General-purpose institutional decisionmaking heuristics: The case of decisionmaking under deep uncertainty

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Abstract

Recent work in judgment and decisionmaking has stressed that institutions, like individuals, often rely on decisionmaking heuristics. But most of the institutional decisionmaking heuristics studied to date are highly firm- and industry-specific. This contrasts to the individual case, in which many heuristics are general-purpose rules suitable for a wide range of decision problems. Are there also general-purpose heuristics for institutional decisionmaking? In this paper, I argue that a number of methods recently developed for decisionmaking under deep uncertainty have a good claim to be understood as general-purpose decisionmaking heuristics suitable for a broad range of institutional decision problems.

1 Introduction

A persistent theme of recent work in judgment and decisionmaking is that rational decisionmakers often rely on cognitive heuristics to make quick and effective decisions in uncertain environments (Gigerenzer and Gaissmaier 2011; Shah and Oppenheimer 2008). More recently, it has been emphasized that not only individuals, but also institutions rely on heuristics (Bingham and Eisenhardt 2011; Eisenhardt and Sull 2001; Loock and Hinnen 2015).

One striking contrast between scholarly work on individual and institutional decisionmaking is that most of the institutional heuristics studied to date are quite firm- and industry-specific. This contrasts to the individual case, where many of the most familiar heuristics are proposed for use in a wide variety of problems and environments. This contrast raises a question: might there also be important families of general-purpose heuristics for institutional decisionmaking?

In this paper, I argue that a number of methods recently developed for decisionmaking under conditions of deep uncertainty have a good claim to be understood as general-purpose institutional decisionmaking heuristics, suitable for a wide range of problems involving institutional decisionmaking under conditions of especially deep uncertainty.[1] Here is the plan.

Section 2 summarizes what is known about individual and institutional heuristic decisionmaking, then argues for the need to identify general-purpose heuristics for institutional decisionmaking. Section 3 argues that we cannot solve this problem by importing familiar individual decisionmaking heuristics for institutional use. Section 4 introduces a class of decision procedures for institutional decisionmaking under conditions of 'deep' uncertainty (DMDU), and proposes that these methods be viewed as institutional decisionmaking heuristics.

I defend this heuristic interpretation in three parts. Section 5 argues that most DMDU methods bear four marks of heuristicality: characteristic features of heuristic decision procedures. Section 6 argues that DMDU methods have features that make them well-adapted to serve as general-purpose decision heuristics for institutional decisionmaking under deep uncertainty. Section 7 argues that a heuristic interpretation of DMDU methods can shed illuminating light on two objections to DMDU methods. Section 8 concludes.

2 Heuristic rationality for individuals and institutions

In this section, I survey the leading paradigms for heuristic cognition in individual and institutional decisionmaking. This survey will reveal a suggestive gap in the types of institutional decisionmaking heuristics proposed to date, which the rest of this paper aims to fill.

[1] For recent philosophical work on decisionmaking under deep uncertainty, see Helgeson (2020); Helgeson et al. (2018, 2021); Mogensen and Thorstad (forthcoming); Ongaro (2021) and Sprenger (2012).

2.1 Heuristics for individuals: The adaptive toolbox

Perhaps the best-known approach to heuristic cognition is the adaptive toolbox approach of Gerd Gigerenzer and colleagues (Gigerenzer and Selten 2001). This approach holds that human decisionmakers have access to an *adaptive toolbox* of fast-and-frugal heuristic strategies for decisionmaking. To say that toolbox heuristics are fast-and-frugal is to say that they are often quick to execute and place modest demands on cognitive resources such as memory, attention and computational bandwidth. To say that fast-and-frugal heuristics constitute an adaptive toolbox is to say that these heuristics are often well-adapted to the problems facing human decisionmakers, and to emphasize that part of the reason why toolbox heuristics are well-adapted for human use is that the heuristics as well as our tendencies to apply them have been shaped through a long process of human evolution, and not merely by the limited experience of individual decisionmakers.

A notable example of an adaptive toolbox heuristic is decisionmaking by satisficing (Selten 1998; Simon 1955). Satisficing decisionmakers fix an aspiration level in one or more goods. For example, a satisficing grocery shopper might aspire to purchase an apple that is ripe, unblemished, medium-sized, and costs under three dollars per pound. Satisficers then examine options one at a time, in this case by looking at apples in the grocery store. A satisficer evaluates each option against her aspiration level. If an option meets all of her aspirations, she halts decisionmaking by taking that option, in this case by buying the given apple. Otherwise deliberation continues until a satisfactory option is found.[2]

The rationality of heuristic decisionmaking is typically defended on three grounds. First, there is often an *accuracy-effort tradeoff* between the quality of decisions and the cognitive effort of making them. Heuristics frequently strike a good balance on the accuracy-effort tradeoff, returning high-quality decisions at low cognitive cost. Second, humans have limited cognitive abilities, as a result of which we are not always capable of applying complex non-heuristic strategies at any cost. And finally, in some situations *less*

[2]More sophisticated forms of satisficing incorporated needed bells-and-whistles, for example procedures of aspiration adaptation during decisionmaking (Selten 1998).

is more: heuristic strategies outperform nonheuristic strategies, even ignoring the costs of cognition (Geman et al. 1992; Gigerenzer and Brighton 2009). Roughly put, this happens because heuristic strategies are less prone to overfitting.[3]

There is nothing in the adaptive toolbox approach that rules out the application of toolbox heuristics to institutional decisionmaking. Indeed, it has been stressed that sometimes toolbox heuristics are appropriate for institutional use.[4] However, we will see in Section 3 that some differences between individual and institutional decisionmakers may serve to make adaptive toolbox heuristics less appropriate in many institutional decisionmaking contexts. As a result, most research on institutional decisionmaking heuristics has focused on identifying new strategies beyond the adaptive toolbox.

2.2 Institutional heuristics: The simple rules approach

Research on institutional heuristics has been dominated by the *simple rules* approach of Kathleen Eisenhardt and colleagues (Bingham and Eisenhardt 2011; Eisenhardt and Sull 2001). The simple rules approach stresses the need for institutions in 'high-velocity' business environments to make good decisions on a rapid timescale. It is held that organizations learn to balance flexibility and efficiency in decisionmaking by developing firm-specific portfolios of simple rules for decisionmaking. These rules come in several types (Eisenhardt and Sull 2001).

How-to rules say how a process is to be carried out. For example, Akamai Technologies requires customer service staff to answer all questions on the first call or email. *Boundary rules* say which opportunities may be pursued. For example, Cisco's '75% rule' requires acquired companies to have no more than 75 employees, at least 75% of whom are engineers. *Timing rules* specify the timelines on which activities must be carried out. For example, Nortel requires product development time to be under 18 months. And *exit rules*

[3]More precisely: heuristics sometimes strike the best balance between model bias and model variance, which together drive predictive accuracy.

[4]For example, the '$1/N$ rule' of allocating assets equally between N asset classes (Benartzi and Thaler 2001) is sometimes compared favorably to more complex strategies used by institutional investors (DeMiguel et al. 2009).

say when projects are to be halted. For example, Oticon required projects to be cancelled whenever a key team member decides to switch from that project to another.

Recent work has stressed a striking difference between the adaptive toolbox approach and the simple rules approach (Bingham and Eisenhardt 2014; Loock and Hinnen 2015). Whereas many toolbox heuristics such as satisficing are general-purpose strategies suitable for a large number of decision problems, simple rules heuristics are often quite firm- and industry-specific in at least two ways.

First, simple rules heuristics are specific in their *domain of applicability*, the problems to which they can be coherently applied at all. For example, Cisco's 75% rule governs only the decision of which companies to acquire, and Akami's rule of answering questions on the first call or email governs only a specific type of customer service interaction. These rules could not be coherently applied outside the context of acquisitions or customer service interactions.

Second, simple rules heuristics have a highly restricted *domain of rationality*: the subset of the domain of applicability in which it would be rational to use a given heuristic. For example, Cisco's 75% rule could be applied by any number of firms, but it would probably not be a good way for most firms to expand. A restaurant chain might balk at hiring so many engineers, and a company with very high market share might acquire larger firms in order to reduce competition.

To be sure, some adaptive toolbox heuristics are highly specific affairs. For example, the gaze heuristic for catching a fly ball instructs outfielders to run until the ball appears to be moving towards them in a straight line (McLeod and Dienes 1996). But many toolbox heuristics are general decisionmaking processes such as satisficing, held to be both applicable to and rational in a number of diverse decisionmaking contexts. For example, satisficing has been favorably discussed as a strategy for foraging (Simon 1956; Ward 1992), learning new capabilities (Winter 2000), and conducting academic research (Prabha et al. 2007).

Now it is often held that the rationality of heuristics is *ecological*, or environmentrelative (Todd and Gigerenzer 2012). Because each heuristic performs well in some environments and badly in others, there can be no question of defending a single heuristic for use in all environments. Nevertheless, it would be surprising if there did not exist institutional decisionmaking heuristics with much wider domains of rationality and applicability, more comparable to toolbox heuristics such as satisficing rather than to simple rules heuristics such as Cisco's 75% rule. While we will see in the next section that there are some relevant differences between individual and institutional decisionmakers, I know of no differences that could ground a large gap in specificity between rational individual and institutional heuristics.

This discussion suggests that we should expect to find interesting classes of general-purpose heuristics for institutional decisionmaking. My project in the rest of this paper is to exhibit one category of decisionmaking processes which have a good claim to be classified as general-purpose institutional decisionmaking heuristics, and which would often be rational for institutions to use.

3 Institutional decisionmaking heuristics: Beyond the adaptive toolbox

A natural place to look for general-purpose institutional decisionmaking heuristics would be within the adaptive toolbox. Because these heuristics are often rational for individual decisionmaking, it would be surprising if they were never suited to institutional decisionmaking, particularly for small institutional decisionmakers solving problems similar to those facing individuals. Indeed, it has been stressed precisely on these grounds that institutions sometimes do and should use heuristics from the adaptive toolbox (Gigerenzer and Gaissmaier 2011).

At the same time, adaptive toolbox heuristics have been proposed for institutional use with much less frequency, and in a narrower range of contexts than they have been proposed for individual use. We can make sense of this gap by developing a point stressed by critics of institutional decisionmaking heuristics (Vuori and Vuori 2014): institutions differ from individuals both in their *agential features*, the types of agents that they are, as well as in their *problem environments*, which determine the problems they are likely to encounter. These differences between individual and institutional decisionmakers suggest that we should often expect different heuristics to be appropriate for individual and institutional decisionmakers.

Here is it impossible to state exceptionless generalizations about the differences between individual and institutional decisionmakers. It is precisely this impossibility which ensures that adaptive toolbox heuristics are sometimes well-suited to institutional decisionmaking or ill-suited to individual decisionmaking. Nevertheless, we can state three agential features and two features of problem environments along which individuals and institutions differ, and which collectively cast doubt on the extent to which institutional decisionmakers should use adaptive toolbox heuristics.

3.1 Agential features

One difference between institutional and individual decisionmakers lies in their cognitive abilities. We saw in Section 2 that one of the standard justifications for adaptive toolbox heuristics is that individual decisionmakers sometimes lack the cognitive ability to apply more complex decision procedures. However, institutional decisionmakers often have higher cognitive abilities which give them access to a wider range of strategies.

For example, institutional decisionmakers are often more cognitively sophisticated than individual decisionmakers. While even intelligent individuals often struggle to apply Bayesian inference strategies (Casscells et al. 1978), many institutional decisionmakers can deploy teams of experts to develop precise Bayesian models. Institutions also have greater access to relevant noncognitive resources. This means that even if heuristic decisionmaking is well-adapted to situations of high uncertainty, institutional decisionmakers can often reduce their uncertainty to the point where heuristic decisionmaking becomes less appropriate, for example by engaging in costly processes of evidence-gathering or hiring consultants.

A second difference between individual and institutional decisionmakers concerns the way in which decisionmaking strategies are acquired. We saw in Section 2 that one reason for the success of adaptive toolbox heuristics is that both the heuristics and our processes of heuristic strategy selection are shaped not only by explicit learning, but also by long processes of biological evolution. This means that individuals' heuristic cognition is informed not only by their own limited experience, but also by millions of years of past experience. By contrast, institutional decisionmaking strategies are never evolved but only learned (Bingham and Haleblian 2012). This means that we have no direct evolutionary grounds on which to expect institutional heuristics to be rational, or to expect adaptive toolbox heuristics to be appropriate for institutional decisionmakers. And in fact, critics of adaptive toolbox heuristics have often stressed that adaptive toolbox heuristics may perform badly outside the contexts to which they were evolutionarily adapted (Boudry et al. 2015; Li et al. 2017).

Finally, institutions and individuals differ in the types of decision processes they engage in. Institutions, unlike solitary individuals, often make decisions through collective deliberation. Collective deliberation processes differ from individual decision processes in many ways. For example, while individual decisionmakers may come to a problem with definite preferences and opinions, collective decisionmakers must aggregate preferences and opinions across a group of heterogenous agents in order to arrive at a collective decision (List and Puppe 2009; List and Pettit 2011). In collective decisionmaking, it is often impossible or unduly time-consuming to arrive at highly structured forms of attitudes that may be relatively easy for individual decisionmakers to achieve. For example, decisionmaking by satisficing demands only a modestly structured attitude from individual decisionmakers: an aspiration level specifying the option characteristics that individuals are prepared to accept as satisfactory. It may be relatively easy for individuals to settle on an aspiration level, but quite difficult for the diverse participants in collective decisionmaking to agree on the precise quantities of goods that would be satisfactory, or even on the types of goods that should be reflected in their aspirations.

Summing up, institutional decisionmakers differ from individual decisionmakers in at least three agential features. Institutional decisionmakers tend to have higher cognitive abilities; do not evolve cognitive strategies; and often engage in collective rather than individual decision processes. In the rest of this section, I summarize two relevant differences between the problem environments confronting individual and collective decisionmakers.

3.2 Problem environments

It is often held that heuristic decisionmaking is more appropriate when the stakes of decisionmaking are low (Kahneman 2011; Martignon and Laskey 1999).[5] When stakes are low, it can make sense to prefer a high-quality decision made at low cognitive cost to a slightly-better decision made a high cognitive cost. For example, we might prefer to buy apples at the grocery store by satisficing since it is better to buy a satisfactory apple in a few seconds than to buy the best apple in the store in a few hours. However, institutional decisionmakers often face higher-stakes cognitive problems. In these problems, it may no longer be appropriate to apply adaptive toolbox heuristics. It is not obviously better to buy a satisfactory apple orchard in a few seconds than to buy the best orchard in a few hours.

A second way in which institutional decisionmakers differ from individual decisionmakers is in their need to make explainable decisions. An individual shopper may not have to justify her apple purchase to anyone but herself. However, an institutional apple purchase will have to be justified both to internal decisionmakers as well as to external stakeholders, such as shareholders and affected community members.

Here it is important to distinguish between two senses of explainability. On the one hand, we may be interested in the explainability of a decision process itself: how was the decision made? It has been rightly stressed that adaptive toolbox heuristics are highly

[5]This is not to deny that heuristic decisionmaking can also be appropriate in some high-stakes contexts. That is the lesson of less-is-more effects.

		Individuals	**Institutions**
Agential features	Cognitive abilities	Low	High
	Deliberation type	Primarily individual	Primarily collective
	Strategy acquisition	Learning/evolution	Learning
Problem environment	Stakes	Low	High
	Need for explanation	Low	High

Table 1: Differences between individual and institutional decisionmaking

explainable in this sense (Marewski and Gigerenzer 2012). For example, it is much easier to explain how satisficing works than to explain a complicated Bayesian model. On the other hand, we may be interested in explaining the correctness of a decision: why was the decision that was made a good decision? It often requires a number of scientific research papers to explain when and why a particular decisionmaking heuristic is a good one, and for this reason it is often taken as an advantage of heuristic decisionmaking that heuristics can be learned and applied by agents who are unable to explain the correctness of heuristic decisions. The upshot of this discussion is that when it is important to explain the correctness of decisions, adaptive toolbox heuristics may not meet explainability demands.

In this section, we have met five dimensions along which individual and institutional decisionmaking differ, summarized in Table 1. Together, these differences suggest that adaptive toolbox heuristics may often be inappropriate to institutional decisionmaking. But, as we have seen, there is every reason to suspect that there will be a range of general-purpose heuristics which are often appropriate to institutional decisionmaking. If the adaptive toolbox does not exhaust these heuristics, then we should look for new heuristics which are better-adapted to the agential features and problem environments of institutional decisionmakers.

Where could we find such heuristics? A natural strategy is to identify a class of decision problems that are especially well-suited to heuristic decisionmaking, then consider existing strategies for institutional decisionmaking in these problems and check whether any of these strategies are naturally classified as heuristics. In the next section, I present a decision context of this type, decisionmaking under deep uncertainty, and introduce some decision procedures that have recently been developed for institutional decisionmaking under deep uncertainty. In Sections 5-7, I argue that many of these procedures should be understood as general-purpose heuristics for confronting a wide range of institutional decisionmaking problems under deep uncertainty.

4 Decisionmaking under deep uncertainty

The past several decades have seen a surge of scholarly interest in decisionmaking under conditions of deep uncertainty (Helgeson 2020; Marchau et al. 2019a; Mogensen and Thorstad forthcoming). The term 'deep uncertainty' is used to describe decision problems with especially high uncertainty about fundamental decision-theoretic parameters such as the probabilities of world-states, the outcomes of options, or the values of those outcomes.[6] An example will illustrate the depth and difficulty of these problems

The Thames Estuary 2100 project set out to reinforce the estuary wall around the river Thames as it flows through central London. The goal was to make improvements that would last for the next century. The task is of critical importance to the city of London. Building the wall too low in the face of rising global sea levels would leave historic areas of central London vulnerable to flooding. Building the wall too high would waste billions of pounds and dampen the city's economy. The problem is made especially difficult by the fact that available general circulation models of the global climate cannot effectively guide local decisionmakers at this timescale: existing models are not currently reliable predictors of local climate phenomena, and there is substantial uncertainty over even global climate changes on long timescales (Frigg et al. 2015; Thompson et al. 2016). The Thames Estuary 2100 project was innovative for its decision to supplement traditional forms of decision-theoretic guidance with ideas from new methods for decisionmaking under deep uncertainty, surveyed below (Ranger et al. 2013).

[6] Despite significant commonalities, there is no generally accepted definition of deep uncertainty. Walker et al. (2003) provide a useful typology which may help to clarify the concept.

Traditional decision-theoretic methods have had mixed track records when applied to such problems (Freedman 1981; Goodwin and Wright 2010; Harremoës et al. 2001). Recent work in decisionmaking under deep uncertainty (DMDU) has proposed a variety of novel decisionmaking methods for DMDU. These methods have been primarily designed and applied with institutional decisionmakers in mind, and we will see in Section 6 that there are a number of reasons why DMDU methods are a good fit for institutional decisionmakers.

One popular method developed by the RAND corporation is *robust decisionmaking* (Lempert 2002; Groves and Lempert 2007).[7] Robust decisionmaking begins with the construction of a *system model* of the target system and a set of *policy alternatives* to be decided between. For example, we might model system features such as water levels and heights of the estuary wall, and let policy alternatives be candidate wall heights. Exploratory computational modeling is used to construct a *landscape of plausible futures* across which policy alternatives will be evaluated, such as scenarios for local and global climate changes. The performance of policy alternatives across this landscape is assessed using one or more decision-theoretic criteria, such as regret-avoidance or minimizing the probability of flooding. The results of this analysis are then used to identify novel policy alternatives which may not yet have been considered, such as novel wall configurations, and to revise the landscape of plausible futures to highlight decision-relevant differences between futures.

A second tradition, *info-gap* decision theory, stresses the difficulty of estimating full probability distributions for deeply uncertain parameters (Ben-Haim 2001).[8] For example, leading climate scientists are often unwilling to commit to full probability distributions over global climate changes, let alone local climate changes (Helgeson et al. 2018). However, they may be willing to commit to something weaker: a best-guess value for parameters such as the water level of the Thames in 2100. Info-gap decision theory applies in

[7] Robust decisionmaking has been applied to advise governments on investments in energy (Popper et al. 2009), water (Groves et al. 2015) and other long-term capital investments.

[8] Info-gap decisionmaking has been applied to model financial risk (Ben-Haim 2005) and to suggest safety parameters for engineering projects (Wu et al. 2015).

situations where decisionmakers are willing to provide best-guess values for one or more parameters, but not to provide full probability distributions. A popular decision rule for info-gap decision theory is the *robust satisficing* rule. Robust satisficing defines a notion of satisfactory performance, such as a utility threshold, and evaluates options by considering the largest extent to which our best-guess parameter estimates could be mistaken while guaranteeing satisfactory performance.

A third tradition, *scenario-based decisionmaking*, considers a small range of discrete future scenarios, typically between two and four (Wack 1985a,b). For example, an oil company might consider the performance of potential drilling projects under high, moderate and low conditions of future political stability in the region. Scenario-based decisionmaking differs from robust decisionmaking in its use of a small number of discrete scenarios, aimed to guide reflection, rather than a wide range of scenarios intended to represent a range of plausible futures.

In coming to grips with DMDU methods, it is important to get clear on what exactly DMDU methods are meant to do. Mogensen and Thorstad (forthcoming) distinguish between two interpretations of DMDU methods. On the one hand, DMDU methods may be criteria of rightness, which "specify the conditions under which a given action counts as right or wrong" (Mogensen and Thorstad forthcoming). Traditional decision-theoretic methods such as expected-utility maximization are often understood as capturing criteria of rightness. On the other hand, DMDU methods may not be criteria of rightness, but rather decision procedures, mental processes used by agents to decide how to act. Decisionmaking heuristics are often understood as decision procedures. Mogensen and Thorstad remain undecided between these two interpretations of DMDU methods.

There are at least two reasons why it is important to determine whether DMDU methods specify criteria of rightness or heuristic decision procedures. First, until we know what DMDU methods are meant to do, we cannot know whether they accomplish that task well or badly. For example, those who accept expected utility maximization as a criterion of rightness may have reason to reject DMDU methods as criteria of rightness, but not yet to reject them as rational decision procedures. Second, my aim in this paper is to treat DMDU methods as a novel class of heuristics for institutional decisionmaking. Making this case commits me to denying that DMDU methods should be treated as novel criteria of rightness for institutional decisionmaking.

In Section 5, I argue that DMDU methods bear four marks of heuristicality, features that are often used to draw a boundary between criteria of correctness and heuristic decision procedures. This warrants treating DMDU methods as decisionmaking heuristics. In Section 6, I argue that typical DMDU methods are well-suited to the specific features of institutional decisionmakers identified in Section 3. This warrants the further claim that DMDU methods are often *rational* heuristics for institutional decisionmaking. In Section 7, I argue that a heuristic interpretation of DMDU methods resolves two common objections to their use. This furthers both the interpretive case for treating DMDU methods as heuristics and the normative case for treating DMDU methods as rational heuristics.

5 Decisionmaking under deep uncertainty: The heuristic interpretation

In this section, I argue that there is a good case to be made for interpreting many DMDU methods as institutional decisionmaking heuristics. How should this case be made?

One approach would be to use a stipulative definition of heuristic cognition, then argue that DMDU methods meet this definition. DMDU methods fare well by this approach: we will see shortly that they have several features which have been taken as definitive of heuristic cognition. Nevertheless, argument by definition has some drawbacks. For one thing, there is no agreed-upon definition of heuristic cognition, so this approach risks lapsing into stipulation. For another, it is hard to state exceptionless claims about heuristic cognition. This means that many proposed definitions of heuristic cognition will admit of exceptions.

A safer approach would be to combine several different *marks of heuristicality*, features generally agreed to be characteristic of heuristic decision processes. In this section, I identify four marks of heuristicality and argue that DMDU methods have all four. By considering four different marks of heuristicality, this approach will reduce the risk of overreliance on a single stipulative definition of heuristic cognition. Likewise, even if we admit that each mark is an imperfect indicator of heuristicality, the fact that DMDU methods have four different marks of heuristicality should count as good evidence that they are, in fact, heuristic decision processes rather than criteria of correctness for decisionmaking.

5.1 Marks of frugality

One characteristic feature of heuristic decisionmaking is its frugality. Gigerenzer and colleagues have held that cognition is characterized by a toolbox of fast-and-frugal heuristics (Gigerenzer and Selten 2001b), and many in the heuristics and biases tradition follow Kahneman (2003) in classifying heuristic cognition as a type of fast and low-effort 'system 1' cognition. Typical DMDU methods bear at least two *marks of frugality* characteristic of heuristic cognition.

One mark of frugality is *informational neglect*. To say that a decision procedure neglects information is to say that it makes no use of some information bearing on the values or likelihoods of outcomes that decisionmakers care about. For example, our satisficing apple-buyer entirely ignores features of apples not reflected in her aspiration level, such as their location of origin. A leading review of heuristic decisionmaking goes so far as to suggest that informational neglect is definitional of heuristic cognition, defining heuristics as "strategies that ignore information to make decisions faster, more frugally, and/or more accurately than more complex methods" (Gigerenzer and Gaissmaier 2011, p. 454).

Most DMDU methods neglect a good deal of information. One reason for this is that most DMDU methods involve *bottom-up* decisionmaking, which begins by specifying a particular choice facing decisionmakers and afterwards specifies relevant information such as possible world-states only insofar as this information is helpful for choosing among the options at hand (Marchau et al. 2019a). For example, robust decisionmaking instructs decisionmakers to "select landscapes [of plausible futures] that appear useful to address the policy questions of interest" (Marchau et al. 2019a, p. 65) and scenario-based models are sometimes constructed with the purpose of challenging decisionmakers' mental models of choice situations rather than characterizing a full range of plausible futures (Wack 1985b). Used well, these forms of informational neglect can help decisionmakers to focus on the information most likely to improve decision quality.

A second mark of frugality is *inferential parsimony*. To say that a decision procedure is inferentially parsimonious is to say that it draws only some of the relevant inferences licensed by available information. Inferential parsimony is distinct from informational parsimony. For example, a satisficer whose aspirations were defined over all relevant goods would be deciding in an inferentially parsimonious manner, insofar as she only draws inferences about whether a given option is satisfactory. But she need not be deciding in an informationally parsimonious manner, since options and outcomes would be characterized along all relevant dimensions.

Most DMDU methods show a similar type of inferential parsimony. For example, info-gap decision theory constructs informationally-rich models of decision situations, but uses this information to draw only a few inferences. On a robust satisficing approach, info-gap decisionmakers characterize only the maximum error in their best-guess model which would guarantee satisfactory performance. They do not draw other inferences, for example about the precise degrees to which performance could be unsatisfactory, even though they may well prefer a slightly unsatisfactory result to a highly unsatisfactory result.

Together, informational neglect and inferential parsimony make the case that typical DMDU methods are frugal both in their inputs and in the amount of processing required to execute them. These facts square naturally with a heuristic interpretation of DMDU methods. By contrast, informational neglect and inferential parsimony are not features we expect to find in standards of correctness for decisionmaking. Standards of correctness have no need for frugality because they are not mental processes at all. On all but the most externalist approaches, any information bearing on the quality or likelihood of outcomes is relevant to the correctness of an agent's decisions. An agent who makes no use of some item of information or fails to infer its normative importance does not thereby nullify or change the normative importance of that information. While we can readily agree that rational decisionmaking heuristics must often neglect information or fail to draw relevant inferences, this alone gives us no reason to conclude that criteria of correctness for decisionmaking take no account of relevant information or of the inferential consequences that this information entails.

5.2 Marks of thick procedurality

Herbert Simon held that a fundamental turn in the study of bounded rationality is the turn from substantive to procedural rationality (Simon 1976). Whereas traditional theories of rational decisionmaking often focus on the last moments of decisionmaking, for example by specifying choice rules, the procedural turn urges us to focus on the entire temporally extended process of decisionmaking, much of which predates the moment of choice. Models of heuristic decisionmaking have tended to be *thickly procedural*, following Simon's suggestion of giving rich characterizations of the decisionmaking process.

One mark of thick procedurality is *search-choice entanglement*. To say that a decision procedure exhibit search-choice entanglement is to say that it specifies both search procedures, such as procedures for gathering evidence and generating options, as well as choice rules for selecting between options. This contrasts to the traditional model on which search and option generation are studied separately from decisionmaking, and on which models of rational decisionmaking often include only a choice rule.

Search-choice entanglement is a characteristic feature of many heuristic decision procedures. For example, satisficing instructs agents to identify options one-by-one and to decide whether to pursue a given option as soon as it is identified. More generally, Gerd Gigerenzer and Reinhard Selten (2001b) hold that a fully-specified heuristic has three parts: a *search rule* telling decisionmakers how to search for options and information; a *stopping rule* telling agents when to halt search; and a *decision rule* for making choices once search halts. This would imply the strong conclusion that all heuristics exhibit search-choice entanglement.

Most DMDU methods exhibit substantial search-choice entanglement. For example, robust decisionmaking is a method for iterated decisionmaking. Decisionmakers begin with an initial set of candidate options, test these options for robustness against a landscape of plausible futures, then use the results of this analysis to identify new options which may outperform the original options, repeating several times until improvements diminish or analysis becomes too expensive. In this way, robust decisionmaking combines cycles of search and choice, using each cycle as a direct input into the next.

A second mark of thick procedurality is *focus on model construction*. Traditional models of rational decisionmaking take many model components for granted — not only the options to be selected among, but also likelihoods, preferences, and other attitudes. By contrast, models of heuristic decisionmaking often aim to capture the process by which agents select among a dizzying array of potentially relevant information stored in memory to determine which information and attitudes will be used during decisionmaking. For example, an early step of many heuristic decision procedures is to construct a *probabilistic mental model* of decisionmaking situations by deciding on a set of decision cues, types of information deemed especially decision-relevant, and retrieving or estimating the values of these cues from memory (Gigerenzer 1991). This process of model construction is as influential as the final choice rule in determining the outcome of rational decisionmaking, because changes in the selection of decision cues or the information used to estimate the values of decision cues will change the outputs of decision rules.

A focus on model construction is front-and-center in most DMDU methods. Indeed, Casey Helgeson (2020) takes this focus on model construction to be one of the key differences between DMDU methods and traditional decision-theoretic approaches. By way of illustration, discussions of scenario-based decisionmaking give detailed advice for constructing scenarios (Amer et al. 2013), and it is common to combine robust decisionmaking with processes of expert- or stakeholder-opinion elicitation in order to generate informed models of plausible futures (Popper et al. 2009). This feature of DMDU methods is no accident. Like other heuristics, DMDU methods neglect a great deal of relevant information, so it is important to construct models based on a relevant sample of information.

In this section, we have seen that typical DMDU methods have two marks of frugality and two marks of thick procedurality, summarized in Table 2. This bolsters a heuristic interpretation of DMDU methods. By contrast, marks of thick procedurality, like marks of frugality, are not features we expect to see in criteria of correctness. Since criteria of correctness are not mental processes of any kind, we should not expect them to capture detailed facts about the structure of decisionmaking processes. Criteria of correctness may well ask some questions about model construction. Perhaps they will ask whether the model probabilities should be subjective credences, objective chances, or evidential probabilities. But criteria of correctness do not tell us when, and why it is a good idea to elicit opinions from experts, nor do they tell us which decision cues to incorporate into our mental models. These latter facts are features of the heuristic decision processes that we use to make decisions, rather than the criteria of correctness for decisions themselves. Together with our previous observations, this suggests that typical DMDU methods are best understood as heuristic decision processes, rather than as novel criteria of correctness for institutional decisionmaking.

Table 2: Marks of heuristicality

Marks of frugality	Informational neglect Inferential parsimony
Marks of thick procedurality	Emphasis on model construction Search/choice entanglement

6 Fitting the job description

In the previous section, we saw that typical DMDU methods are best understood as general-purpose decisionmaking heuristics rather than as novel criteria of correctness. What remains to be done is to argue that DMDU methods are often rational, rather than irrational heuristics for decisionmaking under deep uncertainty. To some extent, the case for the rationality of DMDU methods spans the entire literature, drawing on all that is known about the properties of DMDU methods and their track records in successfully confronting the problems facing institutional decisionmakers. But we can bolster the normative case for DMDU methods by noting (Table 3) that DMDU methods fall on the correct side of each of the dichotomies between individual and institutional decisionmakers proposed in Section 3. This means that exactly the same reasons which led us to doubt that adaptive toolbox heuristics will often be rational for institutional decisionmakers should increase our confidence that DMDU methods are well-suited for many institutional decisionmakers.

Many institutions have high cognitive abilities, which is fitting because DMDU methods require a good deal of cognitive sophistication to apply. Most DMDU methods involve detailed processes of mathematical modeling, and some such as robust decisionmaking involve computer simulation on proprietary software. DMDU methods would be as inappropriate as traditional Bayesian methods for cognitively unsophisticated agents.

Institutions often deliberate collectively, and this is precisely the type of decisionmak-

Table 3: Fit between DMDU methods and institutional decisionmaking demands

		Institutions	**DMDU heuristics**
Agential features	Cognitive abilities	High	High
	Deliberation type	Primarily collective	Primarily collective
	Strategy acquisition	Learning	Learning
Problem environment	Stakes	High	High
	Explainability	High need	High

ing for which DMDU methods are designed. With the possible exception of info-gap decision theory, it is rare to see DMDU methods applied by a single author, and indeed the typical application involves structured processes of consultation between teams of authors, stakeholders and decisionmakers.

Institutional decisionmaking strategies are learned rather than evolved. DMDU methods are learned methods which have been developed within the last half-century for application to precisely the sorts of challenges faced by modern institutional decisionmakers. For example, scenario-based decisionmaking was developed at Royal Dutch / Shell to manage long-term capital investments in the face of severe uncertainty about future oil prices and geopolitical stability (Wack 1985a,b). In the same way that the evolutionary history of adaptive toolbox heuristics is taken as evidence of their suitability for individual decisionmaking, the institutional context in which DMDU methods were learned and developed may be taken as evidence of their suitability for similar decision problems.

Institutions often face high-stakes challenges, and these are precisely the challenges to which DMDU methods are applied. Because DMDU methods are costly and time-consuming, they are not considered appropriate to low-stakes challenges. Because DMDU methods are designed for high-stakes challenges, they are often justified based on their ability to produce good decisions in the face of deep uncertainty, and not merely on the basis of their moderate-to-high deliberation costs.

Finally, institutions need to explain the correctness of their decisions to internal decisionmakers and external stakeholders. Many DMDU methods are touted for their high degree of explainability. Indeed, Vincent Marchau and coauthors have taken it as a general feature of DMDU methods that they illustrate the value tradeoffs involved in accepting various options in a way that allows decisionmakers to make informed choices based on an understanding of the costs and benefits of each option (Marchau et al. 2019b, p. 13). This is especially important in collective decisionmaking applications, where decisionmakers may wish to consider their own values and experiences alongside the conclusions of computational models developed by outside advisors.

Together, these features of DMDU methods suggest that they may form part of what we were looking for: a set of general-purpose heuristics well adapted to institutional decisionmaking under deep uncertainty. For the same reasons that it may be inappropriate to apply adaptive toolbox heuristics under these conditions, it may be highly appropriate to apply DMDU methods under these conditions.

7 Applications

An important test of the heuristic interpretation of DMDU methods is its ability to shed new theoretical light on how DMDU methods and their rationality should be understood. In this section, I conclude by arguing that a heuristic interpretation of DMDU methods provides compelling answers to two standard lines of objection made against DMDU methods by drawing on familiar justifications for the rationality of heuristic cognition. This may be taken as additional evidence for the correctness and importance of a heuristic interpretation of DMDU methods.

An objection that is often raised in conversation is what we might call the *flat-footed objection:* why not just maximize expected utility? After all, expected utility maximization is a well-supported and familiar theory of rational choice in a number of contexts, whereas DMDU methods are comparatively newer and less well-understood. A heuristic interpretation of DMDU methods allows us to see that this objection rests on a mistake.

Philosophers standardly distinguish between the rightness of actions and the rightness of decision procedures that produced them. We may want to make both judgments on the grounds of expected utility maximization, holding that the right actions are the actions which are *optimific*, or expected-utility maximizing, and also that the right decision procedures are the optimific decision procedures. But this does not imply that the right decision procedure always involves explicitly calculating expected utilities (Parfit 1984; Railton 1984). For example, it may be right to be moved to act directly out of love for your family, even if this decision procedure will sometimes cause you to show too much favoritism towards your family, because this procedure will generally produce good decisions and will often allow your family to be loved. In this case, it might be wrong to make decisions involving your family by explicitly calculating expected utilities, because this decision procedure will breed coldness and familial distrust.

A standard defense of heuristic cognition is that heuristics are often right and rational because they are often optimific.[9] DMDU methods, like other heuristics, often strike a good balance on the accuracy-effort tradeoff, returning high-quality decisions at moderate cognitive expense. Under conditions of deep uncertainty it would be enormously expensive to construct traditional Bayesian models of sufficient complexity to match the performance of DMDU methods, and most institutions cannot bear this expense. DMDU methods are often the most reliable methods available to us, since in practice most reputable consultants will often refuse to construct Bayesian models under conditions of especially deep uncertainty, on the grounds that they cannot generate a reliable model. And under deep uncertainty, less can be more: predictive accuracy is only improved by additional model complexity if the additional forecasts or model parameters are not overfit to sparse data or driven astray by familiar cognitive biases in prediction, and these are live concerns for traditional decision-theoretic models under deep uncertainty (Freedman 1981; Goodwin and Wright 2010; Harremoës et al. 2001).

A second objection that is often made to DMDU methods is that they are not novel, because they employ familiar choice rules. For example, it has been objected that info-gap decision theory is a form of maximin decisionmaking: on a robust satisficing interpretation, info-gap decisionmaking instructs decisionmakers to maximize the minimum deviation from their best-estimate model parameters which would guarantee satisfactory performance (Sniedovich 2007). This objection might also be raised to other DMDU methods. For example, robust decisionmaking is typically operationalized by looking for options which have low regret in a range of plausible futures, and this criterion is

[9] If we adopt a weaker satisficing criterion of correctness (Slote 1984), the argument would be that heuristics are often good enough.

sometimes cashed out using explicit rules such as Starr's domain criterion that have been known to decision theorists for a half-century (Starr 1962). In what sense, then, do DMDU methods go beyond familiar choice rules such as maximin and Starr's domain criterion?

Again, the heuristic interpretation of DMDU methods shows us how to respond to this objection. As we saw, a key feature of many heuristic methods is that they are thickly procedural: they give us not only a choice rule for the final moment of choice, but also procedures for constructing models, searching for information and options, and determining when to halt deliberation and make a decision. One of the characteristic features of decisionmaking under deep uncertainty is that there are often profound uncertainties about how each of these steps is to be carried out: there are many more options and items of information than we can consider, and there is always more analysis to be done. Under these conditions it is especially important to say not only what choice rule decisionmakers should use, but also how they should carry out the rest of the decisionmaking process prior to the moment of choice. A large part of the novelty of DMDU methods consists in their explicit and detailed engagement with these prior procedural questions about rational decisionmaking (Helgeson 2020).

In this section, we have seen that a heuristic interpretation of DMDU methods answers two objections raised against DMDU methods by revealing these objections to be special cases of more general objections typically raised to heuristic cognition and responding to these objections in traditional ways. The facts that DMDU methods have been subjected to traditional objections made against heuristic cognition, and that traditional answers to these objections are promising in the case of DMDU methods, provide evidence that a heuristic interpretation of DMDU methods is both correct and theoretically useful.

8 Conclusion

This paper began with a striking contrast. While research on individual decisionmaking heuristics deals often with general-purpose decision procedures, most institutional decisionmaking heuristics studied to date are highly specific affairs. This contrast is surprising, because there are no obvious features of institutional decisionmaking to explain why institutional decisionmakers should not often rely on general-purpose decisionmaking heuristics.

I proposed that many existing DMDU methods should be interpreted as general-purpose heuristics suitable for institutional decisionmaking under conditions of deep uncertainty. In support of a heuristic interpretation of DMDU methods, I argued that DMDU methods bear four marks of heuristicality, including two marks of frugality and two marks of thick procedurality (Section 5). To show that DMDU methods are well-adapted to institutional decisionmaking, I identified five differences between individual and institutional decisionmakers (Section 3) and argued that DMDU methods fall on the correct side of each of these five dichotomies (Section 6). I concluded by showing how a heuristic interpretation of DMDU methods resolves two objections to their use by revealing these objections to be special cases of familiar objections to heuristic decisionmaking (Section 7).

I do not wish to claim that DMDU methods are the only general-purpose heuristics for institutional decisionmaking. For one thing, DMDU methods are suited only to a particular type of context: decisionmaking under deep uncertainty. And for another, the DMDU methods identified to date represent only a small fraction of conceptually possible decision procedures. It is therefore plausible that there should exist other types of relatively general decisionmaking heuristics suitable for institutional decisionmaking. It would be an important and fruitful project for future work to identify and catalog other such heuristics.

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