

Implications of Decision Psychology for Classical Notions of Rationality

Paul J. H. Schoemaker

The Wharton School

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Implications of Decision Psychology for Classical Notions of Rationality¹

Paul J. H. Schoemaker
The Wharton School
University of Pennsylvania
Philadelphia, PA. 19104

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Much of Howard Kunreuther's research has focused on the descriptive as well as prescriptive limitations of the expected utility (EU) model, with a special interest in low probability catastrophic events. His wide ranging interests cover the individual, group, organizational and societal levels, and Howard has always shown a great sensitivity for the perspectives of other disciplines, from anthropology to cognitive psychology. This is remarkable for someone trained in economics and management science, and a tribute to Howard's deep curiosity and open mind about human behavior. His intellectual forays into adjacent and distant domains helped many of us realize that real-world decision making is highly sensitive to context as well as people's information processing strategies. It is unlikely that elegant parsimonious models such as EU or prospect theory (PT), or any of the numerous variations of generalized utility models that blossomed later, can do justice to the many factors that influence people decisions under risk and ambiguity. Moreover, I shall argue that our classic models of rationality, such as expected utility theory and subjective probability theory, can no longer retain their normative status unblemished.

Some Personal History. I was fortunate to meet Howard after he left the University of Chicago for Wharton in the mid 1970s. I was a PhD student in the newly formed Department of Decision Sciences at Wharton and took Howard's doctoral course on decision making. This course changed the direction of my own research. I switched from my PhD in finance into that murky new field called decision sciences. I had always been intrigued about uncertainty, first as a physics major in college and later in terms of how capital markets price risk. But Howard exposed me to a host of anomalies and behavioral perspectives, ranging from the Ellsberg (1961) and Allais (1953) paradoxes to the fascinating work being conducted by Paul Slovic and colleagues, as well as the path breaking work of Kahneman and Tversky (1973). As a result, I quickly became a lost cause for finance where the overly rational Sharpe-Lintner model of capital asset pricing then held sway. I asked Howard to be my thesis advisor; he proved to be a remarkable coach, teacher and friend. We would meet on weekends at his

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house to discuss my experiments, and then play some tennis afterwards or have a drink with Sylvia.

Much influenced by Howard, my thesis examined where and why the EU model failed to describe or predict insurance behavior. I used field surveys and experimental data collected from policy holders of a friendly insurance agency to show that framing and context effects greatly influenced insurance behavior. We published some of this research jointly (Schoemaker and Kunreuther, 1979). Later, with Jack Hershey, we explored why utility functions - as one crucial ingredient to rational choice under risk - were hard to construct and validate in clinical settings (Hershey, Kunreuther and Schoemaker, 1982). During that time, Howard had received a major NSF grant to study flood and earthquake insurance, which yielded multiple influential publications with colleagues plus a seminal book (Kunreuther et al., 1978). All this fervor around the failings of the rational model, plus our desire to define the field of decision sciences more clearly, compelled Howard, Paul Kleindorfer and me to take a stab at writing a graduate text on decision sciences. It was a rather ambitious project aimed at summarizing what was then known descriptively, prescriptively and normatively about decision making at the individual, group, organizational and social levels. It took us about ten years to complete the book (Kleindorfer, Kunreuther and Schoemaker, 1993) and has yet to be updated (don't hold your breath).

An Interesting Conundrum. At one level, behavioral decision theory (BDT) was a blessing for EU as a prescriptive model since it further underscored that people, when left to their own devices, often make unwise choices. So, the need for decision analysis and other forms of decision support seems strengthened by the avalanche of studies on framing, heuristic induced biases, and context effects. But at another level, this research also undermined some core premises of the prescriptive model, concerning the operational feasibility of EU on both the probability and utility side. Research by Howard, focusing on the loss side and ambiguous probabilities, showed that people were rather confused and often sub-optimal in their insurance decisions. For example, they would decline flood and earthquake insurance even when these were heavily subsidized by the Federal government. And yet, people would gladly buy very expensive air-accident insurance (from machines placed at airports) or opt for costly insurance policies with low deductibles. How could people be saved from their own folly? Was it really just a matter of sitting down with a decision analyst, either in the form of a person or a software package, and construct a von Neumann-Morgenstern (NM) utility function? Many BDT types did not think it would be that simple. For EU to work its magic as a prescriptive model, the decision analyst would first need to capture the client's basic taste and preferences, and make sure that they do not violate the NM axioms. In addition, the person's subjective probabilities have to obey various probability axioms that define what it means to have a coherent belief system. Without these basic inputs, the EU model cannot deliver on its promise.

It was clear from various studies, especially the interesting simulated debate between Maurice Allais and Jimmy Savage, that people did not buy into the axioms (Slovic and Tversky, 1974). Many sophisticated subjects would rather violate the independence axiom than change their preference. And on the probability side, more would line up with Ellsberg than Savage when presented with the Ellsberg paradox. Yes, you can perhaps persuade people to revise their preferences and beliefs to comply with the dictates of EU and Bayes, but what then do these preferences represent? Do such artificially constructed measures really capture people's true values and beliefs about risk and return; indeed, do they really measure anything at all Fischhoff (1991) asked? For example, we can counsel people not to pay attention to feelings of regret, either pre or post the decision. But if these sentiments run deep, they cannot be ignored and indeed should not. As Pascal warned, the mind can never fully know what stirs the heart. Telling a child not to be afraid after seeing a scary movie is not necessarily helpful – narrow rationality does not always win and therefore need not always prevail. Howard saw similar forces at work in his field studies of people's reluctance to buy subsidized insurance when living in a flood plain. He focused on the weakest part of the rational model, namely losses and ambiguous probabilities. Over time, this line of research transformed Howard from a rational economist to a behavioral scientist (i.e., an irrational economist), with a rich blend of the best that these two perspectives have to offer when dealing with complex policy questions.

The double edged implication of BDT, on the one hand supporting the need for more analysis to overcome the evident weaknesses of unaided decision making, while on the other hand also undermining the very edifice of rationality of which EU is an exponent, has not been as fully appreciated in the decision making literature as it should. The normative and descriptive camps are like two ships passing in the night, with limited cross fertilization and synthesis. Of course, the normative model was important in defining various biases and evaluating heuristics, but in doing so also questions were raised about the normative benchmarks used (e.g. Gigerenzer, 2003). Whereas few doubt that BDT has revealed the descriptive inadequacy of EU, few would claim that it has wounded its normative status. I shall try to argue the latter view, building on Howard's research that process and context variables, as well as emotional and social factors, are so central in human choice that they render much of the normative EU apparatus inadequate to the task it claims to solve. In addition, I shall comment on what else we can do to improve decision making, since the prescriptive challenge remains of how to improve real world decision making.

Decision Education Foundation. A few years ago I joined the Board of the Decision Education Foundation (DEF), a philanthropic organizations in Palo Alto aimed at improving decision making among adolescents and adults. This organization was founded by Ron

Howard from Stanford (a pioneer of rational decision engineering) with principals of the Strategic Decisions Group (SDG) including Carl Spetzler, Tom Keelin, and Jim Matteson. Our foundation has raised several million dollars and we run summer programs for high school teachers across the country to teach them the basic principles of decision analysis and behavioral decision theory (see www.decisioneducation.org). The aim is to make the teachers our partners in providing high school students with the decision skills needed to live happy and productive lives. Each teacher can adopt key elements in his or her curriculum as appropriate. So, algebra or statistics can be taught using expected value/utility or decision tree ideas, and framing issues can naturally be woven into an English course or history. Our belief is that high schools do not equip students sufficiently to deal with the complex world they live in, as evidenced by high dropout rates, violence, teen pregnancy and drug abuse. Rather than preach to these students to “just to say no” to drugs, violence and other temptations, we encourage them to think through the issues they face and give them the tools to do so.

The decision model we use is the one SDG so successfully deployed to become the largest consultancy focused on decision making, in the domains of business and government. I am using SDG framework here (see Fig. 1) since it offers a broad, well-tested view of what constitutes good decision analysis, including both the sufficient and necessary conditions (within SDG’s view). The model allows much leeway in how each link is improved and the aim is not to be perfect in each link but rather to get to a point where further improvement is not worth the cost. At first glance, this seems a very sensible prescriptive model, aimed at overcoming the many cognitive and emotional challenges that so often stand in the way of good decisions. It reflects the basic tenets of classical rationality models while offering a practical roadmap to guide the decision process along. But as Howard’s work also shows, reality is often very complex and cannot always be tamed and conquered by these models. So, our DEF curriculum pays much attention to behavioral obstacles and decision traps to make sure that a balanced approach is offered of both DA and BDT (see Keelin, Schoemaker, and Spetzler, 2006). Importantly, findings of BDT also present some challenges for DA and other prescriptive models, in addition to being complementary to it, and this has been less well addressed in the normative decision literature.

For example, the metaphor of a chain with six links implies that the weakest link defines the quality of the overall decision efforts. Also, a key distinction is made between the characteristics of a good decision (reflecting the criteria in Fig. 1) and the process for making a decision. Just as the elements that define a good car or a fine meal can be separated from the process used to produce each, SDG applies the same separation principle to decision making. Fig. 1 is meant to offer a snapshot at a given point in time about the quality of the decision, in order to judge if more work is needed. Fig. 1 is silent on which methods to use to improve any one link, although SDG has a broad tool kit for this. Naturally, the methods include decision trees, utility functions, and value of information calculations (Raiffa, 1968).

The basic idea is to undertake actions that move the cursor in each link to the right, while periodically taking stock of the links profile (as in Fig. 2), in order to improve the link that is most deficient. SDG iterates this process until the optimal point is reached for each link, without overshooting any of the six targets.

Although the SDG model is one approach to applying the classical decision model, it shares various key elements with other DA approaches (such as Keeney, 1992). First, they all pursue a divide and conquer strategy, breaking down the decision into *independent* components. This independence assumption is critical to the normative approach, and one BDT has cast doubt upon. Can people really separate values from beliefs? Second, the approach all try to customize the analysis by capturing attitudes and values that are specific to the decision maker (such as subjective beliefs, value trade-offs and risk-aversion). Third, once the component pieces are ready, they are aggregated using normative principles, such as expected utility theory, probability axioms and predicate logic (or other types). Fourth, some form of sensitivity analysis (e.g., tornado diagram is usually conducted to assess which assumptions and other inputs are most in need of revalidation or more precise estimates. Fifth, most DA assumes that decision makers cannot perform the necessary calculations in more informal ways, for example through intuition. The analytic machinery is especially needed to overcome computational complexity, although it can also help perhaps with conceptual and/or value complexities. How well this classic rationality approach works in practice, however, hinges greatly on deeper behavioral issues, as discussed next.

Limits of the Rational Model. I shall address here why and where behavioral perspectives need consideration, starting with the fundamental *decomposition* and *aggregation* assumptions underlying the classic normative model and its application in DA. The decomposition of a decision into components (such as the six links) is behaviorally problematic if humans are not capable of doing so. Consider the most basic decomposition of DA, namely separating beliefs from values. In theory, my subjective probability that tomorrow will bring rain should not be influenced by whether I have a garden party planned or not for tomorrow. But behaviorally it does. Many people suffer from wishful thinking (and some from excessive pessimism), and admonishing them not to do so only goes so far. Deep down, human beings exhibit a wide array of foibles, twitches, quirks that interfere with the rational model. Consider extreme cases, such as trying to get a child suffering from attention deficit disorder (ADD) to engage in a utility elicitation exercise, or an autistic child in expressing subjective beliefs. As well intentioned as classic rationality is, at a deeper level it runs into the very human obstacles it seeks to overcome. I use these extreme cases to point out that classical rationality has its limits, and that BDT research is revealing its limitations more and more. In some sense, we all suffer a bit from ADD and autism, and DA therefore needs to adapt more to us rather than the other way around.

But suppose we actually manage to separate beliefs and values, then the next step in DA is to measure each component further, via subjective probability and utility. This seems rationally straightforward (just ask people some questions), but is behaviorally far more complex. Decades ago, Spetzler and von Holstein (1975) enumerated important biases that complicate probability encoding in clinical settings, from anchoring effects and availability biases to wishful thinking and overconfidence. They also proposed various antidotes to such biases, in an effort to make the encoding process more robust. However the effectiveness of such procedures remains in doubt since subsequent research has shown that de-biasing seldom works (Fischhoff, 1982). Hershey, Kunreuther, and Schoemaker (1982) provided a similar analysis on the utility side, identifying five factors that can significantly affect the shape of the utility function. These factors concern the elicitation methods used for reference gambles, whether the risk was transferred away or assumed, the domain of the gambles (pure gain, mixed or pure loss), the stimuli levels chosen for the probabilities and the payoffs, and the broader context of the reference gambles (from abstract to real-world such as a hypothetical insurance decision). Subsequent work by Hershey and Schoemaker (1985) revealed some of these biases to be deep and not readily rectified. Subjects' responses to elementary gambles represent a complex mix of signal, bias and noise (Schoemaker and Hershey, 1992).

In addition to concerns about the decomposition premise, the rational model encounters aggregation problems. For example, SDG defines overall Decision Quality (DQ) of a given decision as $DQ = \text{Min} [L1, L2, \dots, L6]$, where L_i is the score achieved for link i . The weakest-link notion implies that if a problem is not framed well, working harder on finding better alternatives is a waste of effort. The key in this model is to achieve 100% on each dimension since 100% is defined as the point where additional work not worth its marginal cost. In essence, this view requires a complex portfolio dance, across the attributes, since it runs into the issue of multi-stage complexity. We need to judge how far to improve any one attribute before knowing the cost and benefits of this effort, as well as the limiting scores eventually posted by the other attributes. Let's assume we are at a stage in the decision process where the DQ vector is scored as [30, 60, 40, 80, 50, 90]. In judging how much more effort to put into L1, which is weakest link and thus limits DQ to 30, we must also recognize that the next limit will be L3. Hence, the decision to improve L1 must nest within it the potential gains to be achieved from L3, while further realizing that L5 will become critical thereafter, etc.

It will be suboptimal to improve each link to the next weakest link, improve that new link, and then revisit the original link given the new floor. The key is to balance wasted effort due to incremental myopia against waste stemming from overshooting on any one link. This meta-decision, about how best to approach the original decision, is itself complex and uncertain. It is not clear that it can be solved with the standard framework of Fig. 1; and if it could, we may encounter an infinite regress dilemma. The best we can probably do is to pursue a gradient search algorithm driven by a mix of intuition and analysis. The intuition connects directly with BDT in terms of when it can be trusted, how to hone it, and when to challenge it.

Moreover, the gradient search approach is only a good guide if we are dealing with concave functions. For example, if the link called Creative Alternative Generation contains an inflection point in the benefit curve, then stopping at the margin may yield a local optimum rather than a global one.

Uncertainty and Nestedness. Howard Kunreuther's work acknowledges that uncertainty and nestedness the two interconnected problems discussed above, often complicate not only descriptive analyses of why people behave as they do, but also the prescriptive tasks of offering practical advice that works. Although normative theory can guide such prescriptive work, it runs the risk of excessive abstraction (a common trap for economists and decision analysts) such that the baby gets thrown out with the bathwater. Consider the kinds of problems Howard has studied: persuading people to buy highly subsidized flood and earthquake insurance, reducing the construction of expensive homes along a shore where hurricanes are frequent, deciding where to locate hazardous facilities, creating a market for catastrophe bonds, and how to handle terrorist insurance. In each of these we encounter a multi-layered decision making process, multiple stakeholders, information processing limitations, legitimation challenges, high uncertainty and ambiguity, and major loss exposures with low probabilities. The rational model for risk underwriting (such as EV or EU) may not work when facing ambiguous probabilities, relating to say terrorism or global warming.

BDT is needed to understand where and why various biases stand in the way. Attempts to debias decision makers – by providing incentives, education, additional information, or fines and regulations – requires sensitivity to unintended consequences that are largely behavioral in nature. For example, when car drivers are forced to wear seatbelts they tend to drive faster, or when bike riders wear helmets, cars tend to pass them more closely than they otherwise would. Such system dynamics, stemming from homeostatic risk behavior, misaligned incentives or non-linear feedback loops, illustrate that complex problems seldom yield to a simple, linear solution. Howard and I once detailed these challenges in the context of motivating insurance agents to offer homeowners socially desirable policies against flood and earthquake risk (Kunreuther and Schoemaker, 1981). Later, as I worked more in industry, especially in the areas of scenario planning, emerging technologies, entrepreneurship and innovation, it became clear that the world is far less stable and predictable than assumed in the rational models (Schoemaker, 2002). It also led me to argue in my academic writings that hyper rational approaches to strategy are misleading (Schoemaker, 1990) or that a basic DA notion such as intrinsic risk attitude is on shaky grounds behaviorally as well as conceptually (Schoemaker, 1993). Kleindorfer (2008) offers a wide ranging essay on uncertainty that further underscores the fragility of our classical rationality approaches to risk and complexity.

So, instead of strengthening the case of classic DA, decision psychology can as easily be interpreted as casting serious doubts on the behavioral validity of the premises underlying the normative edifice. It is doubtful that people possess the kind of well behaved preferences and

coherent beliefs, at the elemental level, that are necessary to make the normative model operational. Yes, we can coax people into reflecting on their inconsistencies and biases (defined relative to the normative model), and make a strong abstract case for the normative appeal of the axioms, but it cannot be proved a priori that doing so will yield wiser decisions. For example, if we have to send robots to Mars, to conduct research or harvest minerals, it is not clear that we would necessarily endow them with a decision making apparatus akin to DA. Some of the normative theory would surely be useful, such as updating the robot's belief system or choosing among uncertain courses of action. But some of the software will likely be heuristic in nature, adapted to specific tasks it might encounter (as with chess programs). And perhaps future robots, sent to Mars to create and maintain robot colonies, might even exhibit the kind of biases (emotional and cognitive) that we as human display after millennia of evolution. Garcia and Zangwill of the University of Chicago once tried to deduce the validity of the NM axioms from an evolutionary perspective but failed to prove that these axioms maximize genetic fitness.

How to Go Forward? The better we appreciate the complexities of human decision behavior, the more we also appreciate the limits of our normative apparatus and its associated tools. As is often the case with research, the more we know, the less we know. So, what to do? How do we give practical advice that acknowledges the complexities of the issues facing us while avoiding ad hoc prescriptions devoid of normative wisdom? This is where irrational economists can shine. We need to blend idealized normative precepts with real world messiness, and this requires art as well as science. Returning to the DEF task of improving the decision skills of adolescents, we need to blend a variety of approaches. First, we need to understand more deeply when, where and why teenagers go astray in daily life. Clearly, this varies by social class, culture and the characteristics of the child (e.g., age, gender, etc). Also, we need deep knowledge about developmental psychology since the adolescent's brain is still forming. Young people seem not to integrate emotion and reason as effectively as adults. Imaging studies suggest that the older brain shows less evidence of fear, anger and hatred than young adults who tend to be more impulsive and dwell on negative feelings (Cohen, 2005). Third, we need to decide what the focus of our efforts is: the person or the environment, and also whether we address each decision on its own merits or view it as one in a stream of decisions. Especially for adolescents, viewing decisions as vehicles to learn more about themselves and the world at large may be more important than optimizing any single decision in isolation, such as what summer job to take, who team up with for the prom, or what car to buy.

The prescriptive side of decision making can be approached in at least three distinct ways. Using a sports analogy, we can improve our tennis or golf game by (1) studying how ideally the game should be played, (2) focusing on our own characteristic weaknesses, and (3) changing the environment in which we play or practice to counter our natural biases. Classical rationality follows approach (1) in that we teach people how a decision should

ideally be made. In the context of a golf lesson, this means spending much time on achieving the textbook ideal in terms of the grip, stance and swing. And in more advance golf classes it means understanding the physics of our body, the club, the ball's trajectory and its behavior on the green (i.e., reading the grain or slope). Approach (2) would go light on the general theory at first and focus more on common as well as idiosyncratic traps. The golf coach might say, forget all the theory and just hit hundred balls so that we can see where your greatest weaknesses lie. For most people this results in focusing on the stance and grip, but perhaps also – for some people – on keeping their head still or have shifting their weight better during the swing. The key distinction is that approach (2) starts with specific behavioral observation, not general normative theory. Lastly, there is the approach of changing the environment through decision architecting (Thaler and Sunstein, 2003 and 2008). Once we know that people are subject to biases, such as anchoring in estimation tasks, we might change the environment to always offer multiple anchors. In golf, we may change the lighting for the indoor putting green to counter visual biases. Or we might discourage beginning players from tacking difficult courses, or teeing off the black tees, so that they don't overreach and develop bad habits in the process. For adolescents, we might disable the radio in the first year of driving, add a video recorder in the back of the car or install a tamper proof black box that records engine speeds and unusual break pressures.

As we struggle in DEF to find the right balance among these three approaches, it struck me that Howard Kunreuther developed an early intuition that all three are needed to solve the kind of complex decision problems he studied. Clearly, Howard was deeply rooted in the first approach, given his training and research in such optimality sciences as economics and operations research. But he also recognized quickly the value of the second approach, and became highly conversant with the psychology, sociology and even anthropology of risk-taking. Collaborating with colleagues from diverse disciplines, Howard conducted careful laboratory as well as field studies of say people's insurance choices, with the ultimate aim of improving individual, firm and societal decisions. And last but not least, Howard understood the power of decision architecting, and how to nudge people in the right direction, from how to present information to when to impose fines. It is rare to see such a fine blend of multiple approaches in one scholar and this is what makes his research so remarkable to me. Yes, to achieve all this, Howard did have to become an irrational economist, which early in his career may have seemed like a Faustian bargain (especially while still at the University of Chicago). But the wisdom of his choice became evident as his research added seminal new insights in theory and practice, at multiple levels of social aggregation. It was a very good bargain after all, and a fun journey of discovery to boot. I was privileged to share some of this exciting journey earlier in Howard's career and thank him deeply for it.

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Fig. 1 A Basic Decision Analytic Model

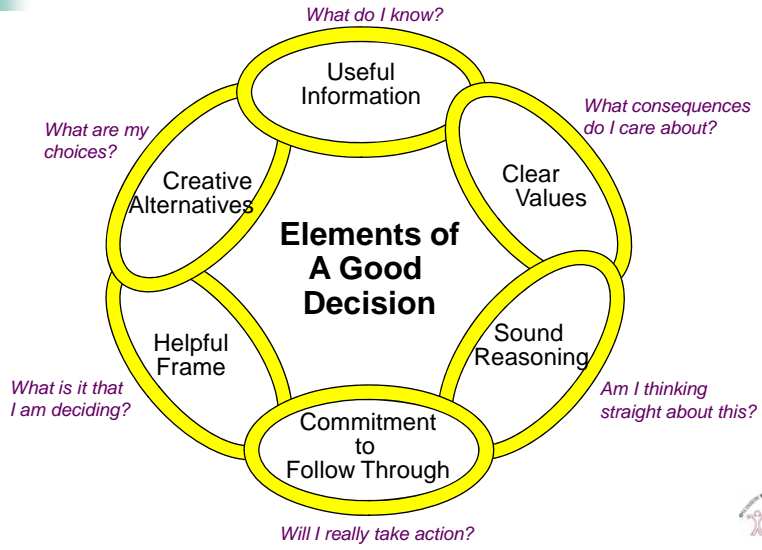
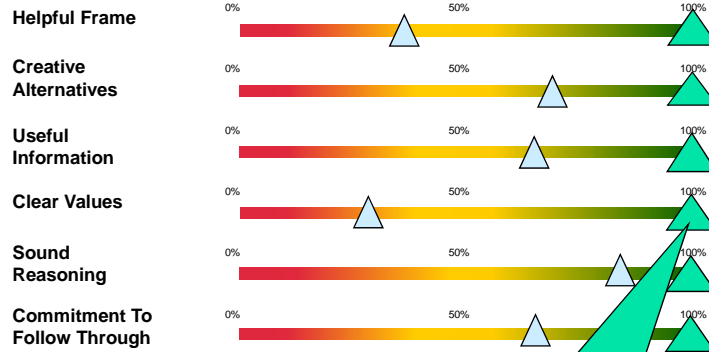


Fig. 2 Profile of A Decision's Quality

Good Decision Checklist

Decision Rating



100% is the point at which additional effort is not worth it.

