2.4 Heuristics and Biases

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Summary

Research on heuristics and biases has greatly influenced the current understanding of bounded rationality in psychology, behavioral economics, cultural anthropology, educational science, and neighboring disciplines of behavioral science (see chapter 1.1 by Sturm, chapter 1.2 by Evans, chapter 2.2. by Wedgwood, and chapter 8.4. by Hill, all in this handbook). The first major section of the present chapter is devoted to Kahneman and Tversky's seminal research program, providing a synopsis of the most prominent heuristics supposed to trigger violations of logical coherence rules: availability, representativeness, anchoring, and the simulation heuristic. A second major section deals with the contrast program advocated by Gigerenzer and colleagues, which highlights the adaptive value of fast and frugal heuristics. The last major section provides a critical discussion of the insights gained from half a century of fascinating research on heuristics and biases, and of the neglected issues—such as normative standards and underlying cognitive mechanisms—which constitute open questions to be resolved in future investigations of rational action and decision making.

1. The Notion of Heuristics and Biases in Rationality Research

Real life is replete with uncertainty. Even the most mundane and superficial actions and decisions involve assumptions about risks, probabilities, costs, and benefits, which are indeterminate and hard to evaluate objectively. Partner choice depends on social judgments of attractiveness, on trust, and on the likelihood of future scenarios. Consumers compare food items for healthiness and tastiness. Teachers' grading decisions entail inferences about students' competence and performance. Lying must be discriminated from veracious statements in everyday communication. Health-related behavior depends on the assessment of risks and dangers of nutrition, hobbies, sports, and transportation means. And predictions of future outcomes—in politics, sports, economic and ecological developments, and private affairs—are virtually never made with certainty.

In such an indeterminate world, there is often no absolute normative criterion for rational behavior. Scientifically approved answers to the question of how risks and costs can be minimized and how benefits and satisfaction can be maximized rely on rules of statistics and probability assessment, as a surrogate for a deterministic rule. Human judgments and decisions often do not rely on the mathematics of probability and statistics but rely instead on an alternative strategy, namely, on simplifying proxies or rules of thumb known as heuristics. Under specific conditions, "these heuristics are highly economical and usually effective, but they lead to systematic and predictable errors" (Tversky & Kahneman, 1974, p. 1131).

The purpose of the present chapter is to provide an overview of half a century of intensive research on heuristics and biases (Gigerenzer & Gaissmaier, 2011), which has had a strong impact on the study of rationality in behavioral science in general and on contemporary work in psychology, economics, biology, and philosophy in particular. Starting from a synopsis of Daniel Kahneman and Amos Tversky's groundbreaking demonstrations of the most prominent heuristics (Gilovich, Griffin, & Kahneman, 2002; Kahneman, Slovic, & Tversky, 1982; Tversky & Kahneman, 1974), we move on to a broader discussion of bounded rationality (Simon, 1982) and of the adaptive beauty of heuristic inferences considered from an alternative perspective by Gerd Gigerenzer and his colleagues (Gigerenzer & Goldstein, 1996; Gigerenzer, Todd, & ABC Research Group, 1999). Another major section will then be devoted to a critical assessment of what insights have been gained from this extremely prominent field of research and what neglected issues remain open to be answered in future investigations.

Let us illustrate the basic idea with an introductory discussion of one specific example, the availability heuristic

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(Tversky & Kahneman, 1973), which is ideally suited to explain the manner in which heuristics allow for accurate judgments in many everyday situations, although in different situations the same heuristics may lead to serious biases and irrational decisions.

2. The Availability Heuristic as an Illustrative Example

The availability heuristic (Tversky & Kahneman, 1973) affords a mental tool for estimating the frequency or probability of events. According to scientific methodology, normatively adequate estimations of such frequentist quantities should be inferred from proportions in representative samples. However, when human individuals estimate the risk (prevalence) of a disease or an accident, or the chances of winning a game in sports or of solving a problem, a representative sample is hardly ever available. Human memory is not a data repository; we do not keep representative data arrays in memory from which random samples could be drawn to inform unbiased frequency or probability estimates. Even when we do sometimes keep traces of ecological events in memory or in some external store, they cannot be expected to be representative of the current reality.

Nevertheless, we do have the capacity to estimate word frequencies or the likelihood of, say, different causes of death (Combs & Slovic, 1979) or of a certain team to become basketball champion, even though we do not keep in memory word counts, sports statistics, or epidemiological data about lethal events. We simply rely on the availability heuristic, which uses the availability of relevant memories as a proxy for frequency and probability estimation. The ease with which relevant memories (of word occurrences, sports teams' past success, lethal events) come to mind affords a useful heuristic of astounding validity. Most of the time, the likelihood of a target event is substantially correlated with the availability of relevant traces in memory. As memories of people dying from cancer are more available than memories of people dying from car accidents, which are more available than memories of suicide or lightning, heuristic estimates reflect the true ordering (cancer > car accidents > suicide > lightning), yielding a remarkably strong correlation between objective frequencies and the results generated by the availability heuristic.

It should be noted in passing that nonheuristic, purportedly normative methods also offer little more than approximate solutions; the norm distribution required to estimate a specific person's exact cancer, accident, or suicide risk is simply unknown. Available statistics that pertain to the entire population, or to crude substrata thereof, may not apply to individual persons with their individual lifestyle, their genetic predispositions, and the countless resulting combinations of risk factors. So, for a fair comparison, heuristics should not be contrasted with "objectively true values" as in psychophysics experiments but with normative surrogate solutions that are themselves debatable and often misleading and that might also be called "heuristic." Yet, despite its relative usefulness, the availability heuristic can lead to distinct biases when available memories depend on distracting, extraneous factors. For instance, selective media reports may render certain infrequent causes of death (e.g., murder, lightning) more available than other, objectively more frequent, causes of death (e.g., suicide, household accidents). These misleading cases are the focus of most pertinent research.

3. Synopsis of Prominent Heuristics, Their Domain, and Associated Biases

Let us now move from availability to a discussion of other prominent heuristics, their domain, and the kinds of biases that result from heuristic inference schemes.

3.1 Representativeness

The domain of the representativeness heuristic, one of the first heuristics specified by Kahneman and Tversky (1972), is categorization, or the diagnostic judgment of the likelihood that an event or person belongs to a category or group. A typical task may provide the following description of a target person: "very shy and withdrawn, invariably helpful, but with little interest in people, or in the world of reality." When participants are asked to judge whether the target person is more likely to be a farmer or a librarian (among other options), most people choose librarian, because the description is more representative of librarians than of farmers. They largely ignore the categories' base rates, that is, the fact that the proportion of farmers in the general population is much higher than the proportion of librarians. This pattern is obtained even when base rates are experimentally controlled (Tversky & Kahneman, 1974).

Similar to the availability heuristic, the representativeness heuristic enables accurate judgments, in this case of categorization, as long as the similarity of the target person description to the vocational stereotype constitutes a viable proxy of the actual profession. However, when likeness diverges from likelihood (Shweder, 1977)—that is, when the person sketch resembles a librarian, whereas farmer is much more likely—the heuristic will be misled by similarity, resulting in a distinct base-rate neglect (Bar-Hillel, 1984; Pennycook & Thompson, 2017).

According to the representativeness heuristic, samples are generally and uncritically assumed to be representative of an underlying entity or population. This assumption works in two directions: first, it is assumed that the properties of the underlying population can always be validly inferred from any given sample. Second, even small samples drawn from a given population are expected to have the same properties as the population at large, whereas deviating samples are supposed to be very unlikely. To illustrate the latter point, Kahneman and Tversky (1972) constructed the following task:

> All families of six children in a city were surveyed. In 72 families the exact order of births of boys [*B*] and girls [*G*] was *G B G B B G*. What is your estimate of the number of families surveyed in which the exact order of births was *B G B B B B*?

Both sequences are equally probable assuming invariance of the gender on successive births. However, they differ markedly from the well-known population distribution in terms of representativeness. Because the "law of small numbers" (Tversky & Kahneman, 1971) suggests that even in a short sequence, the ratio of boys and girls is close to 1:1, participants judged the first sequence to be more likely than the second sequence. In the same vein, seemingly regular chunks like *B B B B* or *B G B G B G* are poor representations of random events at odds of 1:1. Thus, series containing less regular chunks and seemingly less systematic content are judged to occur with a higher likelihood. The same reasoning mistake is at work when an explicit sampling task is replaced by a random process or "lottery": tossing a fair coin with the possible results of heads (*H*) and tails (*T*). Parallel to the above example, the series *H T H T T H* will be judged to occur more frequently than *T H T T T T*, which is again a mistake.

3.2 Anchoring and (Insufficient) Adjustment

Quantitative judgments—for instance, of total costs for a project, of the time required to complete a job, or of the appropriate punishment in a courtroom decision—constitute the domain of the anchoring heuristic (Epley & Gilovich, 2010; Strack, Bahník, & Mussweiler, 2016). Essential for this heuristic is the assumption that quantitative judgments typically start from an anchor, either a low or a high anchor, which is then adjusted in the light of relevant information. However, this adjustment process is typically insufficient or incomplete so that the resulting judgment remains biased toward the initial anchor. The anchoring heuristic thus produces underestimation if the initial anchor is low and overestimation if the initial anchor is high. For example, the overall costs for a holiday trip tend to be underestimated if calculation starts from zero, or from the cheapest base price, to which predictable costs are added. In contrast, costs tend to be overestimated if an overly high anchor is used as a starting point and all nonapplicable costs are subtracted.

For a nice empirical illustration, the starting value of an auction often provides a good predictor of the final price (Ritov, 1996; but see Galinsky, Ku, & Mussweiler, 2009). An intriguing finding from many pertinent experiments says that exposure to fully irrelevant numerical stimuli—such as somebody's Social Security number—can cause an anchoring bias in judgments of completely unrelated quantities (Oppenheimer, LeBoeuf, & Brewer, 2008; Wilson, Houston, Etling, & Brekke, 1996). In a seminal demonstration by Tversky and Kahneman (1974), estimates of the number of African nations in the United Nations were biased toward random numbers generated by a wheel of fortune.

As in the case of the other heuristics, anchoring and (incomplete) adjustment will often result in rather accurate estimates. However, obviously, quantitative estimation can be biased to the extent that the starting anchors misrepresent the true value of the estimated quantity.

3.3 The Simulation Heuristic

The simulation heuristic is sensitive to expectancies resulting from mental simulation. What is easy to imagine or simulate mentally (e.g., one's favorite team winning or losing an important match) will determine not only one's expectations but also one's emotions of regret and disappointment elicited by unexpected outcomes. For instance, one is particularly disappointed and frustrated when one misses a train by a minute rather than by 30 minutes, because the counterfactual simulation of still reaching the train on time is so vivid in the former case. As a consequence, silver-medal winners in Olympic games can be less satisfied and more disappointed than bronze-medal winners, because counterfactual mental simulations may compare silver medals with a missed gold medal but bronze medals with a worse outcome of receiving no medal at all (Medvec, Madey, & Gilovich, 1995).

3.4 Availability

As introduced at the outset, the domain of the availability heuristic encompasses judgments of uncertain frequencies or probabilities. The ease with which memory content comes to mind affords a useful proxy for frequency estimation, although it can lead to distinct biases when ease of memory retrieval itself is biased, for instance, due to selective media coverage (Pachur, Hertwig, & Steinmann, 2012; Reber & Zupanek, 2002).

4. Lopsided Focus on Heuristics as Erroneous Inference Tools

The greatest part of the published literature, to be sure, is concerned with empirical demonstrations of biases and erroneous heuristic inferences; relatively little research has assessed how often heuristic judgments are valid and unbiased. For example, in one of the most frequently cited demonstrations of the availability heuristic, Tversky and Kahneman (1973) showed that the number of English words with the letter "k" in the first position was erroneously judged to be higher than the number of words with a "k" in the third position. This is apparently due to the fact that it is easier to retrieve words with a particular letter in the first than in the third position. However, as Sedlmeier, Hertwig, and Gigerenzer (1998) have shown, this finding does not generalize to all letters of the alphabet; it is peculiar to the few letters on which the original demonstration had concentrated.

Because of this lopsided research focus on the biasing potential of heuristics and the relative neglect of their ecological validity, accuracy, and adaptive value, heuristics are associated with negative connotations in the published literature. References to "heuristic inferences" often characterize them as sloppy, superficial, inaccurate, and irrational. The credo of many dual-process theories (Chaiken & Trope, 1999; Sloman, 1996; Smith & DeCoster, 2000) is that the remedy to cognitive biases and distortions is to switch from a heuristic to a systematic processing mode. Just as the alleged inferiority of heuristic processing is rarely demonstrated in a representative design, the alleged superiority of systematic processing modes is hardly ever proven.

Given the apparent analogy to the classic perceptual illusions of Gestalt psychologists, the negative image of biases or cognitive illusions resulting from distinct heuristics (such as availability) is hard to understand. Perceptual illusions (such as the contrast effect underlying the Ebbinghaus illusion[1]) had typically been understood as rare failures of adaptive and strikingly efficient processing. In the realm of cognitive illusions, though, most researchers inspired by Tversky and Kahneman's (1974) heuristics-and-biases approach were not interested in adaptive functions but almost exclusively in demonstrating cognitive limitations as causal origins of irrational behavior—even in the absence of cogent evidence.[2]

The aforementioned findings on availability effects in estimating causes of death (Combs & Slovic, 1979) provide testimony for this lopsided tendency. The same researchers who, for example, pointed out biased newspaper coverage as a plausible environmental cause of overestimated murder rates (relative to suicide rates) continued to treat these findings as evidence for an alleged cognitive bias in selective retrieval. Neither Combs and Slovic (1979) nor many other authors who drew on their findings ever made an attempt to rule out the possibility that (environmental) biases in newspaper reporting alone may account for the biased estimates even when retrieval processes are completely unbiased. Most researchers largely neglected the obvious fact that heuristics may serve a generally adaptive function, with only a few specific types of situations leading to the biases investigated so feverously by the research community.

5. Heuristics as Indispensable Modules of Adaptive Intelligence

We have already noted that for many real-life problems, there are hardly any purely logical, normative solutions. That is, so-called normative models of reality also rely on heuristics or proxies used to estimate the costs of a construction project, the severity of climate change, the utility of different ecological policies, or the number of participants required in an experiment. Indeed, heuristics are part and parcel of expert systems and of the most intelligent systems of adaptive cognition, as illustrated in the early work of Egon Brunswik. Long before Kahneman and Tversky unleashed this wave of research into the inadequacies of human judgment by cause of heuristics, Brunswik's (1955) *probabilistic functionalism* outlined a very different perspective on heuristics as indispensable modules of adaptive regulation.

According to Brunswik's lens model, the distal entities that are the focus of most judgments in real life—entities such as risk, danger, honesty, attraction, student ability, or interpersonal trust—are not amenable to direct perception through specialized sense organs. We somehow have to construe those distal entities from sets of proximal cues, which bear only weak or modest correlations to the distal entities. The inferential utilization of insufficient but useful and indispensable cues is nothing else but highly functional heuristic processing. For instance, to assess the distal variable of honesty in lie detection, we have to rely on such imperfect heuristic cues as speech hesitation, gaze aversion, pitch of the voice, or disguised smiling (Hartwig & Bond, 2011, 2014), all of which are rather low in diagnosticity. Although all

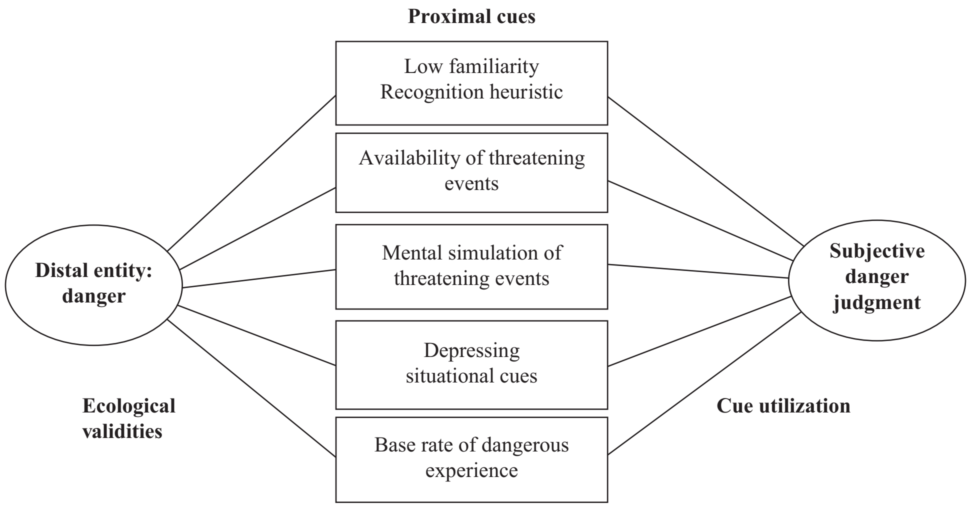

Figure 2.4.1
Brunswik's (1955) lens model applied to subjective judgments of danger, mediated by five proximal cues framed to resemble some of the most well-known heuristics (recognition, availability, simulation heuristic). Statistical relations of proximal cues to distal entities are called ecological validities. The weights given to cues in subjective judgments are referred to as cue utilization.

these cues provide only weak predictors of the distal criterion, honesty, they nevertheless allow for above-chance lie detection when an increasing number of cues of restricted validity are combined. Crucially, there is no alternative to relying on heuristic cues for lie detection, which is of utmost importance for adaptive behavior.

As we have learned from Brunswik (1955), we do not possess sense organs even for the literal perception of many obviously physical attributes, such as distance. Rather, in-depth perception organisms have to infer the perceived distance of an object using such proximal cues as disparity of the retinal images, movement parallax, surface texture, or blurredness of contours. All these cues afford only imperfect correlates of distance; in other words, they allow us to approximate the distal entity in question in a crude heuristic manner only. Moreover, the notion of *vicarious functioning* highlights the substitutability of all these cues, none of which is necessary or essential for depth perception. Still, they are functional because their ecological validity is better than chance and, as mentioned before, there is no alternative to relying on heuristic cues.

5.1 Using the Lens Model to Describe Heuristics' Adaptive Functions

By analogy, Hammond, Stewart, Brehmer, and Steinmann (1986) used the lens model in their social judgment theory to analyze the cues used as proxies for such distal entities as risk, attraction, trust, or required effort expenditure (see figure 2.4.1). Obviously, availability and other heuristics afford reasonable cues, the validity of which is an open empirical question. However, as already mentioned, the validity of any alternative device supposed to be normatively appropriate is also an open empirical question. In any case, the lens model in figure 2.4.1, in analogy with social judgment theory (Hammond et al., 1986), suggests a framework within which the availability heuristic (along with other heuristic cues) serves an uncontested adaptive function—namely, to allow organisms to estimate danger under uncertainty, in the absence of immediate perceptual cues. Similar to Brunswik's in many aspects, an approach that focuses on the adaptive aspects of heuristics emerged after the heuristics-and-biases program had developed into one of the most prosperous research programs: the fast-and-frugal-heuristics program initiated by Gigerenzer et al. (1999).

6. Fast and Frugal Heuristics

Inspired by this Brunswikian perspective and previous work by Edwards (1965) and Peterson and Beach (1967) that had drawn a more optimistic picture of the fit between the human mind and the principles of logic and probability theory, Gigerenzer and colleagues returned to the notion that humans can be considered rational, giving an adaptive interpretation to the term. This alternative research program was deliberately opposed to the common research strategy of the Kahneman–Tversky program, in which cognitive performance was tested against the rules of classical logic and probability theory. Criticism of the standards against which decision making was assessed can be considered the starting point of

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the alternative program on "fast and frugal heuristics" (Gigerenzer, 1991, 1996; Todd & Gigerenzer, 2000).

Rejecting those normative standards as too narrow and unjustifiably content blind (Gigerenzer, 1996), this research group took a different approach to investigating heuristics. They viewed heuristics in the light of bounded rationality—a term coined by Simon (1982) for the view of rationality that takes into account human limitations and implores to relate them to the structure of the environments in which the decisions are made (Todd & Gigerenzer, 2000). Accordingly, they worked on the assumption that heuristics offer a reasonable way for humans to cope with the uncertainty of the world by making use of the structure of information environments. Different heuristics, metaphorically assorted in the "adaptive toolbox" (Gigerenzer et al., 1999), are suitable for different environments. Like a tradesperson who chooses the tool appropriate for the task at hand, we as decision makers are able to determine the heuristic suitable for the information structure of the decision and apply it. Gigerenzer and colleagues set out to discover such heuristic decision strategies, which environment structures they matched, and to what extent people actually use them. Instead of looking at and for heuristics as a way to explain fallacious reasoning and biases in judgment and decision making, they shifted the focus to the search for heuristics' benefits.

Arguably the two most important classes of heuristics advanced by this alternative approach, recognition and Take the Best, shall be illustrated in more detail in the following. Both of them represent single-cue heuristics in a Brunswikian sense. While the former always relies on the same primitive cue of recognition, the latter utilizes a more flexible, adaptive multicue toolbox, from which the best-suited cue is selected for the decision at hand.

6.1 The Recognition Heuristic

The recognition heuristic (Goldstein & Gigerenzer, 2002) is dependent on the decision maker's partial ignorance; indeed, it illustrates the class of ignorance-based decision-making strategies. Faced with a choice between two options, having to judge which has a higher value on some criterion, a decision maker applying this heuristic will simply choose the option that he or she recognizes (i.e., has seen or heard of before) as having a higher value than the unrecognized option. Naturally, the precondition for applying this heuristic is the recognition of merely one of the options—the partial ignorance mentioned above.[3] This heuristic will lead to accurate choices in environments where recognition is a valid cue, positively correlated with the criterion the choice relates to. This may be the case in many domains, especially in the heavily studied paradigm of city population judgments, in which participants have to choose the city with the larger population out of two (Pachur, Todd, Gigerenzer, Schooler, & Goldstein, 2011). Cities that are recognized by many participants can indeed be expected to have larger population sizes. This heuristic affords an adaptive tool in situations characterized by partial ignorance, where only one option is known to them and more concrete knowledge is lacking (Pachur et al., 2011).

However, Oppenheimer (2003) pointed out that the recognition heuristic may not be as simple as initially portrayed. Participants did not apply the heuristic blindly in situations in which they had knowledge of the reason for the recognition, for example, if recognized towns were local or if they were well known due to unusual circumstances, as Chernobyl is for being the location of a nuclear disaster. Pachur et al. (2011) rejected Oppenheimer's criticism. If participants knew that the local towns were small, then they had what is called "criterion knowledge," objective knowledge about one of the options. If that criterion knowledge was conclusive, that is, "enable[d] the decision maker to deduce a solution" (Pachur et al., 2011, p. 7), then the recognition cues need not be utilized. Whether that is actually the case does not seem clear-cut. The fact that participants did not apply the heuristic when they recognized a city due to unusual circumstances connected to it was acknowledged and led to an extension of the recognition heuristic by another process—namely, judging whether the recognition cue is valid in this environment or not. This process comes after the recognition process and can explain the differential use in different environments, which would speak to the adaptive use of the heuristic.

Precisely this aspect of cue validity was also tested directly by examining the use of the recognition heuristic across different domains or environments with varying recognition validity (i.e., varying correlation between recognition and criterion). The higher the recognition validity, the more people relied on the recognition heuristic. Some studies even attest to a fascinating less-is-more effect with regard to knowledge. Those who know less, meaning that they recognize only a subset of options, may perform better under certain circumstances than those who recognize all options. This is because the latter cannot make use of the recognition heuristic but may not know enough about the options, beyond recognizing them, to compensate for it (Pachur et al., 2011).

As a cue, a special status is ascribed to recognition, because it is assumed to regulate the retrieval of all other cues. If an option is not recognized, one is unable to retrieve any other information about it. It can also be retrieved faster than any other cue. If the one cue that a decision is made upon is something other than recognition, one is in the realm of single-cue heuristics, the second class described here.

6.2 The Take the Best Heuristic

The second class of single-cue heuristics, also referred to as one-reason decision making, encompasses all heuristics that use only one cue, or reason, aside from recognition. The decision maker compares the options' values on that cue and chooses the option (among two or more options) with the highest value. These heuristics have in common the assumption that decision makers are capable of estimating the values of the cues they are comparing. Most assume that cue validity, the proportion of instances in which the cue correctly discriminated between options, can be estimated. Which of the cues is selected for the decision depends on the specific heuristic. Cue validity is the crucial dimension along which single-cue heuristics vary.

An entire class of so-called lexicographic strategies relies on the assumption that cues can be sorted by validity, from best to worst (Luce, 1956; Payne, Bettman, & Johnson, 1988; Tversky, 1969). Gigerenzer and Goldstein (1996) aptly termed the most prominent heuristic strategy from this class "Take the Best" (TTB). In TTB, the decision is based on the first cue in the ordering that discriminates between options, with the higher value on that cue determining the option to be chosen.

Gigerenzer and Goldstein (1996) also specified alternative ways of selecting the cue for the decision basis, the first of which is termed "minimalist algorithm" (p. 661) and selects cues at random until one discriminates, and the second of which is called "Take the Last algorithm" (p. 660) and selects the cue that was used for the decision last time. They compare some of those heuristics with complex models, considered normative models of decision making, like the weighted-additive decision strategy or Dawes' rule. Unsurprisingly, the more complex models could be fitted better to the data sets. However, more important, when the decision strategies were tested for how well they generalized to a new data set, TTB outperformed all other strategies in almost all cases. The reason for this is that their simplicity (or frugality) makes heuristics robust and avoids overfitting to one specific data set or environment.

7. Coherence and Correspondence

The issue of how the effectiveness of heuristics should be evaluated is broader than the contrast between fitting decision strategies to given data and generalizing to new data sets. Laws of probability and logic are traditionally the standard against which human decision making is evaluated. Rational, normative decision strategies are all coherent in that they do not violate any of those laws. However, heuristics do not have to adhere to normative rules to be able to lead to good decisions, illustrating the disconnect between the common evaluative standard and real-world requirements. A core aspect of the ABC Research Group's work is a standard for the evaluation of decision strategies that is in line with the view of bounded rationality. Instead of applying coherence criteria that examine whether any formal norms were violated (as was commonplace in research inspired by Kahneman and Tversky), bounded rationality requires that heuristics, and decision strategies in general, be evaluated by how well they correspond to the structure of the information environment in which they are used. They cannot be evaluated fully without at least some connection to real-world decision situations, because it is the heuristic's fit with the way the information is structured in the environment that needs to be assessed. The criteria used for this way of evaluating are called correspondence criteria, in contrast with the standard coherence criteria (Dunwoody, 2009), and include accuracy, frugality, and speed.

This leads to so-called *ecological rationality* (Todd, 2000), to be differentiated from "standard" rationality. Todd and Gigerenzer (2000) argue that this standard for evaluating heuristics is more sensible, because heuristics are not meant to be internally consistent but rather to provide reasonable inferences and adaptive guidance when time and resources are scarce. In addition, coherence criteria seem unsuitable because violations have not been found to be particularly costly (Arkes, Gigerenzer, & Hertwig, 2016). Once again, this highlights the immense advantage and absolute necessity of heuristic strategies: for many situations in the real world, no implementable standard normative strategy (optimization) exists, leaving heuristics as the only strategy.

8. Critical Appraisal of Scientific Insights Gained from Heuristics-and-Biases Approaches

There can be no doubt that the research program on heuristics and biases belongs to the most influential contributions to behavioral sciences. Current psychology would not be what it is today without the fascinating work reviewed so far in this chapter. The prototypical concept of the human mind in basic cognitive psychology was largely shaped by the twofold message that (a) human rationality is restricted, with experts and laypeople alike falling prey to a long list of biases and shortcomings (Nisbett & Ross, 1980), but that (b) apparent violations of manifold reasoning norms can nevertheless be adaptive in a complex and indeterminate world (Todd & Gigerenzer, 2003). Many domains of applied behavioral (and related) sciences have been influenced considerably by this research, including legal psychology (Gigerenzer & Engel, 2006), marketing and consumer research (Scholten, 1996), organizational psychology (West, Christodoulides, & Bonhomme, 2018), learning and education (Koriat & Levy-Sadot, 2001), and several major academic disciplines, such as economics, social and political sciences, and philosophy.

However, despite these signs of success, scientific fertility, and extraordinary impact, there is also room for critical appraisal. Although the empirical search for biases and shortcomings in diverse areas has flourished for almost five decades, some of the most essential theoretical underpinnings have been sorely neglected and never clarified. The debate about biases and alleged norm violations is still devoid of a clearly spelled-out normative fundament. The conceptual background of dual-process theories, in which most pertinent research is theoretically embedded, is weak and questionable. Most important, cogent empirical evidence from well-designed experiments concerning underlying mechanisms and delimiting conditions is conspicuously missing. Half a century after Tversky and Kahneman's first publication (1971), we know very little about what is going on in the black box of judges and decision makers.

8.1 Normative Benchmarks

A research program that relies heavily on empirical demonstrations of biases and transgressions of probability theorems is strongly contingent on normative benchmarks. To classify a judgment or decision as biased, one needs to have a norm or correctness criterion against which empirical deviations can be tested. Biases need to be systematic and of practically relevant size. Therefore, the tasks used for research on heuristics and biases provide participants with all information required to solve a probability calculation task or to choose a normatively optimal decision option (Edwards, Lindman, & Savage, 1963). Participants in the coin-tossing example knew they were observing a fair coin. They could have known that the probability of any series must be equal to that of any other series of equal length since its probability is always ½ to the power of the series' length. The normative solution of this task can be considered stable and easy to implement.

When we take a closer look, however, we see that the coin-tossing example is essentially different from many everyday problems (Hahn & Warren, 2009). First, knowledge that a coin being tossed is fair, and thus the probabilities evenly distributed, may be a common feature in gambling, but it is a rare and highly improbable feature elsewhere. Assuming a trick coin landing heads with a probability of 0.8 and tails at 0.2, the task would be a little harder to solve normatively correctly. Moving away from gambling, we may end up wondering whether it is possible to calculate a normatively appropriate solution at all. We may never argue about how to calculate the odds of a fair coin-tossing series but may very well wonder how the true risk of, say, contracting the flu should be calculated. How can the best investment strategy on the stock market be determined? What is the normatively correct team to bet on in a basketball final? This demonstrates that there is a gap between experimental tasks involving betting and dice tossing, for which there exists an unequivocally correct solution, and real-life problems for which no normative solution exists, so that even experts and robot systems can only rely on approximations of normative solutions.

Unfortunately, this intricate problem of an essentially normative approach was not explicated from the beginning, although the entire research project focuses on deviations from norms. Kahneman and Tversky (1972) postulated a fundamental gap between probability theory and human responses. Despite their initial comparison of cognitive illusions with perceptual illusions (Tversky & Kahneman, 1983), they considered the representativeness heuristic to reflect an irrational illusion, the anchoring heuristic as a serious inability to ignore irrelevant numerical primes (Wilson et al., 1996), and sample-size neglect as a perfect example of irrational behavior.

The choice of normative criterion not only created a problem for Kahneman and Tversky's coherence-based approach to rationality but also represents an unresolved problem for the correspondence perspective taken by Gigerenzer et al. (1999) with its emphasis on the adaptive value of fast and frugal heuristics. Thus, when the Take the Best heuristic or the priority heuristic lead to 70% correct responses in pairwise choice tasks, the ultimate question is whether this can be interpreted as successful in terms of corresponding to the information environment or as a disappointing result. What is the normative benchmark for rationality, or bounded rationality, based on correspondence criteria: 65%, 70%, or maybe 80% correct predictions?

8.2 Dual-Process Theories

As a surrogate for the missing normative or psychophysical framework, many researchers in social cognition, but also in cognitive psychology, have located their work in the context of dual-process or dual-systems approaches (Chaiken & Trope, 1999; Sloman, 1996). These approaches postulate two systems, one that prefers fast and effortless thinking of the heuristic type (System 1) and one that can live up to systematic reasoning in line with rational procedures (System 2). Such a dual-process framework offers a seemingly plausible (but circular) explanation for virtually every empirical test of hypothetical heuristics. If participants exhibit the typical biases predicted by heuristic theories, they were apparently operating in System 1, presumably because time and effort were too costly compared to the reward for rational responding. But if they happen to provide normatively correct responses, then they must have entered System 2, presumably because they are personally involved or motivated to be accurate. Note that for such a conception to allow strict theory testing, a superordinate theory has to make clear-cut predictions about specific conditions under which either System 1 or System 2 is activated. For logical reasons alone, such a metatheory is almost impossible (Keren & Schul, 2009), because it is hard to see why System 1 and System 2 should not overlap, why there should be no more than two systems, and why a single system alone should not be able to account for all the evidence (Kruglanski & Thompson, 1999). In the absence of a metatheory that imposes strong constraints on the conditions that trigger different systems, it remains incomplete and of restricted scientific value. A promising suggestion for such a metatheory is delineated by Marewski and Schooler (2011).

8.3 Numeracy and Expertise

Especially the initial research on heuristics in the early 1970s did not take the perspective of dual-process theories' System 1: fast and loose guessing in the absence of motivation as well as mental and temporal resources. Numeracy and education level of participants have always been assumed to be sufficiently high. One of the first publications on the heuristics-and-biases project recruited members of illustrious psychological societies as participants (Tversky & Kahneman, 1971). Further investigations recruited students in university courses, who were presumably well educated in stochastics. Nevertheless, cognitive biases were shown to be ubiquitous. Even experts fall prey to overconfidence (Klayman, Soll, González-Vallejo, & Barlas, 1999), exhibit marked anchoring biases (Englich, Mussweiler, & Strack, 2006), and fail to engage in proper logical reasoning (Wason, 1968). Risk assessment in highly consequential areas is replete with base-rate fallacies and failures to run appropriate cost–benefit analyses (Swets, Dawes, & Monahan, 2000). Even when it comes to taking advice from medical experts on existential health-related issues, doctors and patients do not live up to normative principles of risk assessment and rational action (Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, & Woloshin, 2007; Wegwarth, Gaissmaier, & Gigerenzer, 2011).

8.4 The Conspicuous Lack of Insights on Underlying Cognitive Mechanisms

Perhaps the most striking critique of half a century of flourishing research on cognitive heuristics, however, refers to the paucity of solid experimental evidence on underlying mechanisms. Although Tversky and Kahneman (1974) introduced all of their heuristics as cognitive-process theories, very few experiments were conducted to isolate selective memory retrieval as the site of the availability heuristic, to specify the precise similarity function of the representativeness heuristic (Nilsson, Juslin, & Olsson, 2008), or to unravel distinct constraints on the (insufficient) adjustment process supposed to explain anchoring effects (Epley & Gilovich, 2001, 2006).

Although Gigerenzer and colleagues themselves started from this critique of missing experimental tests of Kahneman and Tversky's ideas, their own research suffered from the same paucity of unequivocal findings about cognitive mechanisms. There is hardly any cogent evidence on a miraculous algorithm that allows people to rank-order the validity of a longer list of candidate cues, as a precondition for Take the Best. Strict experimental tests of the recognition heuristic are rarely based on the deliberate manipulation of recognizable versus non-recognizable stimuli (e.g., in a paired comparison with selective repeated exposure). While Goldstein and Gigerenzer's (2002) famous demonstration that Germans outperform Americans when judging the population size of pairs of American cities was counted as evidence in favor of the recognition heuristic (because Germans know little about American cities except that they recognize some and do not recognize others), other research did not support this superiority of partial knowledge (Pachur & Biele, 2007; Pohl, 2006).

The cognitive algorithm supposed to underlie the priority heuristic (Brandstätter, Gigerenzer, & Hertwig, 2006) is specified in all detail: when choosing between two lotteries (each described by distinct outcomes *o* obtained with distinct probabilities *p*), the heuristic first tries to make a choice in favor of the lottery with the higher minimal *o*. Only when the lotteries' difference in minimal *o* is not sufficient, the heuristic tries to make a choice in favor of the lottery with the lower *p*(minimal *o*) of a minimal outcome. Only if the difference in *p*(minimal *o*) is not sufficient, the lexicographic algorithm switches to the highest outcome as a criterion, and only if this third cue still does not enable a clear-cut choice, the mechanism resorts to guessing. Although this is a precise algorithm, there is little experimental evidence available to support a cognitive process that follows exactly this sequence. The evidence marshalled in favor of the priority heuristic is, again, largely confined to reporting the percentage with which the heuristic chooses the lottery with the higher expected value. However, an accuracy rate of, say, 70% hardly reveals much about an underlying mechanism. When a deliberate attempt is made to test the heuristic experimentally, the evidence is incompatible with the heuristic: *p*(minimal *o*) exerts a strong impact regardless of whether the preceding minimal-*o* cue is high or low, and maximal *o* exerts a substantial influence regardless of whether both preceding cues, minimal *o* and *p*(minimal *o*), are high or low (Fiedler, 2010).

A continued debate revolves around the "adaptive toolbox" and its contents of many different heuristics. Alternative single-process models have been proposed as more parsimonious accounts and better fit some parameters, although it is very hard to test different approaches against each other (Glöckner, Hilbig, & Jekel, 2014; Söllner & Bröder, 2015). The lack of explanation regarding the way the decision maker chooses heuristics from the diversely filled toolbox in different environments is another important criticism (Cooper, 2000). Feeney (2000) points out that the choice among heuristics may lead to an infinite regress just like the one Gigerenzer and colleagues criticized about the Kahneman–Tversky research program. Todd and Gigerenzer (2000) admit that a metatheory that explains the choice of heuristics is sorely needed as a solution to this problem.

9. Concluding Remarks

By all standards, Kahneman and Tversky have certainly sparked a scientific revolution, and Gigerenzer and colleagues have arguably achieved their goal of initiating a slightly different revolution of the view of the mind. Other leading labs have also made strong contributions to research on rationality, including Fischhoff's (1975) work on the hindsight bias, Einhorn and Hogarth's (1981, 1986) seminal papers on friendly versus wicked decision environments, or recent work by Hertwig and colleagues (Hertwig, Herzog, Schooler, & Reimer, 2008; Hertwig, Hoffrage, & ABC Research Group, 2013; Hoffrage & Hertwig, 2012; see also chapter 8.5 by Hertwig & Kozyreva, this handbook) on the dialectic interplay of organisms and their environments. These pioneers have inspired a flood of research conducted in the spirit of their ideas. However, despite all this fruitful research and all the fascination it has elicited, the research program is far from being complete or exhaustive. We are only beginning to understand the interaction of environmental and cognitive sources of judgment biases and have only recently begun to replace the old-fashioned criterion of accuracy (relative to an elusive norm) by a new criterion of adaptive behavior, which is still conceptually underdeveloped.

To achieve this major developmental goal, it may be necessary, ironically, to rid ourselves of the old paradigmatic idea of a normatively correct solution for judgment and decision problems. The existence of such a normative criterion may turn out to be more the exception than the rule—quite like the dice-tossing problems and betting urns used in many traditional experiments are. As a consequence, there is no alternative to applying useful heuristics even when the smartest are motivated to find optimal solutions with the help of proper calculus (Bayes' theorem) and artificial intelligence (machine learning). Even under such auspicious conditions, there is hardly any normatively correct, conflict-free solution; there is always a need to find a heuristic solution that optimizes the adaptive value of intelligent action.

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Notes

1. The Ebbinghaus illusion produces a contrast effect such that a circle surrounded by four other circles appears larger (smaller) when the surrounding circles are smaller (larger).

2. Given that Kahneman and Tversky (1974) conceived cognitive illusions as analogous to perceptual illusions, this unequal treatment of the two types of illusions appears conspicuous.

3. Along the divide of compensatory and noncompensatory strategies, it is located on the noncompensatory side, meaning that it is not traded off against additional cues.

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