From Meehl to Fast and Frugal Heuristics (and Back)

New Insights into How to Bridge the Clinical–Actuarial Divide

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ABSTRACT. It is difficult to overestimate Paul Meehl's influence on judgment and decision-making research. His 'disturbing little book' (Meehl, 1986, p. 370) *Clinical versus Statistical Prediction: A Theoretical Analysis and a Review of the Evidence* (1954) is known as an attack on human judgment and a call for replacing clinicians with actuarial methods. More than 40 years later, fast and frugal heuristics—proposed as models of human judgment—were formalized, tested, and found to be surprisingly accurate, often more so than the actuarial models that Meehl advocated. We ask three questions: Do the findings of the two programs contradict each other? More generally, how are the programs conceptually connected? Is there anything they can learn from each other? After demonstrating that there need not be a contradiction, we show that both programs converge in their concern to develop (a) domain-specific models of judgment and (b) nonlinear process models that arise from the bounded nature of judgment. We then elaborate the differences between the programs and discuss how these differences can be viewed as mutually instructive: First, we show that the fast and frugal

heuristic models can help bridge the clinical–actuarial divide, that is, they can be developed into actuarial methods that are both accurate and easy to implement by the unaided clinical judge. We then argue that Meehl's insistence on improving judgment makes clear the importance of examining the degree to which heuristics are used in the clinical domain and how acceptable they would be as actuarial tools.

KEY WORDS: actuarial models, clinical judgment, decision making, fast and frugal heuristics, linear models

Paul E. Meehl (1920–2003) does not fall into a ready-made category. In his autobiography, he characterized himself as 'a clinical psychologist who also ran rats and knew how to take a partial derivative' (Meehl, 1954, p. vii). Influenced by Karl Menninger's famous book *The Human Mind* (1930), he initially turned to psychology in order to become a psychotherapist (Meehl, 1986; 1989, p. 339), but graduated from the University of Minnesota, where most psychologists (Hathaway, Paterson, Skinner) were strongly skeptical of psychodynamic theories and where 'the scholarly ethos was objective, skeptical, quantitative, and behavioristic' (Meehl, 1989, p. 345). He was a clinician, trained in the Freudian tradition but open to other methodologies. He was strongly interested in theoretical and philosophical issues (Meehl, 1989, pp. 340, 373). And he was an experimentalist, studying rats in the behaviorist tradition (MacCorquodale & Meehl, 1951; Meehl & MacCorquodale, 1953), and human participants in the field of personality psychology (Meehl & Dahlstrom, 1960).

Meehl is best known for his book *Clinical versus Statistical Prediction: A Theoretical Analysis and a Review of the Evidence* (1954). The academic impact of this classic can hardly be overestimated in terms of the thought, debate, and written work it has stimulated. Together with seminal papers published in the 1950s (Edwards, 1954; Hammond, 1955; Simon, 1956), it gave a decisive push to the study of human judgment (Goldstein & Hogarth, 1997). The book testifies to the diverse interests of its author. Echoing both Meehl's clinical practice and his knowledge of formal methods, such as the Minnesota Multiphasic Personality Inventory (MMPI), to which he himself contributed, the book presents the first comprehensive test of the value of clinical judgment. In contrast to actuarial (or mechanical or statistical) judgment, which is 'arrived at by some straightforward application of an equation or table to the data' (Meehl, 1954, p. 15), clinical judgment is defined as judgments in which the inference or weighting is done by a human judge (Meehl, 1954, p. 16).

The core of Meehl's book consists of a review of 20 empirical studies that compare the accuracy of clinical judgments to the accuracy of actuarial methods for prognosis, that is, when a prediction has to be made on the basis of the characteristics of a patient (e.g., whether a 65-year-old male patient who complains of strong chest pain will develop ischemic heart disease). Before we discuss this review, we want to point out that illuminating ideas can be

found in the rest of the book as well; in fact, we will discuss some of these ideas below. Nevertheless, it seems fair to say that the review is the part of the book that had the greatest impact.

The conclusions that Meehl draws from this review have been replicated numerous times: Whatever their experience, theoretical commitments, feedback opportunities, or the information they have available, clinicians are usually outperformed by actuarial methods (for more recent reviews see Dawes, Faust, & Meehl, 1989; Grove & Meehl, 1996; Grove, Zald, Lebow, Snitz, & Nelson, 2000; Swets, Dawes, & Monahan, 2000).

On the other hand, fast and frugal heuristics—recently proposed by Gigerenzer and colleagues as psychologically plausible models of human judgment (Gigerenzer, Todd, & the ABC Research Group, 1999) —have been found to outperform linear actuarial models such as multiple regression and unit-weight linear models. Crucially, it is these same actuarial models that beat clinical judgment in the studies surveyed by Meehl. The first goal of this article is to resolve this seeming contradiction by contrasting the conditions under which fast and frugal heuristics are successful with the conditions that clinical judges usually face.

The second goal is to explore the similarities between the conceptual views of judgmental processes evinced in Meehl's program and in the program on fast and frugal heuristics, respectively. Meehl's position on descriptive models of human judgment—though often implicit and usually overlooked—reveals itself at a more careful reading of his 'disturbing little book' (Meehl, 1986, p. 370). Specifically, we argue that Meehl and the fast and frugal heuristics program share a concern for developing (a) domain-specific models of judgment and (b) nonlinear process models that take into account the bounded nature of cognition. While elaborating these similarities, we will also trace the conceptual roots of fast and frugal heuristics in the early days of research on judgment and decision making.

Third, we discuss what the two research programs can learn from each other. Although in many of the studies surveyed by Meehl the actuarial models used simple unit weights, other times the models were mathematically more sophisticated and thus relatively complex and insensitive to the limited time, information, and computational power available to the clinical judge. This might explain why Meehl's plea for an increased use of actuarial methods in clinical practice has had little effect. Fast and frugal heuristics, in contrast, explicitly acknowledge the requirements and limits faced by boundedly rational decision makers operating in the real world. We speculate that therefore they might be more acceptable to clinicians than the usual actuarial tools (such as logistic regression). We illustrate how heuristics can be developed into actuarial methods for quick, transparent, and clinician-friendly prognostic prediction that compete well with, or even outperform, more complex actuarial methods. Conversely, one challenge for the fast and frugal heuristics program is to investigate if clinicians would accept and use such methods as

actuarial tools. Furthermore, Meehl insisted on the importance of understanding how the clinical judge operates. Fast and frugal heuristics, however, have only rarely been applied to those important decisions that professionals need to make (for exceptions, see Bryant, 2007; Dhami, 2003; Green & Mehr, 1997). Testing how well fast and frugal heuristics describe decisions in the clinical domain is another challenge posed by Meehl.

Meehl and Fast and Frugal Heuristics: Contradictions?

One of the key conclusions of Meehl's classic work is that actuarial models, such as weighted linear models, are often more accurate than clinicians' intuitive heuristics. In a more recent analysis using 136 studies, Grove et al. (2000) replicated and refined these conclusions. In spite of clinical prediction using more information than actuarial prediction, the results concurred with the ones obtained by Meehl (1954). Almost half of the studies (47%) favored actuarial prediction over clinical prediction, and in only a minority of the studies (6%) clinical prediction prevailed. (In the remaining studies the two methods performed equally well.) In addition, it was found that the use of interview data in clinical prediction increased its inferiority to actuarial prediction, whereas use of medical data decreased the difference between the two methods. Interestingly, the amount of training and experience of the clinical judge did not affect the inferiority of clinical to actuarial prediction, nor did the amount of information available to the judge. Finally, the difference between actuarial and clinical prediction was not affected by whether actuarial prediction was cross-validated or not.

Meehl's finding led to a much more critical attitude toward unaided human judgment and fueled efforts to improve it. More than 40 years later, Gigerenzer and his colleagues (Gigerenzer & Goldstein, 1996; Gigerenzer et al., 1999) proposed simple, nonlinear heuristics, such as *Take The Best* (TTB; described below), which are firmly rooted in bounded rationality and are intended to be descriptive models of judgment by 'real minds … under constraints of limited knowledge and time' (Gigerenzer & Todd, 1999, p. 5). Testing these simple heuristics against models akin to Meehl's actuarial models in computer simulations, Czerlinski, Gigerenzer, and Goldstein (1999) showed that both complex and simpler (i.e., unit weight) linear methods are good, but that TTB—a still simpler, nonlinear, noncompensatory heuristic that ignores information—can be even better. Moreover, as we will outline below, people seem to be using such simple rules in the laboratory. Does this mean Meehl's conclusion that actuarial methods are superior to human judgment is wrong? What is behind this seeming contradiction?

First, on a more abstract level, it should be noted that the two research programs converge in demonstrating the robust beauty of simplicity; Meehl is credited with the insight that 'in most practical situations an un-weighted sum

of a small number of "big" variables will, on average, be preferable to regression equations' (Dawes & Corrigan, 1974, p. 105). Both fast and frugal heuristics and the linear models Meehl tested are mathematically simpler than other models used in statistics and actuarial science, such as neural or Bayesian networks. Second, concerning the accuracy of the processes underlying human judgments, one should recall that in many of the studies included in Meehl's (1954) overview, the playing field for clinical and actuarial judgments was uneven. For instance, the actuarial models were often fed a preselected set of predictors, whereas the clinicians were given a considerably larger set of information and had to sieve out the relevant predictors.

But the apparently opposing findings of Meehl and the fast and frugal heuristics program can be resolved even if one fully accepts that clinicians perform worse than actuarial models. Specifically, Meehl's findings can be interpreted as indicating that due to the conditions in clinical practice, clinicians shy away from using simple heuristics such as TTB. This may be so for a number of reasons.

First, clinicians might not use TTB because they lack the information necessary to exploit the heuristic's virtues. Specifically, it has been argued that clinicians work in a 'wicked' environment (Hogarth, 2001, p. 89) that only rarely provides them with feedback (Einhorn & Hogarth, 1978). Because TTB depends on an approximately correct cue order, it will not be able to perform well without good feedback (though in addition to individual learning, cue orders can also be acquired by social learning).

Second, clinicians might refrain from using simple heuristics because they are often held accountable for their decisions. Studies by Tetlock and his colleagues (Tetlock, 1983; Tetlock & Kim, 1987) show that when decision makers have to justify their decisions, they engage in more thorough information processing. Thus, one might well expect that rather than relying on heuristics that ignore part of the information (such as TTB), clinicians engage in comprehensive and compensatory information processing.

In sum, although Meehl laid bare the inferiority of clinical compared to actuarial models, while fast and frugal heuristics, proposed as accounts of clinical judgment, were shown to outperform actuarial models, the conclusions of the two research programs are not necessarily in conflict. Rather, they can be seen as complementary. Work on fast and frugal heuristics highlights the conditions necessary for intuitive judgment to be accurate (in particular, accurate feedback), and Meehl's findings might indicate that these conditions are not always present in the clinical practice.

Meehl and Fast and Frugal Heuristics: Connections?

If Meehl had constructed process models of clinical judgment, what would they have looked like? Although we are left to speculation, it is likely that two

characteristics would have featured prominently. The first concerns the domain-specificity of human judgment. Meehl emphasized that rather than invariably relying on one general tool, judgment processes might vary between different judgment tasks. In particular, he pointed out that creating a psychological model of the patient—*diagnosis*—is different from *prognosis*. In prognosis, the doctor makes a prediction about how the patient's condition will develop in the future. In both cases, judgments are made, but the information available to the clinical judge is different. Diagnosis unfolds over time as the product of an extended interaction between judge and patient, whereas in prognosis, the judge is simultaneously presented with all available information and cannot refine his or her prediction over time. Prognosis can use the results of diagnosis, but not vice versa.

A second feature concerns the nonlinearity of human judgment. Meehl questioned whether linear models capture the very essence of human judgment (Meehl, 1954, p. 47). Rather, he likened the processes underlying diagnostic prediction to the 'psychological process … involved in the creation of scientific theory' (p. 65), with recurrent generation, testing, and refinement of hypotheses (cf. Fiedler, 1978). Underlining his view that nonlinearity constitutes an important characteristic of human judgment, he wrote: 'The clinician, if sufficiently experienced, might be able to discriminate quite complex and subtle higher-order patterns reflected in the visual profile form' (Meehl, 1959, p. 106).

In the following, we describe fast and frugal heuristics in greater detail, arguing that they offer models of human judgment that accommodate these very two features. Moreover, we show that in fast and frugal heuristics, nonlinear judgments arise from the bounded nature of human cognition. The section concludes by discussing how other models of judgment proposed in the literature tackled the issues of domain-specificity and nonlinearity of human judgment.

Domain-Specific Tools for Clinical Judgment: Ecological Rationality

In the preface of his book, Meehl points out that prognostic and diagnostic tasks call for different prediction methods. He writes: 'There is no convincing reason to assume that explicitly formalized mathematical rules and the clinician's creativity are equally suited for any given kind of task, or that their comparative effectiveness is the same for different tasks' (Meehl, 1954, p. vi.). At the end of the book, he continues the discussion of the differences between prognosis and diagnosis. In pure prognosis, '*all bad ideas tend to subtract from the power of good ones*' (p. 121, emphasis added). A prognostic judgment is made at one point in time, based only on the information available at that point. In diagnosis, in contrast, a prediction is generated differently. Specifically, the clinical judge can operate by trial and error and interact extensively with the patient, collecting new information in order to test and refine his or her hypotheses. Bad ideas are not necessarily damaging in this context. On the contrary, they can trigger good hypotheses:

> Nobody knows what the payoff rate is for these moment-to-moment guesses that come to therapists; but the overall success frequency might be considerably less than 50 percent and still justify the guessing. ... Even if the to-be-discarded hypotheses were pure filler, they would not impede the therapy except as they consumed time. (Meehl, 1954, pp. 120–121; 1989, p. 360)

In sum, by highlighting the differences between prognosis and diagnosis, Meehl emphasizes that the informational structures in these two tasks differ, and thus different processes may apply to perform them.

How should this task- or domain-specificity be accommodated in formal models of human judgment? The fast and frugal heuristics program provides one suggestion (Gigerenzer et al., 1999; Todd & Gigerenzer, 2000). Here, domain-specificity is closely linked to the notion of *ecological rationality*, according to which cognitive processes are not only sensitive to, but even exploit the informational structures of the environments in which they operate (see also Brunswik, 1955; Simon, 1956). Because different domains have different structures, ecologically rational processes need to vary across them.

For example, when German students were asked to decide which of two objects has a larger value with respect to a criterion, say, which of Detroit or Milwaukee has more inhabitants, they seemed to be using the *recognition heuristic* (Goldstein & Gigerenzer, 2002). This heuristic follows a simple rule: If you recognize only one of the two objects, infer that it has the larger criterion value. This prediction holds irrespective of all further cue knowledge that the judge has, making the recognition heuristic a noncompensatory strategy. Goldstein and Gigerenzer (2002) found that people followed the heuristic in 90% of the cases where it could be used. Moreover, in a series of experiments by Pachur, Bröder, and Marewski (2008), many participants chose a recognized over an unrecognized object, even when they had learned three valid cues about the recognized objects that contradicted recognition. People may use recognition information partially because it is provided by the mind at a low cognitive cost (Pachur & Hertwig, 2006). Perhaps more importantly, the recognition heuristic also exploits an environmental regularity. Specifically, it has been shown that recognition is positively correlated with a number of variables in the world such as geographical quantities (Goldstein & Gigerenzer, 2002; Pohl, 2006), quality of American colleges (Hertwig & Todd, 2003), success in sports (Pachur & Biele, 2007; Serwe & Frings, 2006; Snook & Cullen, 2006), political elections (Marewski, Gaissmaier, Dieckmann, Schooler, & Gigerenzer, 2005), and, to some extent, disease incidence rates (Pachur & Hertwig, 2006). Crucially, people's use of the recognition heuristic seems to be highly sensitive to differences in the statistical structure in the environment (Pachur, Todd, Gigerenzer, Schooler, & Goldstein, in press).

A second example of an ecologically rational inference tool is the Take The Best heuristic (Gigerenzer & Goldstein, 1996). The heuristic applies when both objects are recognized and assumes that to render a judgment further

cues (beyond recognition) are searched. Using again the city example mentioned above, such cues could be the presence of a university or the existence of a soccer team. The cues are inspected sequentially in order of decreasing validity (defined as the probability of a correct response based on the cue given that the two options have a different value on the cue). TTB makes a decision based on the first cue that discriminates between the options, and all further cues are ignored. Like the recognition heuristic, TTB is thus a non-compensatory strategy. If, for example, the task is to infer which city, Nuremberg or Leipzig, is more populous, someone who recognizes both cities would then look up the most valid cue, say, the university cue. Because both cities have universities, the next most valid cue would be considered. Assuming that this is the soccer cue, Nuremberg—which has a team—will be picked because Leipzig does not have one.

Like the recognition heuristic, TTB is adapted to certain structures in the environment, of which we mention three. First, when the regression weights are distributed in a noncompensatory way, that is, the weight of each cue is larger than the sum of the weights of the cues that are looked up after this cue in TTB, multiple regression cannot be more accurate than TTB (Katsikopoulos & Fasolo, 2006; Martignon & Hoffrage, 2002). Second, if cue validities are highly dispersed (for the precise meaning of this, see Katsikopoulos & Martignon, 2006) and cues are conditionally independent given the values of the objects on the criterion, then no method—linear or nonlinear—can be more accurate than TTB. Further conditions under which TTB is a rational strategy have been explored by Hogarth and colleagues (Baucells, Carrasco, & Hogarth, in press; Hogarth & Karelaia, 2005a, 2005b, 2006). Third, TTB tends to perform better than a unit-weight model in scarce environments, that is, where only rather few cue values are known (Martignon & Hoffrage, 2002).

There has been considerable work on the descriptive adequacy of TTB, and the evidence suggests that people use this heuristic in an adaptive manner. First, time pressure seems to increase people's use of TTB (Rieskamp & Hoffrage, 1999). Second, the cost of information acquisition affects whether people choose TTB or a compensatory strategy: When the cost of memory retrieval (Bröder & Schiffer, 2003) or information search (Bröder, 2000; Newell & Shanks, 2003) is high, people seem to rely on TTB. Moreover, there is accumulating evidence that people can learn to use simple strategies when it pays off to do so (Bröder, 2003; Rieskamp & Otto, 2006). In sum, empirical work on fast and frugal heuristics demonstrates the contingent nature of people's strategy use and that different processes are at work in different domains.

It should be noted that adaptive decision making has its assumptions. Specifically, the claim that constraints of limited time and cognitive resources should lead to a switching to simpler strategies (e.g., Payne, Bettman, & Johnson, 1993), possibly by forgoing some accuracy, presumes that the decision maker is able to reliably assess the complexity (i.e., the cognitive costs) and accuracy of different strategies. Although there is a large literature that

suggests that decision makers are poor judges of the *absolute* accuracy of the strategies they are using (e.g., Einhorn & Hogarth, 1978), people seem to be able to distinguish between different strategies in terms of their *relative* costs and accuracies (Chu & Spies, 2003).

We now turn to another key concept of fast and frugal heuristics, which is inspired by Simon (1956): the notion of bounded rationality. In particular, we illustrate how nonlinearity can arise from this notion.

Fast and Frugal Heuristics: Nonlinearity as a Consequence of Bounded Rationality

Meehl emphasized that clinical prediction is usually made under considerable time pressure, with limited information, and a paucity of feedback. Put differently, the resources of the clinician are bounded. As Meehl (1954) phrased it:

> … it is impossible for the clinician to get up in the middle of an interview, saying to the patient, 'Leave yourself in suspended animation for 48 hours. Before I respond to your last remark, it is necessary for me to do some work on my calculating machine.' (p. 81)

Clinical prediction has to be done on-line, at least most of the time. Of course, today's clinicians have access to sophisticated data records and computational tools—it is, however, still the case that a lot of clinicians' judging and deciding has to be done while they are examining their patients.

Though clearly acknowledging it, Meehl did not elaborate on the theme of bounded rationality. Nor did he attempt to connect it with the challenge of developing nonlinear models of the cognitive processes underlying judgment. In fast and frugal heuristics, nonlinearity is a consequence of bounded rationality. Specifically, as time and computational resources in the clinical practice are scarce, fast and frugal heuristics follow simple rules. This simplicity gives rise to a *specific* kind of nonlinearity.

So how does nonlinearity arise from simplicity? As pointed out before, fast and frugal heuristics (e.g., TTB or the recognition heuristic) do not integrate cues and are thus noncompensatory. A decision is made after looking up only a fraction of the cues, and sometimes only one. For instance, someone using TTB decides on the basis of only the first discriminating cue. Irrespective of how many cues contradict this discriminating cue, they cannot override it. Avoiding the integration of cues makes fast and frugal heuristics nonlinear. In contrast to linear models, where a judgment is always derived from the integration of all cues $x_1 \ldots x_n$ for the objects A and B (e.g., $Y = \beta_1 x_{1A} - \beta_1 x_{1B} + \beta_2 x_{2A} - \beta_2 x_{2B}$; there are two cues and β are the cue weights), in TTB, the cue determining the judgment can vary depending on the pattern of cue values (e.g., if $x_{1A} \neq x_{1B}$, $Y = x_{1A} - x_{1B}$ but if $x_{1A} = x_{1B}$, $Y = x_{2A} - x_{2B}$). Taken together, fast and frugal heuristics are one way to provide nonlinear models of human

judgment, and their nonlinearity arises from their simplicity—particularly, the noncompensatory nature of the information processing.

By connecting simplicity and nonlinearity, the fast and frugal heuristics program brings together concepts that have been studied since the early days of research on judgment and decision making. For example, Kleinmuntz (1963) modeled experts' interpretation of MMPI scores with nonlinear configural rules and showed how these rules can be viewed as actuarial methods that can improve judgment. Early attempts to formally model the cognitive processes underlying judgment using configural rules have been undertaken, for instance, by Einhorn, Kleinmuntz, and Kleinmuntz (1979). Compared to the configural rules that were designed for a specific application (i.e., diagnosing a patient based on the MMPI score), however, fast and frugal heuristics are more general. Specifically, being composed of building blocks, they can be used to model processes under a wider range of situations. To illustrate, TTB has a search rule (specifying how to search for information), a stopping rule (specifying when to stop search), and a decision rule (specifying how a decision is derived). In addition, the search, stopping, and decision rules of TTB are specified abstractly and not for concrete problems such as diagnosis based on the MMPI.

By emphasizing the notion of noncompensatory information processing, fast and frugal heuristics build upon the pioneering work by Einhorn (1970) on conjunctive and disjunctive rules. Note that lexicographic heuristics such as TTB can be mimicked by a combination of conjunctive and disjunctive rules (Katsikopoulos, in press; Rothrock & Kirlik, 2003). Using the example of comparing city populations by two cues, TTB predicts that Nuremberg is larger than Leipzig if at least one of the following conditions is satisfied: (1) Nuremberg has a university and Leipzig does not have a university; (2) Nuremberg has a university and Leipzig has a university and Nuremberg has a soccer team and Leipzig does not have a soccer team.

Nonlinearity and Domain Specificity in Other Models
of Human Judgment

It would be wrong to say that research in the wake of Meehl (1954) has ignored the challenges of domain-specificity and nonlinearity that he posed to the study of human judgment. In the following we briefly discuss how Meehl's challenges were taken up in other prominent approaches in the judgment and decision-making literature.

As mentioned earlier, Meehl's (1954) results spurred efforts to better understand the cognitive processes underlying clinical judgment. Ironically, much of the descriptive research he inspired relied on models that assume a linear combination of various pieces of information (Hammond, 1955; Hoffman, 1960), that is, the very type of model that Meehl had used to characterize actuarial methods (though these early approaches do not uniformly

claim that linear models describe the cognitive processes of human judgment: B. Brehmer, 1994; see also Gigerenzer & Kurz, 2001).[1] The main conclusions of this descriptive research on linear models can be summarized as follows (B. Brehmer, 1994): Across a wide range of situations, linear models do a very good job of predicting the clinical judgment at a fixed point in time and the inclusion of nonlinear elements increases the predictive power only slightly (Slovic & Lichtenstein, 1971).

Some researchers took these results as indicating that, essentially, the cognitive process involved in judgment is linear (A. Brehmer & Brehmer, 1988). Others remained skeptical of this approach and developed models that use configural cues (e.g., Ganzach, 1995; Goldberg, 1971; Wiggins & Hoffman, 1968). In these *configural models*, it was assumed that people are sensitive not only to cue weights, but also to the interactions between cues. By this virtue, these models were able to account for nonlinear judgments. Though capturing one of Meehl's challenges, configural models were problematic in other respects. For instance, given their high complexity, configural models do not appear as plausible models of bounded rationality.

The issue of bounded rationality was taken up by an alternative account of nonlinear cognitive processes that emerged in the early 1970s. From their extensive review, Slovic and Lichtenstein (1971) concluded that 'subjects are processing information in ways fundamentally different from … regression models' and called for 'more molecular analyses of the heuristic strategies that subjects employ when they integrate information' (p. 729). A few years later, Kahneman and Tversky's 'heuristics and biases' program took on that challenge and broke both with the linear model and the configural model approaches (Tversky & Kahneman, 1974). Instead, it was proposed that decision makers often use nonlinear and simple mental shortcuts. For instance, according to the representativeness heuristic (Kahneman & Tversky, 1973), when making a prediction, people attend to the representativeness rather than the predictive power of information.

Although Meehl's challenges were thus taken up by subsequent research, no single approach was able to address all of them simultaneously. Concerning the nonlinearity challenge, the configural model and the heuristics and biases approaches offered a solution. This virtue, however, came at the price of models that were either too complex to be a valid description of the decision maker, or too vague to render specific predictions (Gigerenzer, 1996).

In addition, none of the approaches provided a strictly domain-specific account. One could object that by using varying cue weights in different contexts, linear models are able to capture processing changes across domains. But the pattern of changes in cue weights does not by itself show what the underlying process is. More generally, no attempt was undertaken to account for the interplay between strategies and environments, necessary for an understanding of the psychology of domain-specificity (but see Payne et al., 1993).

To summarize, in this section we argued that the concern with domain-specific, nonlinear models of clinical judgment is one shared by Meehl and the program on fast and frugal heuristics. By focusing on the differences between the two programs we will now attempt to elaborate in what way they can learn from each other.

Meehl and Fast and Frugal Heuristics: Mutual Lessons

Meehl emphasized that clinical prediction should and can be improved. He suggested replacing clinical judgment by actuarial methods, for instance linear models, *whenever* the latter are more suited. Clinicians, he argued, should dedicate their time and energy to the tasks that cannot be efficiently accomplished by actuarial methods, such as therapy. Nevertheless, Meehl was aware of the lack of impact his plea had on clinical practice, and he complained about it (see Meehl, 1989, p. 380).

What might be behind the little resonance that Meehl's plea had? One possible explanation is that traditional actuarial models place too high a demand on clinicians' time, information, and computational power (Kleinmuntz, 1990). Fast and frugal heuristics, by contrast, are specifically tuned to bounds of real-world decision making, while at the same time (as pointed out earlier in this article) carrying the potential of higher predictive accuracy than linear models. To illustrate the potential contribution of fast and frugal heuristics in the clinical domain, in this section we first review further evidence from the medical literature for the competitiveness of the heuristics. The point is to show that fast and frugal heuristics can be developed into actuarial methods. We see this development as fitting well with Meehl's (1954, p. 131) observation that actuarial methods do not have to be based on linear models. Then, we point out that whether fast and frugal heuristics are already part of the clinician's toolbox of mental strategies and might thus be more readily accepted as actuarial tools is only beginning to be examined by the fast and frugal heuristics program.

Heuristics Can Be Simple and Accurate

So far we have described fast and frugal heuristics only as descriptive models of human judgment. We now argue that these same models can inform how to develop actuarial methods that are both usable and accurate. We illustrate this claim with a model that is related to TTB, but tailored to the typical task in the medical domain: classification.

Green and Mehr (1997) tested the performance of a logistic regression model proposed by Long, Griffith, Selker, and D'Agostino (1993) against the performance of a so-called *fast and frugal tree* (Martignon, Vitouch, Takezawa,

& Forster, 2003) for deciding whether or not a patient has a high risk of ischemic heart disease and should thus be sent to the coronary care unit. Regression models are considered one of the most accurate methods for making such assessments. Surprisingly, however, the fast and frugal tree was more accurate than logistic regression: both models had almost perfect true positive rates, but the fast and frugal tree had a much lower false negative rate.

What are fast and frugal trees? Consider the following medical example. Should antibiotic treatment involving macrolides be prescribed to a young child suffering from community-acquired pneumonia? What makes this decision critical is that pathogens underlying this illness are often resistant to macrolides (Fischer et al., 2002). Therefore, physicians try to avoid prescribing heavy antibiotic medication to children and give macrolides only if a child's pneumonia is classified as a micro-streptococcal infection. Yet the macrolide decision needs to be made fast, as pneumonia spreads rapidly and can lead to more serious problems (including death).

The established technology for supporting decision making is known as decision analysis (see, e.g., von Winterfeldt & Edwards, 1986) and is heavily based on traditional normative models such as Bayes' rule and expected utility theory. The potential usefulness of decision analysis has also been recognized in the medical domain, and physicians are therefore often taught at least the basics of decision analysis. Nevertheless, physicians have started to point out the limitations of decision analysis for the clinical practice (Elwyn, Edwards, Eccles, & Rovner, 2001; Green & Mehr, 1997). Specifically, medical doctors still often feel at a loss when having to apply decision analysis on the spot; often, the information that is required by decision analysis is not available. Instead, they prefer to use simple rules that are easy to communicate to the patients and easy to apply.

For these reasons, a team of pediatricians (Fischer et al., 2002) proposed an alternative to the usual decision-analytic actuarial tools: Rather than consulting tables or other computation aids to integrate variables such as the probability and costs of pathogen resistance, Fischer et al. used a fast and frugal tree. The heuristic considers only two cues: whether the child was older than 3 years, and whether the child had had a fever for more than 2 days.[2] These cues were used because they are usually known and because they are very easy to evaluate. Of course, doctors have access to other cues as well (e.g., whether the patient had a micro-streptococcal infection before). However, as we will see below, the cues fever duration and age suffice to effectively tackle the problem of unwarranted macrolide prescription.

Now, the question is how to combine the cues. Recall that the primary goal is to guard against prescribing macrolides to children who do not need them. Thus, the cues can be combined so that macrolides are prescribed only when both cues suggest that the child requires this intervention. Fischer et al. (2002) proposed the following heuristic rule:

Prescribe macrolides only if the child is older than 3 years *and* the child has had fever for more than 2 days. Otherwise, do not prescribe macrolides.

How accurate is this simple heuristic? To evaluate its performance relative to an established benchmark, Fischer et al. compared it to the performance of a scoring system based on a logistic regression model. In contrast to the fast and frugal tree, the logistic regression always considered both cues and weighted them in an optimal manner. Although, when evaluated on real data, the fast and frugal tree decided for almost 40% of the children not to prescribe macrolides based on only the first cue, it overall correctly classified 72% of those children who actually were at high risk of micro-streptococal pneumonia infection; logistic regression identified 75% of them. In other words, in addition to its simplicity and transparency, the fast and frugal tree had a competitive accuracy.

This tree does not require the evaluation and combination of all possible outcomes for the options of prescribing and not prescribing macrolides. Rather, the cues are inspected in a simple sequential fashion, and if possible, a decision is made after looking up only the first cue, namely whether the duration of fever is shorter than 2 days. Only if the answer is 'no,' then is the second cue—age of the child—looked up, which then leads to a final decision. The heuristic can be visually represented as a tree (Figure 1). Note that a tree in which the cues are inspected in the reverse order would make exactly the same classifications.

This decision tree is frugal because it uses only one or two cues. In addition, it is fast because it processes each cue by just asking one single question. Informally, a fast and frugal tree is a classification tree where it is possible to make a decision and exit the tree after each question. Fast and frugal trees were first formally defined by Martignon et al. (2003), who also described general procedures for constructing them. Future work needs to elaborate how fast and frugal trees can be constructed in practice. One possible approach would be to use data from large clinical studies to identify highly valid cues and use those to build a lexicographic heuristic.

A complete theory of fast and frugal trees is not yet available, but their formal properties have been studied to some extent (Martignon, Katsikopoulos, & Woike, in press). Overall, there are good mathematical reasons why such trees are, under some conditions, *accurate* in fitting and *robust* in generalization. For example, they are robust because they do not attempt to model in detail the interdependencies between cues. Further research is needed to find the boundary conditions under which fast and frugal trees are accurate and robust.

How do fast and frugal trees relate to previous work on nonlinear models? It is instructive to note that the nonlinear configural rules identified in classic work in the judgment and decision-making literature (e.g., Einhorn et al., 1979; Kleinmuntz, 1963, 1990) can be combined to produce fast and frugal trees. Nevertheless, fast and frugal trees represent a special collection of rules: In contrast to the nonlinear configural rules, fast and frugal trees allow
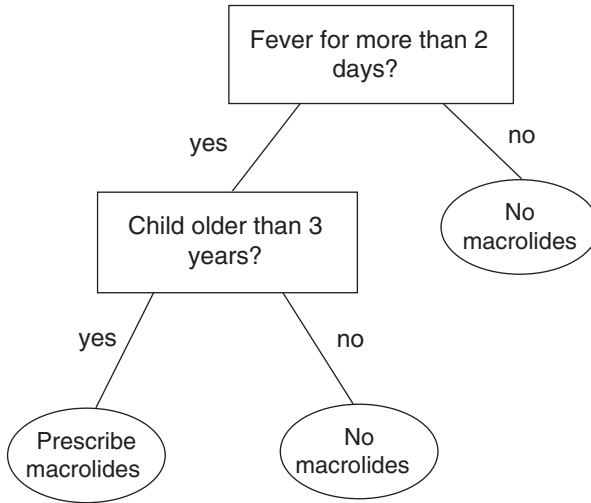
FIGURE 1. The fast and frugal tree proposed by Fischer et al. (2002) for making macrolide prescription decisions.

making a final decision and thus exiting the tree each time a rule is applied. To the best of our knowledge, this psychological structure is a novel one.

Acceptance and Use of Heuristics by Clinicians

Meehl was frustrated by the clinicians' reluctance to use actuarial methods for making predictions. Recently, Dawes (2002; Dawes et al., 1989) and Bishop (2000) have called for an increased use of actuarial methods. But there is little indication that these pleas have had much of an effect. A great deal of effort has been invested in to understand the reluctance to use actuarial methods more (for a review, see Kleinmuntz, 1990). One common argument is that it is unclear to the physicians that the benefits of using actuarial methods outweigh their costs.

Although we agree that this might go some way toward explaining the resistance to actuarial methods, we suspect that the main reason hindering their more widespread use is their complexity and lack of transparency. Fast and frugal trees, in contrast, are easier to communicate, understand, and apply than linear models (this hypothesis could be extended to include other fast and frugal heuristics)—a speculation physicians themselves seem to confirm (Elwyn et al., 2001; Green & Mehr, 1997).[3] One possible reason why fast and frugal actuarial methods could be accepted more in the clinical practice is that they bear resemblance to the mental tools physicians already have in their intuitive repertoire.

This brings us back to another of Meehl's challenges for the fast and frugal heuristics program: to test if these heuristics describe clinical judgment in professional decisions. So far, there is only indirect evidence for this claim, in the sense that, for instance, for aviation, medical, legal, and criminal decisions, professionals behavior often coincides with the heuristics' predictions (Bryant, 2007; Dhami & Ayton, 2001; Green & Mehr, 1997; Kee et al., 2003; Smith & Gilhooly, 2006; Snook, Taylor, & Bennell, 2004). As mentioned earlier, owing to factors such as accountability and incomplete feedback, clinicians might shy away from using fast and frugal heuristics, or, when attempting to use them, might not use them properly. On the other hand, heuristics are indispensable tools under conditions of limited time, information, and computational resources. Therefore, in spite of the accumulating evidence, future research will need to find out more about which simple heuristics clinicians use to deal with these bounds, as well as when they use such heuristics.

Conclusions

Meehl's *Clinical versus Statistical Prediction* (1954) is one of the classic contributions to research on judgment and decision making and one of the landmarks that gave rise to the field. It concluded that (unaided) clinical judgment is unable to outperform, and is usually inferior to, judgment based on actuarial models. The recent fast and frugal heuristics program seems to conflict with this conclusion, showing that simple heuristics, proposed as plausible models of clinical judgments, can outperform standard actuarial models.

In this article, we started by arguing that this contradiction may be more apparent than real. For instance, we proposed that clinicians, *when unaided*, might not always be able to properly apply fast and frugal heuristics. Furthermore, the two research programs address similar concerns. Specifically, we proposed that fast and frugal heuristics offer one way of providing models of human judgment that both are context-specific and nonlinear and also acknowledge the natural boundedness of human cognition—characteristics that Meehl viewed as fundamental to human judgment.

Moreover, we illustrated that the two research programs might enrich each other. On the one hand, the program of fast and frugal heuristics exemplifies how the clinical–actuarial divide can be bridged: For instance, actuarial methods could be improved by becoming faster and more frugal. Note that we do not advocate that clinicians be left alone to construct fast and frugal actuarial methods; owing to the lack of feedback in the clinical domain, they can be expected to have difficulty singling out the most valid predictors.

On the other hand, Meehl's work suggests that clinicians are not always using fast and frugal heuristics, or at least that they might not always be able to use them properly (otherwise they would have approximate or surpass the accuracy of linear actuarial methods). Thus, tests in the clinical domain pose an interesting challenge for the approach of fast and frugal heuristics.

Finally, we argued for actuarial methods that are fast and frugal, but emphasized that they are also friendly. Because evidence suggests that such simple but surprisingly accurate heuristics mirror the cognitive processes underlying judgment and are easy to understand and apply (e.g., Snook et al., 2004), they can be used as highly user-friendly actuarial methods. In addition, owing to their transparency, fast and frugal heuristics might allow clinical decision makers to still feel in control (Elwyn et al., 2001; Green & Mehr, 1997).

The inferiority of clinical to statistical judgment identified by Meehl (1954) need thus not lead to the conclusion that clinicians must be supplemented with complex prediction aids. Rather, as simple actuarial methods can achieve equally (or even more) accurate predictions and arguably are highly user-friendly to the clinician, they might hold promise to eventually improve clinical judgment.

Notes

1. Instead, researchers in the paramorphic tradition, such as Hoffman (1960), were merely interested in modeling the relationship between input variables and output variables in judgment and simply viewed linear regression as a conventional tool to describe this relationship (see Kurz-Milcke & Martignon, 2002). In contrast to this 'as if' approach, proponents of the Brunswikian perspective (e.g., Hammond, 1955) appeared to take linear models as describing actual cognitive processes of human judgment.
2. We are not aware of the procedure by which it was decided to use these particular cut-offs for dichotomizing the two cues.
3. An interesting objection was suggested by an anonymous reviewer: First, instead of being too complicated, it is possible that linear models are not used because clinicians find them too *simple* and do not trust them to be effective. If this reasoning is valid, the simplicity of fast and frugal heuristics might even reduce, rather than increase, their acceptance in the clinical practice.

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