-reason heuristics, as was used by Musk. The second concerns the class of fast-and-frugal trees, as was used by Bezos.

When Is One Reason As Good As (or Better Than) More Reasons?

In situations of uncertainty, one cannot, by definition, foresee what the optimal strategy is. But one can derive relative statements, such as that

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strategy A will lead to more accurate decisions than strategy B, given environment E. Thus, let us ask whether we can identify a general condition under which a one-good-reason heuristic, such as Musk's heuristic, cannot be outperformed by a standard approach to prediction, that is, linear strategies (such as linear regression). Linear strategies use the same one reason as the heuristics but also take into account further valid reasons. To simplify the exposition, let us consider linear strategies that use n binary cues $x_1, \ldots, x_n$, with values of either +1 or −1, where the positive value indicates a better candidate. The weights of the cues are $w_1, \ldots, w_n$, all of which are positive:

$$y = w_1x_1 + w_2x_2 + w_3x_3 + \cdots + w_nx_n,$$

The linear rule makes the inference "hire" if $y > 0$, otherwise "not hire." We denote the single cue used by the one-good-reason heuristic as 1 and give the remaining cues the numbers 2, . . ., n. The weights of each of the remaining cues reflect their *additional* contribution to the higher ranked cues, as do the beta weights in a linear regression. If the following condition holds, no linear rule can lead to more accurate inferences than a one-good-reason heuristic:[17]

Dominant cue condition: The weights $w_1, w_2, w_3, \ldots, w_n$ form a dominant cue structure if they satisfy the constraint:

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

Expressed in words, the weight of the first cue is larger than the sum of the weights of all other cues. The weights 1, 1/2, 1/4, and 1/8 are an example, as illustrated in Figure 5.3 (a). If this condition holds, maximizing expected utility or any other linear rule will always yield the same decision as a one-good-reason heuristic. This is because a dominant cue cannot be outvoted or compensated by the sum of all lower ranking cues.[18]

Dominant cues appear to be the rule rather than the exception in many real-world situations.[19] They guarantee that one-good-reason heuristics are as accurate as linear strategies, and faster and less effortful to boot. The fact that models with free parameters such as linear models tend to overfit (e.g., when the sample size is small) explains why one-good-reason heuristics can lead to more accurate predictions.[20]

[17] Gigerenzer (2021a). [18] Martignon & Hoffrage (2002). [19] Şimşek (2013).
[20] Brighton & Gigerenzer (2015); Gigerenzer & Brighton (2009).

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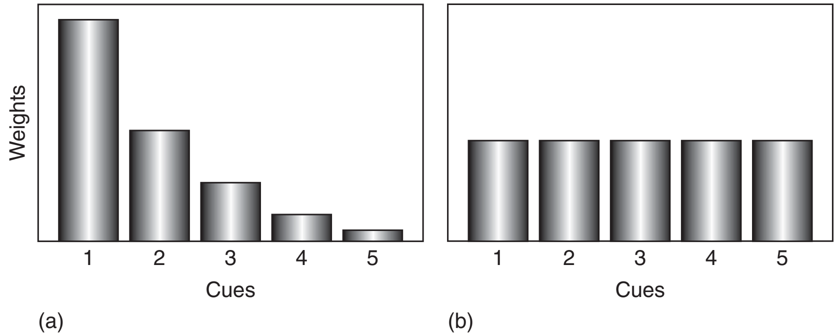

Figure 5.3. Ecological rationality. (a) The weights form a dominant cue structure that one-good-reason heuristics exploit. In this case, no linear strategy that uses all five valid cues (reasons) can yield more accurate decisions than a one-good-reason heuristic that relies on the first cue alone and ignores all others. (b) A structure of cues that can be exploited by the class of tallying heuristics, which does not estimate weights, but, instead, assigns equal weights. Here, a one-good-reason heuristic would be less accurate than linear models and tallying.

How Can False Positives Be Balanced With Misses?

Hiring decisions, like other binary classifications, 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 crucial point is that there is a trade-off: Reducing false positives increases misses and vice versa. For instance, a rule that hires everyone will have no misses (a hit rate of 100 percent), but it will also have a false-positive rate of 100 percent (all of the wrong persons will be hired). Thus, heuristics need to be designed so that they reflect the desired trade-off. Figure 5.4 shows the process for fast-and-frugal trees.[21]

For three cues with the same order, one can construct four possible fast-and-frugal trees. Tree (a) in Figure 5.4 minimizes false positives because it is conservative and leads to an offer only if a candidate qualifies on all three questions. To reduce misses instead of false positives, one can alter the first two exits of the tree. The further to the right the tree is located in Figure 5.4, the fewer are misses and the more are false positives. These four trees correspond to four points on the receiver-operator curve in the signal detection theory.[22] Bezos' heuristic (tree (a)) is the best strategy for those whose main concern is to avoid making offers to the wrong candidates. The trees are ecologically rational, that is, their rationality depends

[21] Adapted from Gigerenzer et al. (2022a). [22] Luan et al. (2011).

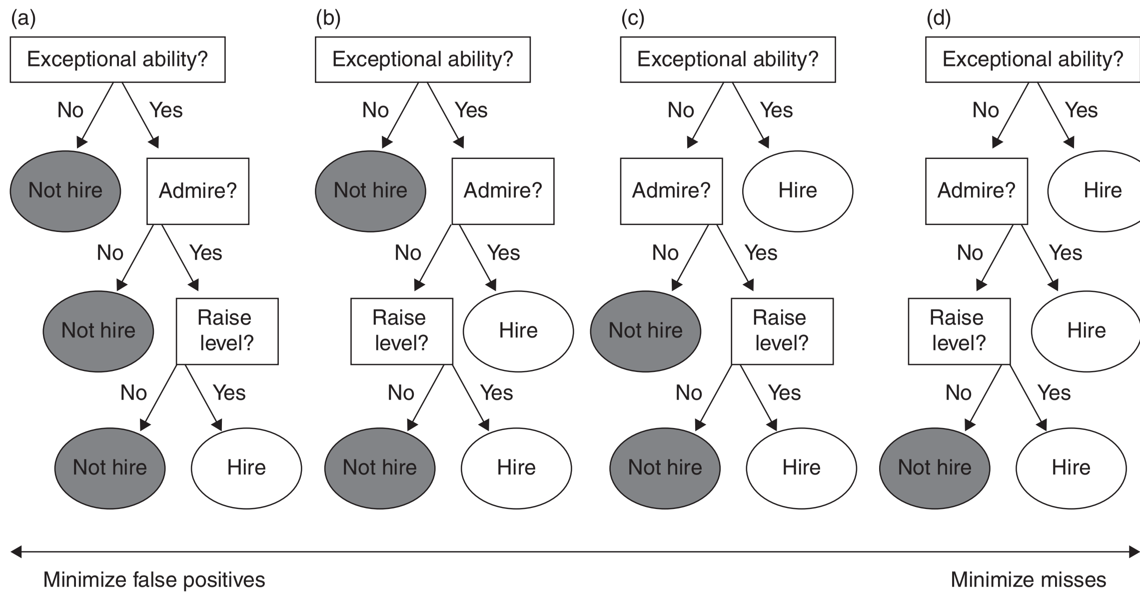

Figure 5.4. Balancing false positives and misses. For three cues, four possible fast-and-frugal trees containing the same cue order exist. (a) is Bezos' tree (Figure 5.2), which minimizes false positives, while (d) minimizes misses. From Gigerenzer et al. (2022).

on the environment. For instance, in European countries in which it is more difficult to fire employees, avoiding false positives would be more appropriate, whereas in the "hire-and-fire" culture of the USA and the UK, one might be less concerned with hiring the wrong candidates.

This example illustrates the steps of the program: Begin with empirical observation or experiments to analyze the conscious or intuitive decision processes under uncertainty and then model the process in terms of search, stopping, and decision rules, which, finally, facilitates determining the conditions under which a heuristic is successful in terms of a specified goal. Thanks to the transparency of heuristics, it is possible to check and improve their performance continuously and also to teach them easily.

The Adaptive Toolbox

As mentioned in the section "Ecological Rationality," the adaptive toolbox is the repertoire of heuristics an individual, team, or organization has at its disposal, consisting of heuristics, their building blocks, and the core capacities that heuristics exploit. The qualifier *adaptive* reflects that the question of a heuristic's rationality cannot be answered by simply looking at the heuristic. At issue is how a heuristic matches with the environment, that is, its ecological rationality. Beside fluency heuristics, one-good-reason heuristics, and fast-and-frugal trees, other tools can be found in the adaptive toolbox.

Decision-Making by Recognition

Recognition is an intuitive process, a cognitive core capacity that allows people to recognize a face without being able to specify its features. It enables chess players to recognize familiar positions, physicians to recognize symptoms, and consumers to recognize brand names. The combination of recognition with heuristic search leads to the *recognition heuristic*.[23]

My colleagues and I discovered this heuristic when we encountered a puzzling "less-is-more" effect: People with less knowledge managed to answer more trivia questions correctly than people with more knowledge. In one study, we asked a class of US college students: "Which city has the larger population: Detroit or Milwaukee?" Some 40 percent of the students voted for Milwaukee, the others for Detroit.[24] When an equivalent class of German students was asked, virtually everyone gave the correct

[23] Goldstein & Gigerenzer (2002). [24] Ibid. See also Gigerenzer & Goldstein (2011).

answer, Detroit. One might conclude that the German students knew more about US cities, yet the opposite was the case. Many had not even heard of Milwaukee. The intuition of the Germans relied on the *recognition heuristic*:

If you recognize the name of one city, but not the other, then infer that the recognized city has the larger population.

The US students could not use the heuristic because they had heard of both cities. The heuristic exploits semi-ignorance – here, the fact that someone does not recognize all cities. Relying on the recognition heuristic is ecologically rational if:

$$\text{recognition validity } \rho > .5,$$

where ρ is the proportion of correct inferences the heuristic achieves when one alternative (here: city) is recognized and the other is not. The larger the size of ρ is, the more successful is the heuristic. In other words, the heuristic exploits situations where a lack of recognition is informative. Figure 5.5 shows how to measure the ecological rationality of the recognition heuristic. There are mediators, such as newspapers, between a person and a criterion that reflect (but do not reveal) the criterion value. Consider the 100 largest US cities and the number of articles mentioning these cities in the German newspaper *Die Zeit*. The *ecological correlation* between the population and number of articles is .72, and thus quite substantial. The *surrogate correlation* between the number of articles mentioning a US city and the number of people recognizing it is .86, even higher. These two correlations result in a substantive recognition correlation of .66 (the recognition validity is expressed here as a correlation, for better comparison). Replicating the same analysis for the 100 largest German cities mentioned in the *Chicago Tribune* results in similar values (the second set of values in Figure 5.5).

As the Detroit–Milwaukee example shows, the recognition heuristic can lead to a counterintuitive *less-is-more effect*. A less-is-more effect occurs if the following condition holds:

$$\text{recognition validity } \rho > \text{knowledge validity } \kappa.$$

The knowledge validity κ is measured by proportion correct when both objects are recognized, that is, when the recognition heuristic is not applicable.

Can the less-is-more effect be shown in sports? Consider predicting the outcomes of the 127 matches played by the 128 players who compete in

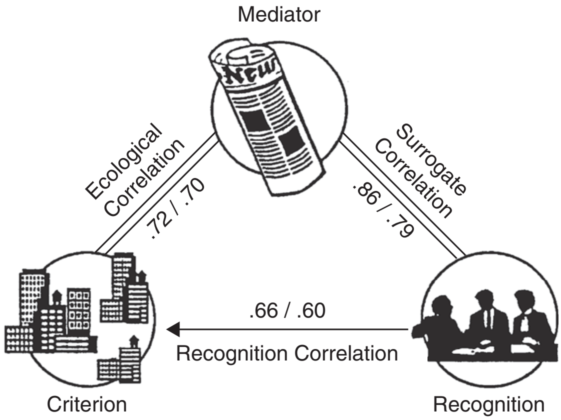

Figure 5.5. An Illustration of the ecological rationality of the recognition heuristic. The goal is to estimate an unknown criterion (here, the population of a foreign city). The unknown criterion is mediated by the ecological correlation and the surrogate correlation. Note that the recognition validity is expressed, for comparability, as a correlation between the number of people who recognize the name of a city and its population. For all three correlations, the first value is for US cities and the German newspaper *Die Zeit* as mediator; the second is for German cities and the *Chicago Tribune* as mediator.[25]

the Wimbledon Gentlemen's Singles. The Association of Tennis Professionals (ATP) Rankings and the seedings of the experts predicted between 66 percent and 69 percent of all matches correctly. These are measures of the validity of the knowledge available. Using the recognition of amateur tennis players who had only heard of the names of about half of the players, in contrast, led to 72 percent correct predictions.[26] Here, the recognition validity was higher than the knowledge validity, a condition that generates a less-is-more effect. The amateurs could make better predictions by drawing on the power of the recognition heuristic, while those who are familiar with all names cannot exploit the information provided by lack of recognition.

Name recognition also plays a role in electoral contests. Unlike high-profile presidential contests, the majority of elections feature candidates who are virtually unknowns to many voters. Various studies have shown that, in these elections, voters rely on name recognition, which increases their support for a candidate or for a party.[27]

[25] From Goldstein & Gigerenzer (2002).
[26] Serwe & Frings (2006). The results were replicated by Scheibehenne & Bröder (2007).
[27] Kam & Zechmeister (2013); Marewski et al. (2010).

Humans not only excel in name recognition but also in rapidly recognizing pictures, faces, voices, or music. In perhaps the most extensive recognition memory test ever performed, participants were shown 10,000 photographs for 5 seconds each.[28] Two days later, when shown 10,000 pairs of photographs, each pair comprising one previously seen and one that was novel, they were able to identify 83 percent correctly. Note that the recognition of a face on a photo, or of a piece of music, does not mean that one also recalls the person's name or the piece's composer. Recognition is primary; recall may come later. The process of recognition, along with reliance on the recognition heuristic, typically proceeds without awareness, but the heuristic can also be used consciously, as when deliberately investing in stocks with high name recognition.[29]

Do people use the recognition heuristic in an automatic or an adaptive way? Studies have shown that people do not automatically rely on the heuristic, but adapt their use to its ecological rationality (the recognition validity ρ).[30] Can one also find traces of this adaptive use in the brain? The adaptive hypothesis entails two processes: mere recognition, which assesses whether or not alternatives are recognized, and evaluation, which assesses whether the recognition heuristic should be applied. In a functional magnetic resonance imaging (fMRI) study, we found support for the adaptive hypothesis.[31] Tasks that involved mere recognition drew on medial parietal areas of the brain, which are taken to reflect recognition memory processes, whereas tasks that involved the use of the recognition heuristic drew additionally on the anterior medical prefrontal cortex, which is assumed to reflect metajudgments, such as of ecological rationality. Thus, both behavioral data and the fMRI analysis are consistent with the hypothesis that an intuition based on the recognition heuristic involves an adaptive process of judging the heuristic's ecological rationality.

Decision-Making by Satisficing

Another heuristic for choices in uncertain situations such as buying a house or selling a car is the satisficing heuristic, which uses aspiration level adaptation:[32]

Step 1: Set an aspiration level α.
Step 2: Choose the first option that satisfies α.

[28] Standing (1973). [29] Ortmann et al. (2008).
[30] Pachur, Mata & Schooler (2009); Pohl (2006). For an overview, see Gigerenzer & Goldstein (2011).
[31] Volz et al. (2006). [32] Artinger et al. (2022).

Step 3: If after time β no option has satisfied α, then change α by an amount γ, and continue until an option is found.

Satisficing can be relied on unconsciously, which generates intuitive decisions. In that case, rather than stating the aspiration level, one simply has a feeling that the option is good enough and that no time should be wasted in trying to find a marginally better one. Aspiration levels determine whether people feel successful and content in everyday life or feel insufficient and incapable of meeting expectations. Aspiration levels set too high can create a life of perceived failures. The German psychologist Kurt Lewin, who promoted the concept of aspiration, maintained that successful people are those who set attainable goals.

Like every heuristic, satisficing can also be used consciously. One instance of this is pricing used cars. A study on how 628 car dealers set the prices of 16,356 used BMWs online (from the 3 and 7 Series) found that 97 percent relied on a satisficing rule.[33] The most frequent strategy was to set the initial aspiration level α in the middle of the price range of comparable cars on the market, maintain the price for a fixed time β of 3 to 4 weeks on average, and then lower the price by about 5 percent if the car was not sold in that period. With this version of satisficing, 64 percent of all cars were sold. An analysis of the adaptive use of the heuristic showed that β was shorter with an increasing density of both of population and of competing dealerships in the region. The heuristic implies price stickiness and the *cheap twin paradox*, where two virtually identical cars ("twins") in the same dealership are systematically priced differently. The paradox occurs when one of these two cars entered the dealership earlier and had one or more reductions by γ than the newer twin, a counterintuitive prediction that was verified across dealerships.

The Scissors of Intuition

The term *ecological rationality* was not only coined by my research group and myself but was also introduced independently by economist Vernon Smith in his Nobel lecture.[34] Smith juxtaposes ecological with constructive rationality, a concept he traces back to Descartes, who argued that all worthwhile institutions were and should be created by deliberate, deductive processes of reasoning. Although constructivist rationality has led to important achievements of the human intellect, the constant burden of

[33] Artinger & Gigerenzer (2016). [34] Smith (2003).

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self-conscious monitoring and planning of every single action would incur huge opportunity costs and not get humans through the day. Much of what we do occurs without much thinking: judging the intentions of others, catching a fly ball, playing speed chess, or conducting a symphony. For Smith, ecological rationality emerges from the unconscious brain rather than from the conscious mind, from intuitions, traditions, heuristics, norms, and other cultural and biological processes. Accordingly, the study of ecological rationality is to reconstruct, using deliberate thinking, how we make decisions outside the domain of constructive rationality. Smith's emphasis on the study of "home-grown principles of action" is much akin to ecological rationality as I understand it. In his own words:[35]

> The term "ecological rationality" has been used fittingly by Gigerenzer et al. (1999) for application to important discoveries captured in the concept of "fast and frugal decision making" by individuals . . . My application of the term is concerned with adaptations that occur within institutions, markets, management, social, and other associations governed by informal or formal rule systems – in fact, any of the terms might be used in place of "heuristic" and this definition works for me.

The common denominator is Simon's scissors, the process of adaptation, and coevolution. In line with this analogy, Smith is deeply suspicious of the lists of biases produced by those behavioral economists who study the cognitive blade only, which leads to what appears to be deep flaws. And, as already seen in Chapter 3, Smith's suspicion is justified.

Simon's three principles provide a useful template for freeing behavioral economics from its focus on deviations from utility theory and the routine (mis)interpretation of these deviations as flaws in the mind rather than in the theory. We need to take uncertainty and intractability seriously, be it in economic or other settings, instead of pretending that our world can be modeled as just risk and ambiguity. We need to take heuristics seriously, instead of clinging to the notion that optimization is the best solution to all problems. Finally, we need to accept that there is no single solution to all problems and, instead, become aware of and develop an adaptive cognitive toolbox containing multiple tools, each useful for different classes of problems. The human brain evolved to find solutions to problems without wasting time and energy, and fast-and-frugal heuristics embody this value. This is the stuff that intuitions are made of.

[35] Smith (2008), p. 36.