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Andreas Glöckner

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Max Planck Institute for Research on Collective Goods, Kurt-Schumacher-Str. 10, D-53113 Bonn
http://www.coll.mpg.de

How Evolution Outwits Bounded Rationality
The Efficient Interaction of Automatic and Deliberate Processes in Decision Making and Implications for Institutions*

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Abstract

Classic behavioral decision research has intensively explored deliberate processes in decision making. Accordingly, individuals are viewed as bounded rational actors who, because of cognitive limitations, use simple heuristics that are successful in certain environments. In this chapter, it is postulated that human cognitive capacity is less severely limited than has previously been assumed. When automatic processes are considered, one finds that cognitive capacity is not a binding constraint for many decision problems. The general parallel constraint satisfaction (PCS) approach is outlined, which aims at describing these automatic processes, and evidence supporting this approach is summarized. It is further argued, that in order to describe decision making comprehensively, models must account for the interaction between automatic and deliberate processes. The PCS rule is delineated which specifies this interaction. The model shifts the bounds of rationality considerably and has further evolutionary advantages. Implications for the efficient design of institutions are outlined. Finally, the German legal system is reviewed in terms of its ability to support efficient decision making by implementing many of the prescriptions derived from the PCS rule without explicit knowledge about the underlying processes.

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Introduction

One of the most intriguing psychological phenomena is the human ability to make decisions in a complex and uncertain world. Decision experts, such as managers and lawyers, must often make determinations based on myriad pieces of probabilistic and incomplete information. In the tradition of the bounded rationality approach (H. A. Simon 1955), it has been repeatedly argued that fast and frugal heuristics, which are based on simple decision rules and which ignore information, offer one important way for humans to reach solutions to complex decision tasks (Gigerenzer 2006). In this chapter, I summarize theoretical models and empirical findings that suggest an extended perspective; namely, individuals are able to integrate multitudinous information by relying partially on intuitive automatic processes. Specifically, I argue that individuals make use of automatic parallel constraint satisfaction (PCS) processes that have developed through evolution on the basis of perceptual processes. PCS processes can be mathematically simulated using connectionist networks. Both accounts will be discussed in light of recent evidence. Thereafter I describe the PCS rule (Glöckner and Betsch in press), a hierarchical network model that integrates both approaches, and takes into account the interaction between automatic and deliberate processes in decision making. I outline the evolutionary advantage of such a model and discuss the implications this can have for the development and improvement of institutions.

Theories in Behavioral Decision Research

In classic behavioral decision research, two major approaches can be distinguished. First, there are modifications of rational choice theory (RCT) that hold to the general assumption that information is integrated in a *weighted compensatory* manner. For example, prospect theory (Kahneman and Tversky 1979) assumes that individuals select the option with the higher subjective expected utility, which is calculated as the weighted sum of subjective utilities and subjective probabilities. Transformation functions from objective values and probabilities to subjective ones have been specified in light of empirically observed systematic deviations from RCT. Second, following the fundamental critique of H. A. Simon (1955) that such complex computations might overload human cognitive capacity, several heuristic models have been developed which postulate that individuals apply simple integration rules, thereby ignoring most information. Currently, the most influential model of this *bounded rationality approach* is the adaptive toolbox model (Gigerenzer, Todd et al. 1999). It assumes a set of fast and frugal heuristics that are applied adaptively and lead to very accurate decisions by exploiting the structure of the environment. The prototypical fast and frugal heuristic is Take the Best, in which only the most valid piece of information is inspected. If this information favors one option, it is instantly selected; only when this is not the case is the second-most valid piece of information inspected, and so on. The recently developed priority heuristic extended this concept to classic gambling decision tasks (Brandstätter et al. 2006). There is a controversy over which approach is more appropriate (e.g., Brandstätter et al. 2006; Glöckner and Betsch, submitted). In the shadow of this conflict and the debates within both approaches, a third idea rooted in cognitive (Schneider and Shiffrin 1977) and social psychology (Bargh and Chartrand 1999; Petty and Cacioppo 1986) has been discussed, albeit less intensively, in behavioral decision research for many years: the *dual-processing approach* (for an overview, see Kahneman and Frederick 2002). According to this approach, individuals use both a deliberate and an intuitive system to make decisions. In contrast to the controlled deliberate system, in which information is consciously integrated according to certain rules and in a sequential manner, the intuitive system relies on automatic, unconscious processing of information.[1] The field of behavioral decision research is still in the early stages of investigating and building theories on processes of the intuitive system, and has not yet sufficiently considered findings from cognitive and social psychology. Even less is known about the interaction between the deliberate and automatic systems. Prominent general approaches that have the potential to explain processes of the intuitive system are cognition and affect based memory storage and retrieval models (Anderson and Lebiere 1998; Busemeyer and Townsend 1993; Damasio 1994; Dougherty et al. 1999; Ratcliff et al. 1999; Slovic et al. 2002), as well as PCS models. The former postulate that automatic processes of storage in and retrieval from long-term memory are utilized in decision making. PCS models assume that automatic processes of maximizing consistency between information in temporarily activated networks drive our decision processes.

The PCS Approach to Decision Making

Many cognitive operations function without deliberate control. Behavioral research provides a multitude of empirical findings evidencing the power of the unconscious automatic system. For instance, in the course of adaptive learning, organisms automatically record fundamental aspects of the empirical world, such as the frequency (Hasher and Zacks 1984) and value (Betsch, Plessner et al. 2001) of events or objects. It has been demonstrated repeatedly that automatic processes overrule even deliberately formed intentions: individuals act against their intentions and fall back into routines if they have to make decisions under time pressure (Betsch et al. 2004); they are unable to prevent stereotypes and prejudices from being automatically activated (Devine 1989); and the deliberate intention not to think about an object actually increases the likelihood that it will come to mind (Wegner 1994).

Automatic processes are essential for making sense of a world that provides incomplete information. Automatic processes of perception and social perception enable individuals to recognize objects and social constellations immediately, even if only a small fraction of the total information is available. Research in classic Gestalt psychology (Koffka 1922) provides persuasive demonstrations of these unconscious mechanisms. For example, when presented with an image of changing figure-ground relationships (e.g., the “Rubinian vase”), individuals perceive either a vase or two faces on the basis of exactly the same information. By shifting the focus of attention,

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1 Kahneman and Frederick (2002) use the terms *automatic*, *process opaque* (unconscious), and *parallel* to describe process characteristics of the intuitive system. Note that these characteristics are not independent, nor do they perfectly coincide.

perception may flip to the opposite interpretation. Conceptually, a myriad of conflicting information is unconsciously integrated in one consistent interpretation (e.g., vase). In this process, the interpretation of information is modified. Information that speaks against the dominant interpretation (e.g., an object that shades a part of the figure) is suppressed, whereas information that supports the dominant interpretation (e.g., a characteristic shape) is accentuated.

The PCS approach to decision making is based on the same principle (Read et al. 1997; Holyoak and D. Simon 1999). As soon as individuals are confronted with a decision task, automatic processes are initiated which work to form a consistent mental representation of the task. In the process, information supporting the emerging mental representation is accepted while conflicting information is devaluated. Conceptually, automatic processes weigh interpretations of information against each other by taking into account the complex constellation of the information. The best interpretation wins the competition, and conflicting information is eliminated as far as possible. Individuals are not aware of these processes; they are only aware of the results.

Connectionist Implementation of PCS Processes

Connectionist networks allow us to model PCS processes for complex decision tasks. Initially, PCS networks were introduced in psychology to model processes of word perception (McClelland and Rumelhart 1981). Later it was argued that the underlying organizing principle of maximizing consistency among pieces of information is fundamental to a wide range of psychological phenomena, such as social perception (Read and Miller 1998), analogical mapping (Holyoak and Thagard 1989), the evaluation of explanations (Thagard 1989), dissonance reduction (Schultz and Lepper 1996), impression formation (Kunda and Thagard 1996), the selection of plans (Thagard and Millgram 1995), legal decision making (Holyoak and D. Simon 1999; Thagard 2003; D. Simon 2004), preferential choice (D. Simon et al. 2004), and probabilistic decisions (Glöckner 2006, 2007; Glöckner and Betsch, submitted).

For pragmatic reasons, let us focus on simple probabilistic decision tasks that have been used predominantly to investigate fast and frugal heuristics (Gigerenzer, Todd et al. 1999). One prominent example is the city-size task: when presented with two cities, a person should select the one which has the larger population based on different probabilistic information. Conceptually, a decision has to be made about a distal criterion (i.e., population of the city) on the basis of proximal probabilistic *cues* (e.g., whether it is the capital of its state) with dichotomous *cue values* (i.e., yes or no) that differ in *cue validity* (i.e., the conditional likelihood that the option is better on the criterion, given a positive or negative cue value).

Connectionist models provide different possibilities to model such probabilistic decision tasks. Fitting connectionist models a posteriori to empirical data provides only weak support for them because of the many degrees of freedom in the models. Thus, I propose an a priori modeling approach which reduces degrees of freedom by specifying the structure of the network a priori. This general structure of a connectionist network for probabilistic decision tasks is delineated in

Figure 1 and can be used in systematic simulations to derive testable predictions that enable the PCS approach to be differentiated empirically from other models (Glöckner 2006).

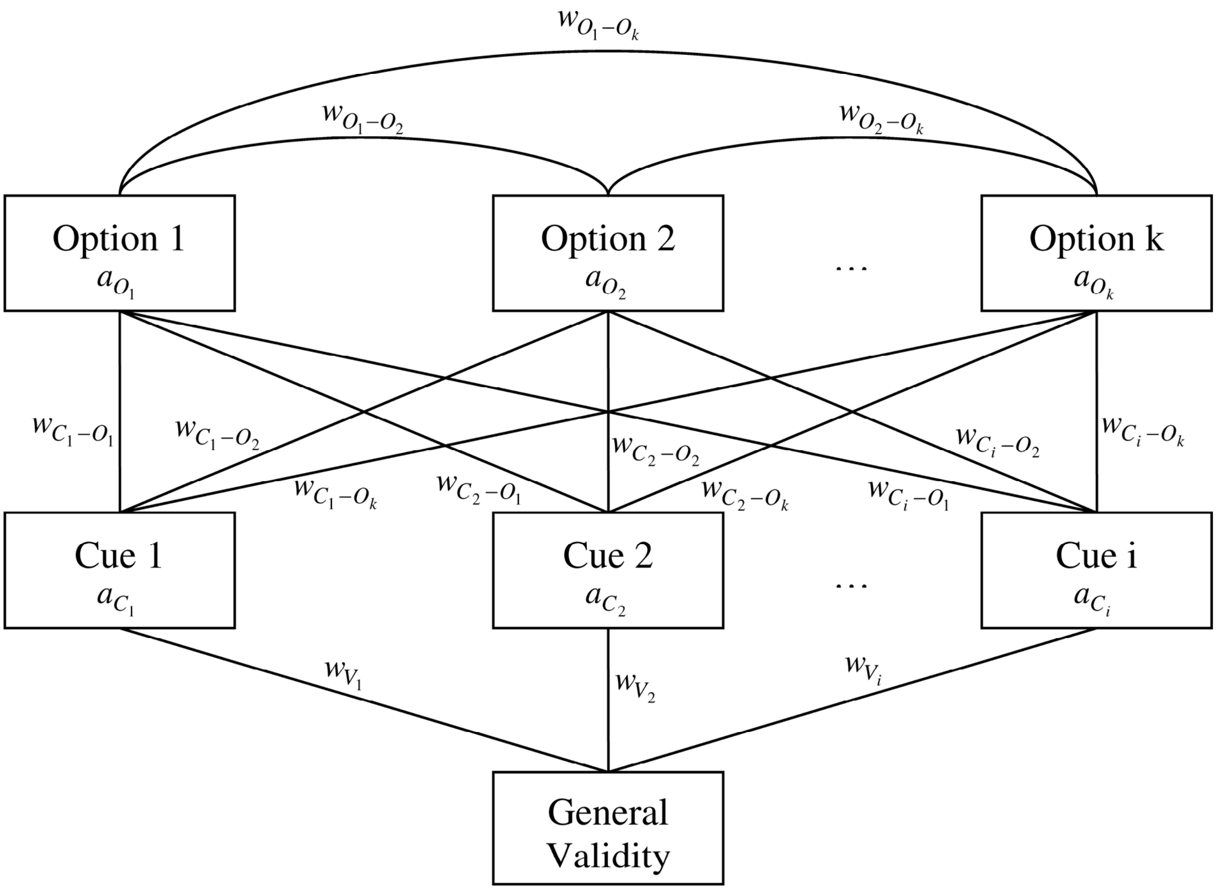

Figure 1
General structure of the PCS network for probabilistic decision tasks. Boxes represent nodes. The activation, *a*, of the nodes is modified within the PCS process. Lines represent links between nodes that are all bidirectional and can be inhibitory or excitatory. Links have different weights, *w*, and are fixed constraints in the network that result from learning or from explicitly provided information.

In the suggested network, cues and options are represented by nodes, which may have different levels of activation, a. Nodes are interconnected by links that have certain strength, represented by weights, w. All links are bidirectional and can be excitatory ($w > 0$) or inhibitory ($w < 0$). Options and cues are connected by links that represent cue values. Positive predictions of a cue about an option are represented by excitatory links, whereas negative predictions are represented by inhibitory links. Options are interconnected by strong inhibitory links, because only one option can be chosen. Cues are connected with a general validity node, which is used to activate the network and has a constant activation of 1. The strength of the links w_V represents the initial subjective cue validities that result from learning experience or explicitly provided information.

The connectionist network captures the logical constraints of the decision problem, as represented in the temporarily activated mental representation. In this structure, some elements support each other (e.g., cues and options for which the former make a positive prediction) while others conflict (e.g., cues and options for which the former make a negative prediction). The activation of each node can be interpreted as a subjective judgment of the goodness of the underlying concept (i.e., the attractiveness of the options and the subjective validity of the cues). Note that there is an important distinction between the initial validity of cues, which are represented by the links w_V, and the perceived validity of cues, which are represented by the activation of the nodes a_C. The former are stable constraints in the network, whereas the latter, which will be referred to as *resulting cue validities*, are results of the PCS processes.

As soon as the network is constructed, PCS processes are initiated and alter the activation of nodes until a solution with a high level of consistency is found. Mathematically, the process can be captured by an iterative updating algorithm, which simulates spreading activation in the network (McClelland and Rumelhart 1981):

$$a_i(t+1) = a_i(t)(1-decay) + \begin{cases} if\ input_i(t) < 0 & input_i(t)(a_i(t) - floor) \\ if\ input_i(t) \geq 0 & input_i(t)(ceiling - a_i(t)) \end{cases} \quad (1)$$

The activation a_i at time $t + 1$ is computed by the activation of the node at time t, multiplied by the decay factor plus the incoming activation for this node, $input_i(t)$, multiplied by a scaling factor. The scaling factor limits the activation of the nodes to the range –1 to +1 and leads to an S-shaped activation function. The $input_i(t)$ to node i is computed as the sum of the activation of all other nodes multiplied by the weight of the connection with node i:

$$input_i(t) = \sum_{j=1 \to n} w_{ij} a_j(t) \quad (2)$$

The updating algorithm maximizes the consistency (i.e., the degree of organization) in the network and minimizes contradiction or energy. The energy can be computed by:

$$Energy(t) = -\sum_i \sum_j w_{ij} a_i a_j \ , \quad (3)$$

where all weights w_{ij} are multiplied by the activations of the pair of nodes they connect and the resulting products are combined (Read et al. 1997). This means, for instance, that positive connections between positively activated elements increase the level of consistency, whereas negative connections between positively activated concepts decrease it (cf. Heider 1958). The iterative updating algorithm operates to maximize consistency. After a number of iterations, a state of maximal consistency under the given constraints is usually found and activations reach asymptotic levels. The option with the highest activation is selected. The number of iterations an algorithm needs to find the stable solution can be interpreted as the decision time predicted by the model.

In contrast to memory storage and retrieval models, the PCS approach does not describe long-term learning processes of relations in the network. PCS processes simulate ad hoc interpretations of the available evidence, based on constraints that result from learning or from the information that has been provided. Only the interpretation of the evidence is temporarily changed to form a consistent mental representation.

Predictions

Based on theoretical considerations and systematic simulations (Glöckner 2006; Holyoak and D. Simon 1999), five distinct predictions of the PCS approach can be derived:

1. *High computational capacity*: Individuals are able to integrate quickly a multitude of information by relying on automatic processes.

2. *Coherence shifts*: The decision process is inherently constructivist. Subjective cue validities are changed in the decision process to fit the emerging representation of the decision task, resulting in coherence shifts (D. Simon 2004): cues that point away from the favored option are devalued and cues that support the favored option are strengthened. Thus, resulting cue validities depend on the structure of the decision task and differ from initial cue validities.

3. *Approximation of weighted compensatory models*: Choices roughly approximate the weighted compensatory integration of cue values and cue validities.

4. *Decision time differences*: Decision time increases with a decrease in the initial consistency between the pieces of information. If all cues point toward the same option, consistency is high and decision time is short. If almost equally strong sets of cues favor different options, consistency is low and decision time is long.

5. *Confidence judgment differences*: The subjective confidence in a choice is higher in decision tasks when the consistency among pieces of information that cannot be resolved in the PCS process is low. If a highly consistent solution is found, confidence is high; if the resulting interpretation is still rather inconsistent, confidence in the decision is low.

Note that this set of qualitative predictions differs from that of most other decision-making models and thus allows for empirical testing against these models. Most decision-making models, including RCT, the adaptive toolbox, as well as memory storage and retrieval models, rely on the assumption that decision making is based on *unidirectional reasoning*: they assume that individuals select information from a given set and integrate it using certain algorithms to make a decision. Information is merely put into different algorithms; the information itself is not changed in the process. In contrast, the PCS approach suggests that decision making is based on *bidirectional reasoning* (Holyoak and D. Simon 1999): in a holistic process, the constellation of information and options is considered, and options and evidence are weighed jointly. Thus, individuals should not only reason from information to options, they should also infer the validity of cues from the informational constellation in a kind of automatic backward reasoning.

According to the adaptive toolbox model and the bounded rationality approach, individuals should not be able to integrate information quickly in a weighted compensatory manner because human cognitive capacity is too limited. Decision times should not be sensitive to the fact that different pieces of information convey conflicting evidence; only the number of computational steps needed to apply the heuristic should matter (Brandstätter et al. 2006); and confidence judgments should depend solely on the validity of the cue that differentiates between options (Gigerenzer et al. 1991).

Summary of Empirical Evidence

Coherence Shifts

The most comprehensive empirical work on coherence shifts in decision making has been done by Dan Simon and colleagues (Holyoak and D. Simon 1999; D. Simon et al. 2004; D. Simon 2004). For part of their experiments, participants were presented with complex legal cases and asked to judge the subjective validity of the evidence before and after the decision was made. They were able to demonstrate strong coherence shifts (i.e., differences in the ratings of the evidence before and after the decision). The participants, however, were not aware of these shifts, and the ensuing decision was "experienced as rationally warranted by the inherent values of the variables, rather than by an inflated perception imposed by the cognitive system" (D. Simon 2004, p. 545). Interestingly, Simon was able to show that PCS processes not only influence information directly involved in the decision, but also beliefs and background knowledge. Motivation and attitudes influenced the direction of coherence shifts. In line with the assumption that PCS processes are based on temporarily activated networks, it could be shown that coherence shifts are of a transitory nature and disappear after a certain time. Using different material, Glöckner, Betsch, and Schindler (submitted) found that coherence shifts are instantly initiated as soon as a decision task is perceived, even without a decision being made at all. Furthermore, it could be shown that coherence shifts occur in city-size decision tasks. As predicted by the PCS approach, coherence shifts seem to be a stable and general phenomenon that can be observed in a broad range of decision tasks.

Fast Compensatory Information Integration

Bröder (2003) extensively investigated individual decision strategies in probabilistic decision tasks and found that some of the participants searched for information and selected options in accordance with the predictions of fast and frugal heuristics. Furthermore, corresponding to the predictions of the adaptive toolbox model, he found that individuals adapted their behavior to the structure of the environment. However, he concluded that "a [weighted] compensatory strategy may be something like a default strategy that is applied at the beginning of the procedure" (Bröder 2003, p. 617). Considering the fundamental bounded rationality argument (i.e., that human cognitive capacity is limited), this finding seems surprising. Why should individuals use a complex strategy as a default strategy when it could easily overload their cognitive capacity?

To investigate the decision strategies in the city-size decision tasks further, I conducted several experiments (Glöckner 2006). All information was presented simultaneously to measure a person's computational capacity, without limiting information search by the research method (Figure 2). Participants were instructed to make good decisions and to proceed as quickly as possible.

	City A	City B
State Capital	+	−
University	+	+
1st League Soccer Team	−	+
Art Gallery	+	−
Airport	−	+
Cathedral	−	+

Figure 2
Example for a city-size decision task.

A maximum likelihood analysis of the individual choice patterns revealed that, for the majority of participants, choice patterns were most likely produced by the weighted compensatory integration of cue values and cue validities. The average decision time was under three seconds. Thus, in line with the predictions of the PCS approach, individuals are indeed able to integrate quickly multitudinous information in a weighted compensatory manner.[2] These findings converge with those by Bröder (2003), indicating that this kind of information integration seems to be the default strategy if no available feedback indicates that a different strategy should be used.

Decision Time and Confidence Judgments

To test the predictions concerning decision times and confidence judgments, Glöckner and Hodges (submitted) conducted a series of experiments on memory-based decisions. University students in the United States were given information about German cities and were asked thereafter to make a memory-based decision as to which city is larger (cf. Hastie and Park 1986). Monetary incentives for correct decisions were used to assure high motivation. Consistency was varied between decision tasks (see Figure 3). For participants that estimated the cue “first division soccer team” as the least valid one, consistency was lower in the decision task depicted on the left than in the decision task on the right. According to fast and frugal heuristics (i.e., Take the Best or the equal weight heuristic), decision times should not differ between the two decision tasks because the number of computational steps that are necessary to select an option does not differ between decision tasks. According to the PCS approach, in the decision task on the left, decision time should be higher and confidence judgments should be lower than in the decision task on the right. The PCS predictions could be supported empirically, and the findings could be replicated using different decision tasks, including online tasks and different materials.

2 This finding is robust and could be replicated in studies using the city-size decision tasks (Glöckner 2007), purchasing decisions based on probabilistic information and classic gambling tasks (Glöckner and Betsch, submitted).

	Wiesbaden	Freiburg
State Capital	+	−
University	−	+
1st League Soccer	−	+

	Dresden	Leverkusen
State Capital	+	−
University	+	−
1st League Soccer	−	+

Figure 3
Decision tasks with less consistency (left-hand side) and more consistency (right-hand side).

To summarize, the predictions of the PCS approach are well supported empirically. Individuals are able to integrate quickly multitudinous information in a weighted compensatory manner and even seem to use this as a default strategy. The interpretation of information is changed in the decision process, and decision times and confidence judgments are systematically influenced by the level of consistency in decision tasks.[3]

What about Bounded Rationality?

Obviously, these findings conflict with the bounded rationality approach and, more specifically, with the adaptive toolbox model. Could the reported findings be explained by the fact that decision tasks induced the usage of decision strategies other than fast and frugal heuristics? Could the PCS approach be understood as just another tool in the adaptive toolbox? To address these questions, it is worthwhile to recapitulate the three fundamental premises of the adaptive toolbox approach (Gigerenzer 2001).

First, the research approach proposed by Gigerenzer and colleagues aims to “understand how actual humans (or ants, bees, chimpanzees, etc.) make decisions, as opposed to heavenly beings equipped with practically unlimited time, knowledge, memory, and other infinite resources” (Gigerenzer 2001, p. 38). Decisions rules should be *psychologically plausible* (i.e., they should be based on the actual cognitive repertoire of a species), since they rely on simple search as well as stopping and decision rules. In light of the PCS findings reported above, the adaptive toolbox underestimates the human ability for information integration. As postulated by the PCS approach and demonstrated by empirical evidence, parallel automatic processes that allow multitudinous information to be quickly integrated in a complex way are a part of humans’ cognitive repertoire. Consequently, PCS processes seem to be psychologically plausible without relying on simple search and stopping and decision rules. In contrast to the prevailing view, as soon as automatic processes are considered, the mathematical complexity of the algorithm leading to a decision (i.e., the number of elementary information processes; Payne et al. 1988) fails to provide a valid

3 It should be noted that the PCS approach can be understood as a generalization of the most prominent model for jury decision making: the story-telling model (Pennington and Hastie 1992). That model is empirically well supported, and part of the evidence (cf. Hastie and Wittenbrink 2006) lends additional support to the PCS approach.

measure of the effort to solve a decision task. According to the above reported findings (Glöckner 2006), people are able to make decisions based on complex algorithms almost instantly that would otherwise take computers several seconds to compute.

Second, the "adaptive toolbox offers a collection of heuristics that are specialized rather than domain general as would be the case in subjective expected utility (SEU)" (Gigerenzer 2001, p. 38). Thus, Gigerenzer argues that the structure of the domain induces the application of different decision algorithms. Although the evidence does not yet allow for final conclusions, the findings reported above indicate that PCS processes are rather general because they are automatically initiated as soon as a decision task is perceived. Individuals are not aware of them and often cannot avoid them. The PCS mechanism itself is always the same, but the structure of the temporarily activated network is adapted to the specific decision task; that is, it reflects the subjective perception of the specific content, learning experiences, and general knowledge.

Third, according to the adaptive toolbox, the structure of the environment has to be taken into account when exploring the efficiency of decision strategies. Heuristics are claimed to be successful because they are domain specific; that is, they adapt to the structure of the environment. In comprehensive simulations of real-world data, it has been shown that there are domains in which fast and frugal heuristics lead to very accurate decisions (e.g., in city-size decision tasks: Gigerenzer and Goldstein 1996). Thus, the domains used in the PCS experiments reported above have to be closely investigated before premature conclusions are drawn. However, a predominant usage of compensatory strategies was observed precisely in the city-size domain. Why did participants not behave adaptively to the environment? Upon closer inspection of the simulation data reported in Gigerenzer and Goldstein (1996) one sees a possible answer: on average, the performance advantage of the Take the Best heuristic over weighted compensatory models in cross prediction was 3 percent. Although people have powerful mechanisms of frequency learning, it would take them far more than 100 learning trials with perfect feedback to learn this advantage. Real life does not usually provide such a perfect and highly repetitive learning environment. Consequently, it is rather unlikely that such a small difference will be learned.

Furthermore, when one abstracts from the process of information integration and considers only choices, one often overlooks that fast and frugal heuristics are always a special case of weighted compensatory decision strategies (Bergert and Nosofsky 2007; Lee and Cummins 2004). Fast and frugal heuristics (i.e., Take the Best and equal weight heuristic) can always be perfectly modeled through weighted compensatory strategies. Thus, for purely mathematical reasons, fast and frugal heuristics can never be better than weighted compensatory models at predicting choices, except when nonoptimal weights are used (as may be the case in cross prediction because of overfitting).

In summary, the materials used in the experiments make it very unlikely that the findings can be simply explained by the fact that the decision tasks hindered the application of fast and frugal heuristics and induced the usage of more complex strategies. Furthermore, the PCS approach cannot be seen as just another fast and frugal heuristic because it conflicts with basic premises of the adaptive toolbox approach: the PCS approach is not based on simple rules for information integration; it does not ignore the majority of information (i.e., it is not frugal); and it does not appear to be domain specific but is instead domain general. Below, I summarize ways in which the adaptive toolbox approach and the PCS approach can be integrated into a more general model.

Toward an Integrative Interactionist Approach

As argued above, the majority of decision-making models view the decision process as a simple unidirectional process: information required for the task is searched or retrieved and integrated to derive a decision. The underlying processes are often considered to be deliberate; some more recent models assume automatic processes. Most models consider either deliberate or automatic processes, but not the interaction between them. Based on the observation that patterns of information search differ systematically, models based on the bounded rationality approach, in particular, lead us to conclude that individuals have a set of decision strategies from which they can select, in contrast to just one universal decision strategy (but see Lee and Cummins 2004).

The PCS Rule and its Evolutionary Advantage

Based on the general PCS approach, Glöckner and Betsch (in press) suggest that the PCS rule be viewed as an alternative integrative model for decision making (Figure 4). They postulate that automatic PCS processes form the computational core of decision making and that deliberate processes merely supervise or modify the network on which these automatic processes act. A dual-level network architecture is assumed: in the primary network, evidence and options are weighed in their complex constellation; in the secondary network, if necessary, deliberate strategies are weighed that support consistency maximizing in the primary network and allow for quick adaptations.

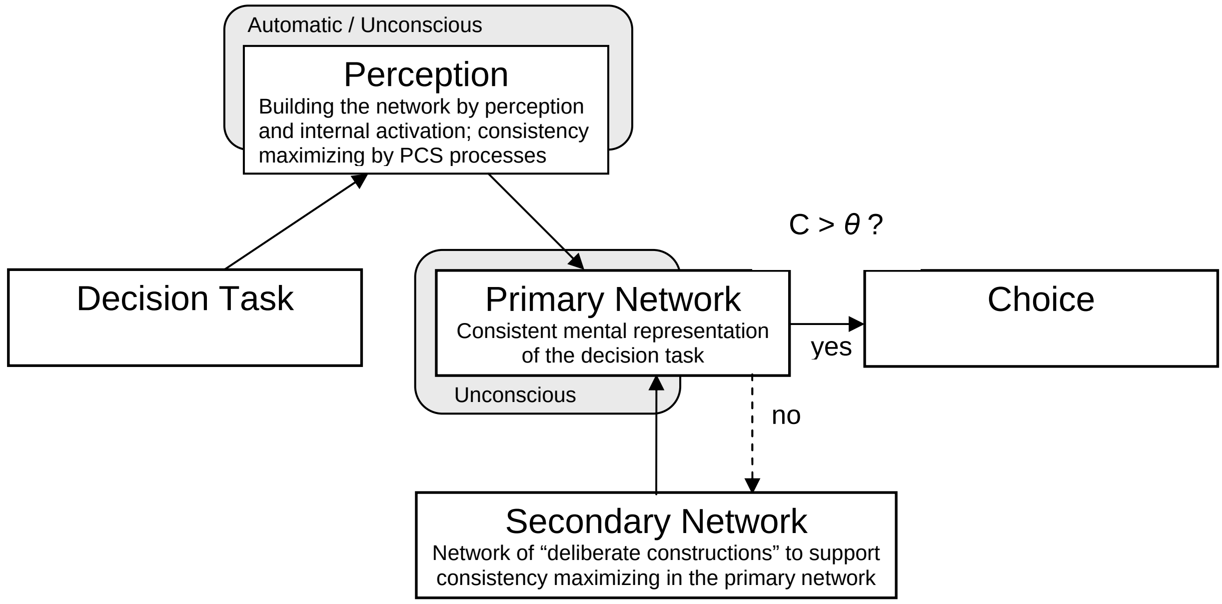

Figure 4
Schematic process model of the PCS rule.

The Primary Network

As soon as individuals are confronted with a decision task, automatic processes of information search and retrieval take place and lead to the construction of a temporarily activated network (cf. Figure 1). Within the network, PCS processes are initiated that serve to maximize consistency by changing the activation level of the contained elements. The architecture of the network provides the constraints under which the quest for consistency evolves. Thus, the final level of consistency is bounded by the network structure. If the level of consistency in the network (C) exceeds a certain threshold (θ), PCS processes are terminated and the option with the highest activation is chosen. The network of options and information is referred to as the *primary network*.

Primary networks also capture the automatic processes of behavioral selection in animals, and should thus be considered the older part of decision-making processes in evolutionary terms. Parallel to processes of object perception, information is weighed in its complex constellation; the dominant interpretation is automatically detected and accentuated. This may explain the finding that even sticklebacks have the computational capacity to select mating partners by integrating trait information in a complex compensatory manner (Künzler and Bakker 2001; see also Glimcher et al. 2005). For human decision making, the operations of the primary network lead to the often described phenomenon of “intuition”; that is, which option should be selected it is instantly “seen.” No deliberation is necessary to reach this insight, and no deliberation appears necessary to validate it. The level of awareness of the resulting mental representation can, however, differ. In some cases, individuals are totally aware of the consistent mental representation and are able to explicate it. In others, only a vague feeling is perceived.

The Secondary Network

If the level of consistency *C* in the primary network is below the threshold, a secondary network is formed that is instrumental to the primary network. In the secondary network, deliberate strategies are weighed against each other to support consistency maximizing in the primary network. Glöckner and Betsch (in press) postulate that deliberate processes cannot directly influence automatic PCS processes; they can only modify the network on which PCS processes act. For instance, deliberate processes may be used to include additional information in the network or to change its structure. These deliberate processes, which aim to modify the primary network, are referred to as *deliberate constructions*. They are also assumed to be weighed and selected based on PCS processes. The deliberate construction that is most activated is then implemented. It is reasonable to assume that, if repeatedly trained, deliberate constructions will become automatic (cf. Anderson and Lebiere 1998).

There are two main reasons for a low level of consistency. First, insufficient information is included in the network or the network is nearly empty. In this case, deliberate processes of information search and production are used to add information to the network. Second, the degree of contradiction in the network can be so high that it cannot be sufficiently resolved by PCS processes. To avoid a long period in which one is incapable of action, deliberate processes can temporarily modify the structure of the network or additionally activate or inhibit elements to increase consistency. This mechanism can also be used to simulate different interpretations of the data that could not be reached by mere automatic processes (cf. Bischof 1987; Hastie and Wittenbrink 2006). The reason for this may be that the PCS algorithm is caught in a local maximum of consistency, thereby overlooking a global maximum (Read et al. 1997).

In contrast to lower animals, humans have developed the ability to supervise and manipulate deliberately the powerful but inflexible automatic processes of the primary network (Betsch 2005). Glöckner and Betsch (in press) assume that the relations between elements in the primary network are determined mainly by slow learning processes. Thus, changes in these relations usually take a long time, and quick adaptations to environmental change are impossible (Betsch et al. 2001, 2004). The evolutionary advantage of the additional deliberate system is that it facilitates faster behavioral adaptations and allows for directed information search, qualified information production, and simulations to find the global maxima. However, without the automatic system, the deliberate system would be computationally overloaded on a chronic basis.

Integrating Fast and Frugal Heuristics and the PCS Rule

One of the essential findings of the adaptive toolbox research program is that individuals adapt their decision strategy and, in particular, their search for information to the environmental structure. Simply stated, if individuals receive repeated feedback that the usage of less valid cues is not useful in a certain environment, they will focus, after sufficient learning trials, on the most important cue (Bröder 2003; Rieskamp 2006; Rieskamp and Otto 2006). It is important to differentiate between two classes of situations: those in which information is instantly accessible and those in which it is not (cf. Glöckner and Betsch, submitted). When it is not, which is predominantly the case in experimental research, the primary network is nearly empty at the onset, and consistency is low. Thus, the secondary network is formed to support processes that maximize consistency. Repeated feedback reinforces the deliberate construction "look up information for the most important cue only," and, after sufficient trials, individuals change from a default deliberate-construction strategy (e.g., "look up all information along options") to the alternative deliberate-construction strategy. From this point in time, the primary network consists only of the options and the information for the most important cue. Consequently, choice predictions align with that of the Take the Best heuristic. From such a perspective, the Take the Best heuristic (as well as other fast and frugal heuristics) can be understood as one of many deliberate-construction strategies that are possible elements of the secondary network. However, in each case the decision is based ultimately on the resulting activation in the primary network.

In situations in which information is accessible immediately, the primary network is instantly constructed. Individuals will make decisions based on the network. However, from repeated feedback, the structure of the environment will be learned. Thus, in a noncompensatory environment (i.e., an environment in which the most valid cue is stronger than all the remaining cues taken together), after sufficient learning trials, the dominance of the initial validity of the most valid cue will become more pronounced. As a result, its influence on the decision will decrease, although the lower valid cue information will not be ignored. Over time, this also leads to choices that align with the predictions of the Take the Best heuristic.

In summary, I suggest that the adaptive learning processes highlighted by the adaptive toolbox model are important in decision making; however, they should be integrated into the PCS rule: changes in the relations between elements in the primary network as well as the relations between specific deliberate constructions for certain decision tasks in the secondary network are learned from feedback. Further research will be needed to differentiate and test this hypothesis empirically.

The PCS Rule and Institutions

Work on the PCS rule is still in its early stages, and I wish to emphasize that the model must be further specified and empirically tested. However, it provides a fruitful starting point for rethinking issues relevant to the development and design of institutions. Jointly considering cognitive processes and the structure of institutions facilitates learning from and for institutions (cf. Engel and Weber, submitted). We must assume that institutions are shaped similarly to humans by evolutionary forces and learning mechanisms to optimize their structure over time (Hodgson 1988). If the PCS rule is a valid model, indirect evidence in support of it can be derived by investigating whether successful institutions align with its predictions. Some of the major hypotheses concerning the structure of efficient institutions, according to the PCS rule, are presented below.

Predictions of the PCS Rule for the Design of Efficient Institutions

1. Individual decisions are good as long as the structure of the primary network represents the structure of the environment. Efficient institutions support the construction of representative primary networks.

2. The structure of the primary network is influenced by unconscious motivational and emotional factors. Institutions have been developed to reduce the influence of these factors as well as to increase the objectivity of the network.

3. PCS mechanisms artificially increase the consistency of information by eliminating contrary information, which naturally leads to overconfidence. Efficient institutions reduce overconfidence by forcing individuals or groups to consider alternative interpretations.

4. Decision making in diverse groups is problematic because members can form different but fairly stable interpretations of the situation. PCS processes increase divergences in the interpretation of information, which makes them more resistant to change. Institutions have been established to ensure that groups nevertheless reach decisions in time without disintegrating.

5. Decisions based on automatic PCS processes are hard to communicate and justify, because parts of the mental representation of the decision might be unconscious. Institutions provide rules that make decisions easier to communicate and which facilitate an increase in the level of acceptance of the decision.

6. Institutions increase the consistency of decisions over time by providing a set of explicit rules for deliberate constructions (secondary network). As a result, certain important information is always included in the primary network; this stabilizes the general structure, which in turn increases consistency over time.

7. Efficient institutions accommodate and utilize PCS processes. The structure of the environment should be analyzed, and decision makers should be provided with the results. These results can facilitate the construction of more adequate mental representations. However, it is not necessary to provide decision makers with overly simple decision rules because they can manage complexity.

8. PCS processes enhance the efficiency of social interaction in organizations. If institutions ensure that the fundamental goals of the organizations are always included in the primary network, individual decisions will be automatically aligned to the organizational goals, thus eliminating the necessity of specifying a complete set of behavioral rules for all situations.

9. Effective institutions make use of the error detection capabilities of PCS processes and leave room for exploring feelings of mismatch. The conscious part of the mental representation does not equate to the whole representation and might overlook important facts that exert unconsciously an influence.

10. Efficient institutions make use of trained expert decision makers. Expert decision makers are able to manage larger informational networks than lay people. Expert decision makers learn to include automatically a large set of important elements in the network.

11. Efficient institutions establish revision units that (a) test the decision-making process to ensure that all relevant information has been included and (b) provide learning feedback for deliberate constructions as well as for the structure of the primary network.

The German Legal System and the PCS Rule

Successful institutions can be used to test the predictions of the PCS rule. It is my assumption that such institutions have already implemented part of the mechanisms prescribed by the PCS rule, through the process of institutional evolution and learning. Using the German legal system, let us proceed to examine the predictions of the PCS rule for institutions.

Construction of Representative Primary Networks

One of the aims of modern legal systems (e.g. current systems in Anglo-American countries and Germany) is that in decisions all relevant evidence be taken into account according to its level of importance (for a discussion of different models see Jackson 1996). One specific example for this principle in German law is that the German Federal Supreme Court prohibits explicitly the application of simple, schematic rules (i.e., heuristics) in expert assessments of the trustworthiness of eyewitness reports (Decision of the Federal Supreme Court [BGH] July, 30 1999, Az.1 StR 618/98). In line with the predictions 1, 6, and 7, this court decision specifies a set of valid cues (*Realkennzeichen*) which must be considered during the assessment. With this prescription, the institution ensures that these cues are included in the primary network and supports the construction of representative primary networks by the judge. On a more general level, the principle of exhaustive consideration of relevant evidence is a fundamental requirement imposed by the German code of criminal procedure (Schoreit 2003; StPO §261). This code also obligates judges to take into account not only the formal evidence of the case, but also the holistic impressions and insights that arise during the trial (*Gesamteindruck der Hauptverhandlung*; Schoreit 2003).

Ensuring Objectivity and the Requirement to Consider Alternative Interpretations

Another basic aim of modern legal systems is that decisions should be reached objectively. This can be supported through a process of considering alternate interpretations (cf. predictions 2 and 3), which reduces subjective biases in judgments of the evidence caused by coherence shifts (D.

Simon (2004). The different roles of prosecutors and defenders are designed to ensure that all relevant information is available in the primary network and that different interpretations can be considered. This availability allows a neutral judge to weigh interpretations against each other, in order to reach a global rather than local maximum of consistency. Likewise, the German code of criminal procedure obligates judges to consider all plausible alternative assessments (or interpretations) of the evidence (Schoreit 2003). Consideration of evidence is invalid if only one of various equally plausible interpretations is taken into account (Schoreit 2003).

Decision Rules in Multiple-judge Courts

Legal institutions have implemented voting rules to enable decision making even if different, stable interpretations of the case have been formed by judges in multiple-judge courts (cf. prediction 4). It is not always necessary to convince all judges to agree on one interpretation; majority rules are often applied. This is the case, for example, with the German Federal Constitutional Court. Furthermore, decisions of this court are used as a basis in further legal argumentations (cf. prediction 5).

Installing Revision Units

In the German legal system, appellate courts function as revision units. The German code of criminal procedure requires that decisions be revised if they are found invalid as a result of procedural violations. An example of this would be if it can be proved that relevant aspects or alternative interpretations of the evidence were not considered in the first procedure (Schoreit 2003; cf. predictions 1 and 11).

Use of Expert Decision Makers

Taking a somewhat broader perspective, German legal doctrine can be interpreted as providing a large set of features that have to be regarded as a complex constellation in legal cases. When thinking about a case, experienced lawyers (because of their training) automatically and unconsciously include many (or hopefully all) of the relevant aspects in their primary network, whereas law students use deliberate-construction strategies to include them in a sequential manner (cf. predictions 8 and 10). Furthermore, within defined parameters, German law allows judges to exercise leeway in their judgment, thus allowing them to act on their impressions, which result from automatic PCS processes (cf. prediction 9).

In summary, supporting evidence for the PCS rule can be found when analyzing the German legal system. Many of the predictions for efficient institutions have already been implemented. However, a systematic investigation is needed to strengthen this argument and to inspire a premeditated improvement of the institution of German law as well as of other institutions, if necessary.

Conclusions and Outlook

The PCS rule is a complex model, which presently should be considered a work in progress. To strengthen the model, the secondary network will need to be specified further and empirical tests will need to be performed on the interaction between the networks. Nevertheless, evidence already supports clearly the central claim: individuals are capable of quickly integrating a great deal of information in decision making. Based on this finding, some recommendations for institutions that have been derived from the bounded rationality approach should be reconsidered; others are highlighted even more. As argued by Gigerenzer (2001), it is very important to understand the environmental structure of decision tasks in order to enhance the quality of decisions. However, according to the PCS rule, institutions should try to support individuals to construct more adequate mental representations of the decision task (cf. Gigerenzer and Hoffrage 1995). In some decisions, this might be accomplished by instructing individuals to include only the most valid information in the network; however, in complex decision tasks, this will not likely be the case.

Can the PCS Rule Account for Biases in Decision Making?

By taking a positive perspective in this chapter, my intent was to call attention to the astonishingly rich human cognitive capabilities for decision making. This stands in contrast to the more prominent views that individuals are poor decision makers who often show biases in decision making (Kahneman et al. 1982) or that the cognitive capacity of humans is severely limited but adaptive selection of simplifying strategies nevertheless leads to good decisions (Gigerenzer et al. 1999). Glöckner and Betsch (in press) propose the PCS rule as a descriptive model for decision making; it should also be able to predict when decisions go astray. Thus, it should be able to account for the multitude of evidence showing deviations from rationality in decisions and, in fact, it is able to do so. According to the PCS rule, all deviations from optimal decisions are essentially caused by the fact that the mental representation of the decision task (i.e., the primary network) represents the real structure of the decision task inaccurately. Thus, in contrast to the heuristics and biases program (Kahneman et al. 1982), the PCS rule does not assume that different heuristics lead to certain biases but that one single mechanism accounts for all of them. Systematic misperceptions can be caused by all of the factors that have been repeatedly discussed in the literature, such as framing, anchoring, salience, status quo, mental accounting (for an overview, see Baron 2000). More research will be needed for a systematic empirical investigation of the influence of these factors on mental representations.

How Does the PCS Rule Connect to Neuroscience Research?

In addition to investigating the PCS rule from a psychological and an institutional perspective, it is necessary to connect the model to recent research in neuroscience. The PCS rule is based on a connectionist network and is at a medium level of abstraction. It opens the opportunity to connect findings and models on the neuronal level with findings and models on the behavioral level.

Until now, empirical research on the PCS rule has focused entirely on the behavioral level. However, the PCS rule bears a high resemblance to nonlinear neuroscientific models as advocated by Singer (2003). I argue that the proposed processes of synchronization and binding describe the nonlinear integration processes of the PCS rule on the neuronal implementation level. From such a perspective, the PCS rule is a model that reduces the complexity of neuronal implementations but retains the basic underlying mechanism and allows for deriving testable predictions for human decisions in complex decision tasks.[4]

The PCS model also shares some structural similarities with the global neuronal workspace model proposed by Dehaene et al. (2006), which has been successfully used to integrate a wide range of neuroscience findings concerning conscious, preconscious, and subliminal processing. An important difference between both models that should be addressed in future research concerns the question of whether a single network or a hierarchical two-level network model is more appropriate for representing complex decision tasks.

The close relation of the PCS rule to models of perception might allow a comparison of patterns of activation using neuroimaging techniques, taking into account recent neuroscientific findings on perception and perceptual decision making (Heekeren et al. 2004; Summerfield et al. 2006).

Is Decision Making Based on Linear or Nonlinear Information Integration?

In behavioral decision research as well as in neuroscience, there has been much debate as to whether information integration in perception and decision making is based on a linear aggregation of evidence or on a nonlinear integration process. Gold and Shadlen (2007) report findings that support linear evidence accumulation models, which have been also proposed in behavioral decision research (Busemeyer and Townsend 1993; Ratcliff et al. 1999). In this chapter, I have summarized behavioral findings in support of the nonlinear PCS rule that are coherent with neuroscientific models of synchronization and binding (Singer 2003). Although these findings cannot be easily explained by linear models, the debate between approaches can be expected to continue. However, I would like to highlight two very general points. First, mathematically, linear models are partial models of nonlinear models. Thus, nonlinear models can usually account for all findings of linear models, but not the other way around. Second, it is not possible to differentiate between linear and nonlinear models in simple decision tasks (which are, for practical reasons, commonly used in neuroscience research on apes) because in such tasks, the predictions of both classes of models converge. A differentiation is only possible in complex decision tasks that allow for nonlinear effects.

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4 Wagar and Thagard (2004) suggest a subsymbolic network that more closely resembles neurons than the PCS rule does and which aims to copy relevant areas in the brain. However, I argue that the symbolic representations used in the PCS rule (in contrast to the sub-symbolic ones used by Wagar and Thagard 2004) are sufficient to capture the major mechanisms of decision making.

Evolution, Cognitive Limitations, and the Bounded Rationality Perspective on Decision Making

Evolution has equipped animals and human beings with powerful automatic mechanisms to integrate large amounts of information. According to the PCS rule, humans have developed the additional ability of being able to supervise and manipulate deliberately the primary network. Although the deliberate processes are rather limited in their computational capacity, they allow for better and faster adaptations by providing further information and temporarily changing the network so as to find quickly a consistent solution and a global maximum of consistency.

The title of this paper was intentionally provocative in promising to explain how evolution “outwits” bounded rationality. It refers to *bounded rationality* in two respects: first, in the narrow sense as limits in capacity for cognitive reasoning; second, in a broader sense as a prominent school of thought in decision research. With the PCS rule, Betsch and I have proposed a decision-making model based on the assumption that decision-making mechanisms have developed phylogenetically from perceptual processes. The model breaks with the assumption that decision making is mainly driven by deliberate reasoning and is sometimes influenced by automatic/unconscious processes or that there are two systems for decision making between which people can switch. In contrast, it postulates that the core processes of decision making are automatic processes that resemble processes of perception. In phylogenesis, these processes have been supplemented by deliberate processes that provided further evolutionary advantages.

With respect to the narrow meaning of bounded rationality, nobody would seriously doubt that there are limits to cognitive capacity. However, I argue that humans have developed capabilities to use automatic and deliberate processes efficiently so that their cognitive capacity is sufficient to solve even highly complex real-world problems, such as legal and managerial decisions. In this sense, evolution has found a way to shift the “bounds of rationality” dramatically.

As for the meaning of bounded rationality as a school of thought in decision making, evolution appears to be way ahead of scientific endeavors: while decision researchers are still focusing on deliberate decision strategies and arguing about the boundaries of rationality, evolution has long taken care of the problem by endowing humans (and animals) with powerful computational capabilities. This paper has attempted to catch up with the fascinating inventor called evolution as well as to direct our queries towards other long known but unfortunately sometimes forgotten possibilities:

> My first empirical proposition is that there is a complete lack of evidence that, in actual choice situations of any complexity, these [expected utility] computations can be, or are in fact, performed...but we cannot, of course, rule out the possibility that the unconscious is a better decision maker than the conscious (H. A. Simon 1955, p. 104).

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