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Studies in Ecological Rationality

Ralph Hertwig,[a] Christina Leuker,[a,b] Thorsten Pachur,[a]
Leonidas Spiliopoulos,[a] Timothy J. Pleskac[a,c]

[a]*Center for Adaptive Rationality, Max Planck Institute for Human Development*
[b]*Science Communication Unit, Robert Koch-Institute*
[c]*Department of Psychology, University of Kansas*

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Abstract

Ecological rationality represents an alternative to classic frameworks of rationality. Extending on Herbert Simon's concept of bounded rationality, it holds that cognitive processes, including simple heuristics, are not per se rational or irrational, but that their success rests on their degree of fit to relevant environmental structures. The key is therefore to understand how cognitive and environmental structures slot together. In recent years, a growing set of analyses of heuristic–environment systems has deepened the understanding of the human mind and how boundedly rational heuristics can result in successful decision making. This article is concerned with three conceptual challenges in the study of ecological rationality. First, do heuristics also succeed in dynamic contexts involving competitive agents? Second, can the mind adapt to environmental structures via an unsupervised learning process? Third, how can research go beyond mere descriptions of environmental structures to develop theories of the mechanisms that give rise to those structures? In addressing these questions, we illustrate that a successful theory of rationality will focus on the adaptive aspects of the mind and will need to account

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Correspondence should be sent to Ralph Hertwig, Center for Adaptive Rationality, Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany. E-mail: hertwig@mpib-berlin.mpg.de

for three components: the mind's information processing, the environment to which the mind adapts, and the intersection between the environment and the mind.

Keywords: Decision-making; Heuristics; Ecological rationality; Adaptive rationality; Environmental structures; Risk-reward structures; Strategic games

1. Studies in ecological rationality

> Both organism and environment will have to be seen as systems, each with properties of its own, yet both hewn from basically the same block. [….] It follows that, much as psychology must be concerned with the texture of the organism …, it also must be concerned with the texture of the environment ….
>
> Egon Brunswik (1957/2001, p. 300)

Traditional theories of rationality commonly assume that a single universal decision policy determines the best course of action. Accordingly, theories such as expected utility theory or Bayesian decision theory are not concerned with when and where this universal tool works better or worse than other approaches. From these perspectives, there is only one tool or approach. Optimal is optimal—case closed. In addition, these theories do not conceptualize the mind as consisting of cognition–environment systems in which the processes and strategies of the human mind are closely intertwined with the environment. This does not imply that Bayesian decision models do not make assumptions about the environment; standard Bayesian models (e.g., conditional independence) frequently do. Yet Bayesian decision models are not necessarily valid in the natural environment and appear to be primarily driven by mathematical convenience—and less so by Brunswik's argument (1957/2001; Dhami, Hertwig, & Hoffrage, 2004) that cognition and environment are indivisible, like a married couple who have come to terms with each other through mutual adaptation. Simon (1956) likewise emphasized the collaborative relationship between cognition and environment. He suggested that the structural properties of the environment can come to the rescue of a computationally and otherwise bounded mind by facilitating the use of simpler decision mechanisms without a prohibitive loss in efficiency. In this view, the environment is not an obstacle complicating formalisms or an incontestable fact that the mind has to reckon with; rather it can ideally become an important ally of any organism whose computational and cognitive powers will, inevitably, be limited relative to the complexities of the physical and social world. This idea is the foundational premise of the ecological rationality framework (see also Kozyreva & Hertwig, 2021; Kozyreva, Pleskac, Pachur, & Hertwig, 2019).

Before we turn to this framework, and to appreciate the notion of a cognition–environment system beyond the domain of rationality, let us consider Duncker's (1945) work on *functional fixedness*. Gestalt psychologist Duncker presented participants with a rather odd problem: He asked them to mount a candle on a wall in such a way that, when the candle was lit, the melting wax did not drip onto the table below. They could use only the objects in front of them: a small candle, a book of matches, and a box of thumbtacks. To solve the problem, participants had to figure out that the box of thumbtacks can function not only as a container but also as a flat surface that can be tacked to the wall, providing a mount for the candle. Yet participants were less likely to arrive at this solution than to attempt other, unsuccessful approaches—not because they were engaged in a process of trial and error (see Newell, 1985), but because they generated solutions from the "concrete, specific substratum of its problem situation" (Duncker, 1945, p. 20). In the candle experiment, the artifact required for the solution—the box—has an established use and design function (containment) that hinders the discovery of a new function (as a supporting plane). Functional fixedness can be seen as arising from the co-occurrence of an environmental artifact and its conventional use. The statistical structure of the environment thus thwarts efficient solutions (see also German & Barrett, 2005).

Yet the opposite can also hold: The statistical structure of the environment can facilitate efficient solutions. Just imagine if human reasoning were a blank slate, free of functional fixedness. When opening a toolbox and looking for something to tighten a screw, a person would need to test out every tool in the box; with functional fixedness, they can just grab a screwdriver. Functional fixedness thus reflects the frequency and recency of past use of artifacts (see Anderson & Schooler, 1991). In technologically sophisticated environments populated with countless artificial objects with highly specific functions (e.g., olive pitters, computer track pads, cordless impact drivers; Tomasello, 1999), functional fixedness is likely to be an indispensable ingredient of cognition–environment systems. That said, as Lévi-Strauss (1962) pointed out, the ability to transcend functional fixedness in the service of innovation by making do ("bricolage") and applying existing resources and tools to new problems and opportunities can also be very important, both in nonindustrial societies and in contemporary organizations (Duymedjian & Rüling, 2010).[1]

Although an environment-informed approach to cognition is not the default approach in the cognitive sciences, there have been important theoretical attempts to describe cognition–environment systems (e.g., Anderson, 1990; Brunswik, 1952; Gibson, 1966; Greeno, 1994; Shepard, 1994). Modeling the mind in terms of cognition–environment systems also effects a shift in the conceptualization and measurement of rationality: If intelligent reasoning and behavior emerge from the interaction of mind and the world, their rationality can be described, predicted, and evaluated only by taking this entrenchment and the associated mind–world coevolution into account. Research on ecological rationality (Gigerenzer, Todd, & the ABC Research Group, 1999; Hertwig, Pleskac, & Pachur, 2019; Todd, Gigerenzer, & the ABC Research Group, 2012) seeks to describe, analyze, and model such cognition–environment systems (Kozyreva et al., 2019), with a particular focus on the role and environmentally contingent success of simple cognitive strategies: *heuristics*. In this article, we first outline the study of ecological rationality, and then turn to three conceptual challenges on which notable progress has recently been made:

> *How do heuristics fare in competitive and strategic worlds?* Can heuristics succeed even when interactive, competing agents engage in dynamically shifting behaviors? If so, what are the environmental structures that render possible the ecological rationality of heuristics in social games?

How do people learn environmental structures? Is it conceivable that the mind adapts to ecological structures by means of the incidental, unsupervised learning that is common in many real-world contexts?

How to theorize rather than describe environmental structures? What kind of theories of environmental structures are needed to predict, rather than merely describe, how human reasoning and behavior are a function of specific environments?

We begin with a brief history of the notion of ecological rationality.

2. Ecological rationality: Process simplification enabled by the environment

The study of ecological rationality builds and extends on Herbert Simon's notion of *bounded rationality* (Todd et al., 2012). Simon aimed to formulate a psychologically realistic theory of rational choice capable of explaining how people make decisions and achieve their goals under internal (cognitive) and external (environmental) constraints. His objection to the classical models of rational choice (e.g., the family of expected utility approaches) was that their norms, postulates, and commitment to optimization make unrealistic demands on decision makers, expecting them to be able to specify all possible outcomes, rank their quality, and then assign them probabilities. In real life, people often have access to only some of the information or are unable to integrate that information in the sophisticated way mandated by expected utility theory; consequently, they may rely on simplifying procedures. What do these constraints mean for the quality of people's choices? Simon (1956) conjectured that real organisms' behavior probably "falls far short of the ideal of 'maximizing' postulated in economic theory" (Simon, 1956, p. 129).

Decision scientists sometimes argue that humans "obviously" maximize some function and that it is the scientist's job to find out which function that is. This was not Simon's position. In view of the formidable demands on decision makers, which render the ideal of maximization and optimization unrealistic irrespective of the underlying function, he suggested a different rationality ideal, namely, that of "good enough decisions" or satisficing (Simon, 1979, p. 498; see also Artinger, Gigerenzer, & Jacobs, in press). According to this approach, "satisficing models … provide good enough decisions with reasonable costs of computation. By giving up optimization, a richer set of properties of the real world can be retained in the models." Simon's (1956) work also took a second, complementary direction, proposing that "the environments to which [an organism] must adapt possess properties that permit further simplification of its choice mechanisms" (p. 129). In other words, structural properties of the environment enable the use of cognitive processes that ease the cognitive demands on decision makers.

This is where the study of ecological rationality begins. It aims to identify the environmental properties that permit the simplification of the decision strategy and to ascertain the potential price of that simplification in terms of measures such as accuracy (Schurz & Hertwig, 2019). The key class of simplifying strategies is that of heuristics (e.g., Hertwig & Pachur, 2015). A heuristic is a strategy that "ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods" (Gigerenzer & Gaissmaier, 2011, p. 454). Ecologically rational heuristics benefit from environmental structures that support the policy of foregoing part of the information and computation. Extensive work on the ecological rationality of heuristics (e.g., Gigerenzer & Brighton, 2009; Gigerenzer, Hertwig, & Pachur, 2011; Hertwig, Woike, Pachur, & Brandstätter, 2019; Todd et al., 2012) has produced two major findings: First, less information, computation, and time can still lead to surprisingly high levels of success. Second, there is evidence for a growing set of environmental structures that fit the cognitive architecture of specific heuristics, thus facilitating their success.

Interestingly, the observation that computational and informational simplicity can result in highly successful outcomes dates back to a time in psychology in which the currently dominant view that heuristic decision making is associated with systematic and severe errors was evolving. Dawes and Corrigan (1974) showed that simple prediction models assuming equal-weight regression coefficients (predictors, cues) perform surprisingly well, yielding more accurate predictions than models with regression weights obtained by the least-squares algorithm under some conditions. The study of the conditions under which improper (unit-weight) models succeed (see, e.g., Davis-Stober, Dana, & Budescu, 2010; Einhorn & Hogarth, 1975) can be understood as one of the first lines of research into ecological rationality (see Davis-Stober et al., 2010; Dawes & Corrigan, 1974; Einhorn & Hogarth, 1975).

Analyses of the interdependency of cognitive and environmental structures continued to be exceptions in psychology (for another example, see the influential work on the *adaptive decision maker* in the domain of preferential choice; Payne, Bettman, & Johnson, 1993). Yet interest in environmental structures intensified with the emergence of work on fast and frugal heuristics (Gigerenzer & Goldstein, 1996; Gigerenzer et al., 1999). Studies demonstrating that simple heuristics using limited search, stopping rules, and aspiration levels can sometimes lead to more accurate outcomes than their more sophisticated competitors (e.g., logistic regression, classification, and regression trees) accumulated, and the key question was now another one: Which statistical structures—that is, patterns of information distribution in the environment—are conducive to the success of informational and computational simplicity and, equally importantly, which are not? In other words, returning to Simon (1956), which environmental properties permit simplification of the choice mechanism without compromising its success?

Some answers to this question are now clear: Structural properties such as the degree of uncertainty or predictability (how well the available cues predict the criterion), sample size of available data, number and dispersion of alternatives, variance (distribution of outcomes and probabilities), functional relations between cues and criterion (e.g., linear or nonlinear), distribution of weights (e.g., compensatory or noncompensatory), cue redundancy (level of intercue correlations), and dominance all affect the performance of simpler cognitive strategies (see DeMiguel, Garlappi, & Uppal, 2007; Hertwig et al., 2019; Hogarth & Karelaia, 2006, 2007; Katsikopoulos & Martignon, 2006; Katsikopoulos, Schooler, & Hertwig, 2010; Marewski & Schooler, 2011; Martignon & Hoffrage, 2002; Pachur, Hertwig, & Rieskamp, 2013; Şimşek, 2013; Todd et al., 2012). Yet the benefits of simplicity remain counterintuitive to many scholars of the mind. In the next section, we turn to a key controversy over the merits and limits of simplicity.

3. How do heuristics fare in competitive and strategic worlds?

Social environments populated with intelligent individuals acting strategically are thought to be much more complex and cognitively demanding than nonsocial ones (e.g., Whiten & Byrne, 1988, 1997). The philosopher Sterelny (2003) argued that environments in which simple heuristics perform well "rarely involve competitive, interacting, responsive aspects of the environment" (p. 208) and that heuristics will flounder in socially competitive and dynamic worlds:

> We need to see some experimental (or modeling) work on, for example, judgments about whether others are lying to you; on whether others will be reliable partners in cooperative tasks; on whether a partner is engaging in extra-pair copulation. (p. 208)
>
> For it is precisely in such situations that simple rules of thumb will go wrong .... Catching a ball is one problem; catching a liar is another. (p. 53)

But is Sterelny's (2003) intuition correct? To find out, Spiliopoulos and Hertwig (2020) conducted an extensive analysis involving an enormous collection of strategic interactions, namely, the population of all (1,828,915,200) types of one-shot 3×3 normal-form games with simultaneous moves. Substantial experimental evidence has demonstrated that people rarely play the Nash equilibrium in one-shot games; rather, they appear to rely on various simple heuristics (see table 3 in Spiliopoulos & Hertwig, 2020). Does this mean that these "deviations from equilibrium decisions" (Costa-Gomes, Crawford, & Broseta, 2001, p. 1193) simply signal lower levels of strategic sophistication and are the price of humans' limited cognitive capacity (Polonio, Di Guida, & Coricelli, 2015)? If one accepts the assumptions of the normative game-theoretic framework (i.e., the concept of the Nash equilibrium), one cannot help but conclude that people's use of heuristics reflects second-best processes and solutions. Yet according to the notion of ecological rationality, if simple heuristics are adapted to the presence of strategic and payoff uncertainty in these interactions, their use could be highly beneficial. In which types of social games does a particular heuristic succeed, and in which does it fail?

4. Why heuristics may be indispensable in complex social worlds

One key discovery in the study of ecological rationality has been that, ceteris paribus, the greater the uncertainty, the more likely simple heuristics will be to perform on par with—or even outperform—more complex strategies (see the analysis of the bias–variance dilemma; Gigerenzer & Brighton, 2009; Katsikopoulos et al., 2010). Strategic environments typically manifest as less stable and thus more uncertain than nonstrategic environments because the behavior of cognizant agents is arguably less predictable than that of entities populating a stable nonsocial environment (what economists often call "nature"). Their payoffs depend on the actions of others, which introduces immense *strategic uncertainty*, which is in turn amplified by the heterogeneity and stochasticity of agents' preferences and decision-making strategies. This renders it virtually impossible to infer the type of agent one is facing in one- or limited-shot interactions and, by extension, to predict their behavior.

Note that strategic uncertainty is also a challenge to normative solutions for at least two reasons. First and foremost, the Nash equilibrium is optimal only if one's opponent is also playing Nash. Under strategic uncertainty, a player may be competing (or believe themself to be competing) against an opponent who is not playing Nash. Second, many games admit more than one Nash equilibrium. Many simpler normative solutions, such as rationalizability (Bernheim, 1984; Pearce, 1984) and correlated equilibrium (Aumann, 1974) suffer even more than the Nash equilibrium from the problem of solution nonuniqueness, that is, suggesting more than one action to be rational. This makes it even less likely that players will coordinate on the same equilibrium. Simple heuristics, which are especially suited to coping with uncertainty, may thus represent particularly successful and robust tools for navigating competitive worlds. One such candidate heuristic is Level 1 (L1). This heuristic recommends playing the best response under the assumption that the opponent is playing randomly or, equivalently, choosing the action with the highest average payoff computed over the opponent's possible actions. Another candidate heuristic is Dominance 1 (D1). This heuristic differs from L1 by assuming that an opponent randomizes over their *nondominated* actions, that is, that the opponent would never play an action that is necessarily inferior to another, regardless of the other player's choice.

5. Mapping the success of heuristics in uncertain strategic worlds

The goal of Spiliopoulos and Hertwig's (2020) computer tournament was to investigate the success of simple heuristics in strategic one-shot interactions and to map simple decision policies to environmental niches. Three properties of the environment were systematically varied:

1. the number of actions available to each player in a game (from 2 to 20);
2. the degree of correlation, ρ, between the randomly drawn payoffs of games: discordant or competitive environments, $\rho = -0.5$; neutral environments, $\rho = 0$; and harmonious or cooperative environments, $\rho = 0.5$;
3. the payoff uncertainty experienced by the players, operationalized as the percentage of payoffs that were unavailable to the players, from 0% (perfect knowledge of the game) to 80%.

The analysis covered 10 decision strategies, ranging from the highly complex Nash equilibrium via moderately complex heuristics (e.g., level-k models; for a detailed description of all strategies, see table 2 in Spiliopoulos & Hertwig, 2020) to simple heuristics

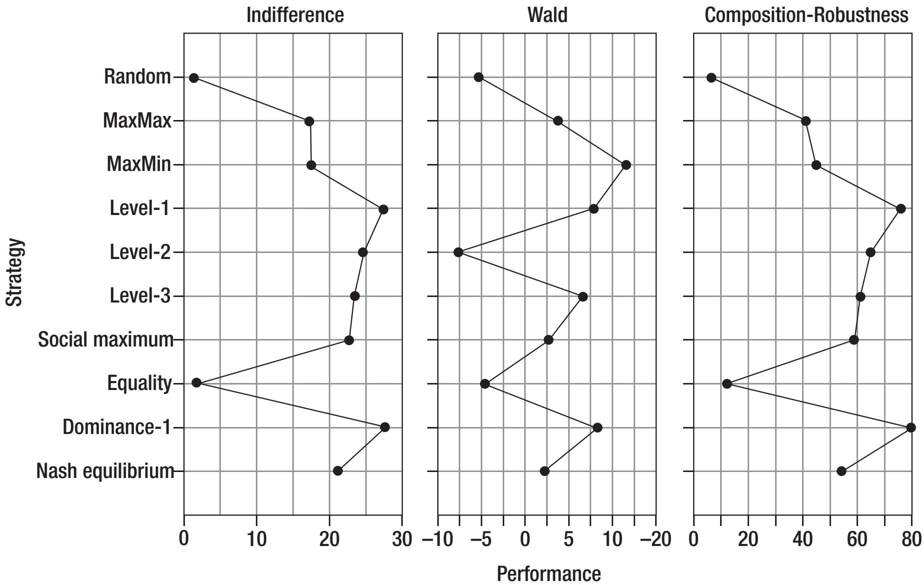

Fig. 1. Summary of the performance of the decision strategies tested in Spiliopoulos and Hertwig (2020), pooled across all environments investigated (competitive, neutral, and cooperative) and all levels of payoff uncertainty according to three performance criteria (panel columns): indifference criterion (i.e., all opponent strategies are equally likely), Wald criterion (i.e., paired with the worst-case opponent strategy), and composition-robustness criterion (i.e., percentile ranking of a strategy's performance averaged across all possible population mixtures). Strategies are sorted in increasing order of complexity. Their policies are described in table 2 in Spiliopoulos and Hertwig (2020); the results plotted are based on data reported in table 4 of Spiliopoulos and Hertwig (2020).

(e.g., MaxMax and MaxMin). The policies were pitted against each other in randomly drawn games while varying the three environmental properties mentioned above, for a total of 969 different environments. The success of the decision policies was measured by three performance criteria, all of which average the payoffs accruing from all possible games in an environment: The *indifference criterion* is the average expected performance of a policy if the population of opponents' decision policies is uniformly distributed. The *Wald criterion* is the performance of a given policy if it is unlucky enough to be paired with its worst possible opponent (i.e., the opponent that minimizes a policy's performance). This criterion indicates a policy's robustness to extreme strategic uncertainty. Finally, the *composition-robustness* criterion allows for every possible mixture (composition) of opponent policies in the population and is calculated using the percentile ranking (in terms of the expected payoffs) of a decision policy in an environment, averaged across all possible compositions of opponent policies.[2]

Let us consider three of the main results. First, which of the 10 decision strategies performed well across the game environments? Fig. 1 plots the performance of each policy averaged over all possible environments. Contrary to Sterelny's (2003) intuition, the L1 heuristic, a relatively simple heuristic that is often observed in games (see table 3 in Spiliopoulos & Hertwig, 2020) performed very well across a wide range of environments and opponent types.

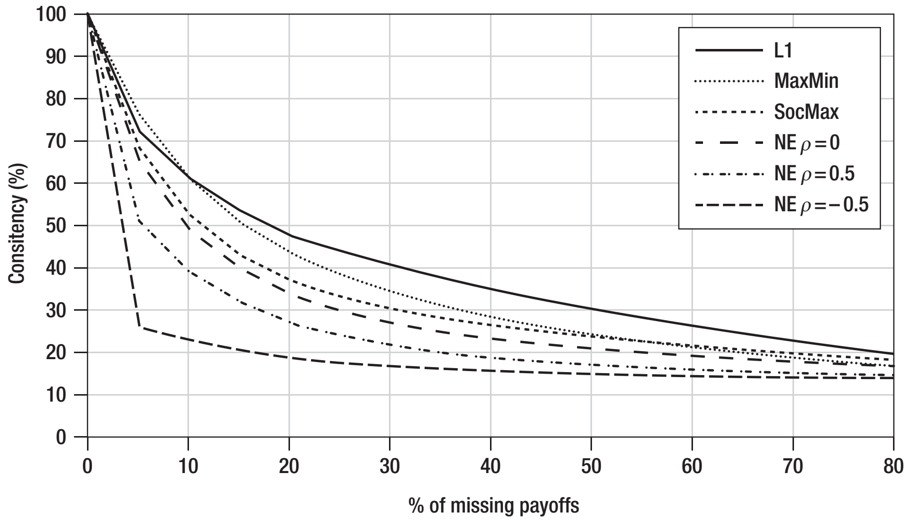

Fig. 2. Robustness of selected decision strategies and environments in face of uncertainty about payoffs (ranging from 0% to 80% missing payoffs). Consistency is defined as the percentage of choices made by a strategy across games that are identical to the choices that would have been made had there been full knowledge of payoffs (i.e., 0% missing payoffs). From Spiliopoulos and Hertwig (2020). Copyright 2020 by American Psychological Association. Reproduced with permission.

That is, the L1 heuristic was robust to uncertainty (as was the similar, but more complex, D1 heuristic). Relative to the normative Nash equilibrium solution, the L1 heuristic makes two simplifications: It completely ignores the opponent's payoffs, and it assumes equal weighting when calculating the expected payoffs for each action, choosing the action with the maximum expected payoff. Equal weighting ensures that a heuristic will not choose a dominated strategy, which would be suboptimal regardless of the type of opponent. This is an example of a heuristic adhering to a property that is beneficial regardless of the environmental characteristics. Second, as Fig. 1 shows, the Nash equilibrium was not the best performer by any of the three criteria and was dominated by both L1 and D1. This result is diametrically opposed to Sterelny's (2003) argument about competitive environments. Recall that the Nash equilibrium is the best response to an opponent also playing Nash; it is not guaranteed to perform well against other heuristics. Third, as Fig. 2 illustrates, the L1 heuristic also proved to be much more robust than the Nash equilibrium in the face of uncertainty caused by incomplete knowledge about payoffs. Spiliopoulos and Hertwig (2020) also produced, separately for each strategy, maps of ecological rationality, that is, descriptions of ecological niches (defined by the extent of payoff uncertainty and the size of the action set) in which a given strategy performs well and where it falls behind other strategies. Fig. 3 shows the maps for the L1 heuristic and the Nash equilibrium.

To conclude, this analysis shows that (some) simple heuristics can also perform very well in highly competitive and strategic environments. Complexity in social environments does not spell doom for heuristic approaches. As detailed in Spiliopoulos and Hertwig (2020), the

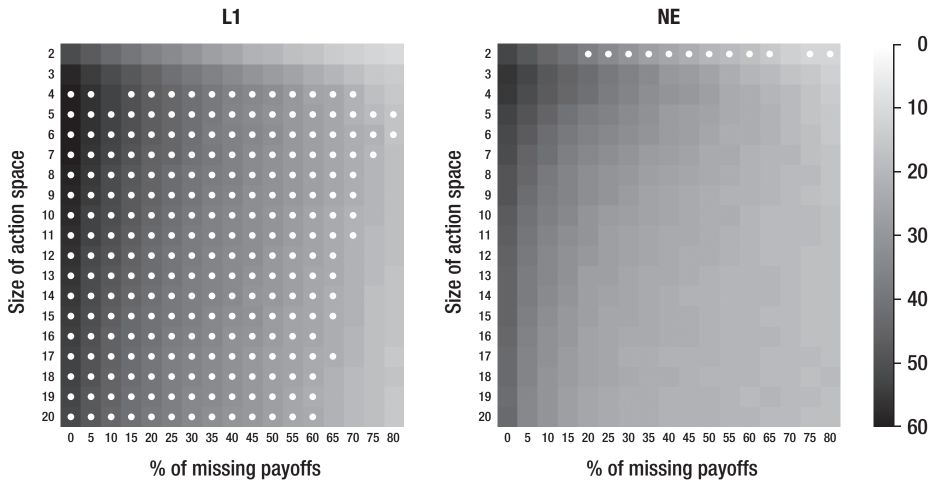

Fig. 3. Ecological map of the performance of the L1 heuristic and the Nash equilibrium (NE) in neutral environments according to the indifference criterion. The darker the shading, the better the performance. A white dot means that in these niches the respective strategy belongs to the top-performing policies. From Spiliopoulos and Hertwig (2020). Copyright 2020 by American Psychological Association. Reproduced with permission.

heuristics commonly used by participants in experimental studies of games (e.g., L1 and D1) proved to be ecologically rational policies for those specific environments. Thus, abandoning normative axioms and Bayesian principles in strategic interactions is not a recipe for disaster and should not be summarily dismissed as irrational. But how do decision makers learn about environmental structures and become able to select cognitive tools appropriate to the environment in question?

6. How do people learn environmental structures?

For cognitive strategies to be successful, their use needs to be matched to the structure of the environment. But how does the mind learn and adapt to relevant environmental structures? The process of learning can take different paths. One path is for the mind to piggyback on the experiences of others (see Katsikopoulos et al., 2010, for a related discussion of how probabilistic cues enter the mind). That is, evolution, culture, and vicarious experience can transmit knowledge about environmental structures. Yet sometimes people find themselves with nobody to consult, observe, or imitate, with no explicit instruction, and even without feedback on the consequences of their choices. Can they nevertheless learn important environmental structures in an unsupervised or self-supervised manner? If this were the case, the coupling of a heuristic with a particular environment would not have to be learned through explicit instruction. The question of how people learn environmental structures has been investigated in the context of risk–reward environments.

Risks and rewards are typically inversely related: Large rewards tend to be rare, whereas small to medium rewards tend to occur more often. This inverse risk–reward relationship is a ubiquitous structure in the world (Pleskac & Hertwig, 2014). Being cognizant of this inverse relationship offers an enormous return: It lifts the veil of ignorance about the likelihood that an uncertain event (e.g., winning the lottery) will happen. As Pleskac and Hertwig proposed, people can harness the risk–reward structure by applying a heuristic that infers the probability that an event will occur from the payoff associated with that event. This heuristic can be operationalized as follows:

> For gambles that offer a single positive payoff and otherwise nothing, infer the probability of winning a payoff, p'_g, from the ratio of the cost of playing [l] to the total amount of possible winnings [g] as follows: $p'_g = l/(l + g)$. (p. 2006).

The heuristic is premised on people having learned the statistical regularity with which risk and rewards are related—and being able to identify when they are unrelated (see Pleskac, Conradt, Leuker, & Hertwig, 2021, for examples). To find out how such an awareness can arise, Leuker, Pachur, Hertwig, and Pleskac (2018; see also Pleskac, Hertwig, Leuker, & Conradt, 2019) conducted a series of experiments. One presented participants with three different risk–reward environments—one negatively correlated, one positively correlated, and one uncorrelated—in which the events in question were represented as monetary gambles (see Fig. 4). In each environment, gambles were constructed using the same marginal distributions of payoffs and probabilities but different construction rules (e.g., high rewards linked to low probabilities in the negatively correlated environment), plus noise.

In an initial learning phase, participants were presented with gambles (each consisting of a reward and its associated probability) and asked to state the price at which they would be willing to sell each gamble. Each participant was exposed to one of the three environments. In a test phase, they were asked to choose between, for instance, a 100% chance of winning E$50 and an unknown chance of winning E$100. In addition, they estimated each gamble's probability. Importantly, people were not explicitly instructed to pay attention to the relationship between payoffs and probabilities, neither did they receive any feedback. Are there any indications that they nevertheless figured out the structure of the risk–reward environment they were facing?

Fig. 5 shows observed choices and estimates in the test phase. Participants' preference, as revealed through their choices of the option with an unknown probability, matched the environment they had experienced. When the uncertain option offered a high payoff, participants chose this option about three out of five times in the positively correlated environment, but only about one out of five times in the negatively correlated environment. Relatedly, participants' estimates of the unknown probability largely tracked the structure of the risk–reward environment that they experienced in the learning phase.

These findings suggest that people can learn about risk–reward structures, and presumably other environmental structures, via incidental, unsupervised learning (Love, 2002). The learning process may thus be similar in nature to the largely effortless one underlying concept learning (e.g., Nelson, 1984; Ward & Scott, 1987). Note also that the positive risk–reward

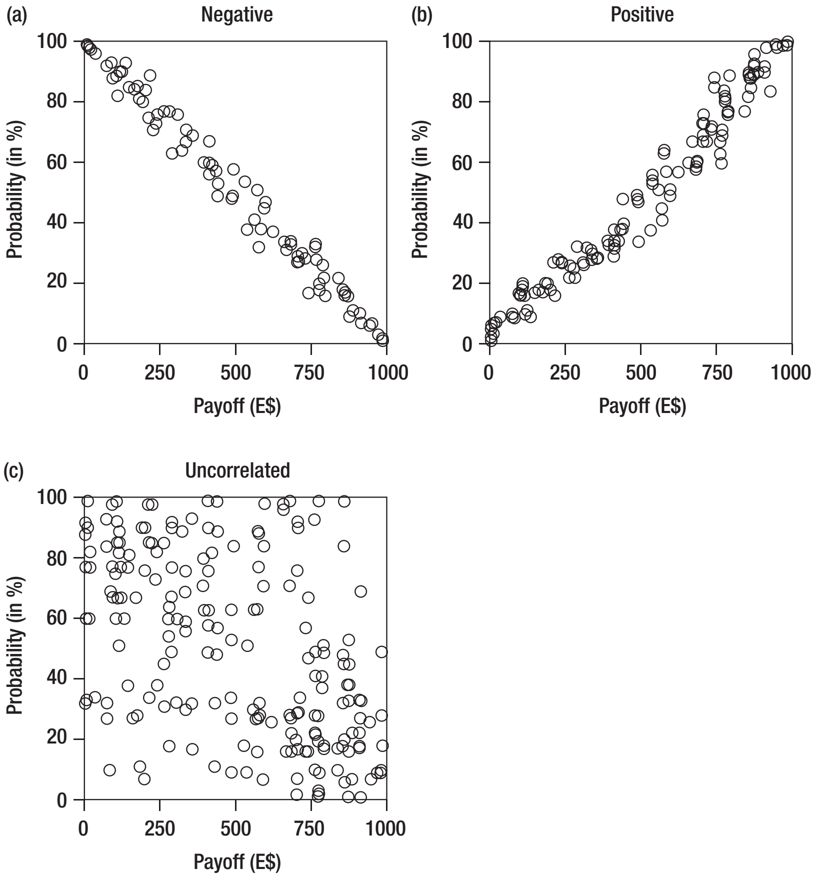

Fig. 4. Three experimentally manipulated risk–reward relationships. Payoffs were made in laboratory currency E$ to minimize the risk of participants enlisting risk–reward knowledge from real-world sources. Recreated from Leuker et al. (2018). Copyright 2018 with permission from Elsevier. This version from Pleskac et al. (2019). Reprinted courtesy of The MIT Press.

structure proved to be more difficult to learn than the negative one—perhaps because people rarely, if ever, encounter positive relationships outside the laboratory, and thus require more evidence to pick it up. After all, in the real world, there is "no free lunch." It would therefore seem that people' experiential priors may inform and anchor this process of unsupervised learning.

Implicit learning processes can thus be an important aspect in building a representation of the environment that, in turn, guides choice behavior. Other mechanisms that are likely at play at this intersection between environment and cognition are reinforcement learning processes (Rieskamp & Otto, 2006) and memory processes (Marewski & Schooler, 2011). Revealing how representations of the environment are formed is a necessary step toward understanding which strategies work where. If the risk–reward structure were frequent and recurrent, but decision makers were unable to learn and represent this structure, any fit between environment

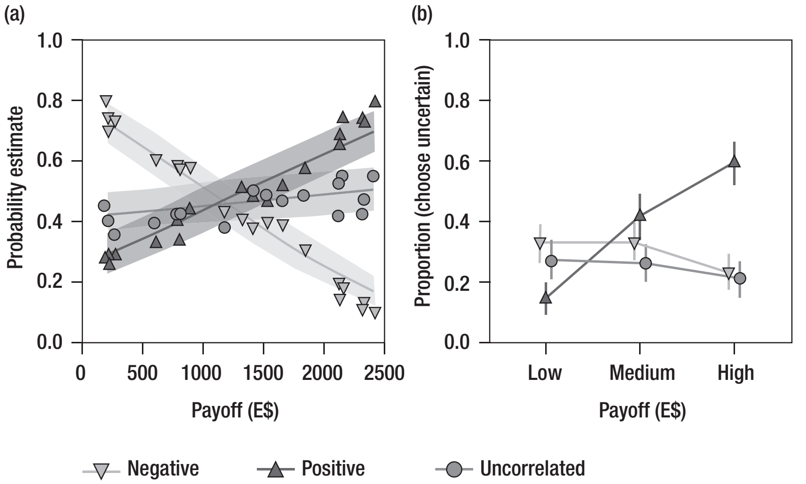

Fig. 5. (a) Average probability estimates for each of the payoff levels in the probability estimation tasks. (b) Proportion of times the uncertain option was chosen in the lottery tasks (the uncertain option did state a monetary amount but left out its probability). Adapted from Leuker et al. (2018). Copyright 2018 with permission from Elsevier. This version from Pleskac et al. (2019). Reprinted courtesy of The MIT Press.

and heuristic architecture would be difficult to attain. Next, we address an equally important issue: A theory of ecological rationality also requires a theory of the environment.

7. How to theorize rather than describe environmental structures?

Simon (1990) characterized the study of bounded rationality as follows:

> Since we can rarely solve our problems exactly, … [w]e must find techniques for solving our problems approximately, and we arrive at different solutions depending on what approximations we hit upon. Hence, to describe, predict and explain the behavior of a system of bounded rationality, we must both construct a theory of the system's processes and *describe the environments to which it is adapting*. (pp. 6–7; emphasis added)

Simon's call to analyze systems of bounded rationality has been heeded. Since the mid-1990s, models of boundedly rational heuristics and, admittedly to a lesser extent, the ecological structures to which these heuristics are adapting have been identified (see Hertwig et al., 2019; Todd et al., 2012). There is now a growing catalog of environmental structures conducive to the success of one heuristic or a class of heuristics: structures such as number of alternatives, intercorrelations between cues (redundancy), and variability in the importance of cues (see Todd et al., 2012). But the risk of simply listing these environmental structures is that it impedes the ability to predict where and when decision-making tools should or should not be applied. Moreover, a taxonomy of environments implies that the underlying structures are stable and that the plasticity of the cognitive process enables adaptation to recurrent structures. Yet environmental structures—especially if they have coevolved with the mind—need not be in a state of equilibrium. A cognitive process seeking to exploit a specific structure may therefore make the wrong bet. It is important to study these boundary conditions, as analyses of cognition–environment systems also need to find out when a system stutters or breaks apart. A theory of the mechanisms that give rise to environmental structures is therefore needed. Only then will it be possible to predict if a given heuristic will succeed or fail. These considerations were the starting point for Pleskac et al. (2021), who proposed that Simon's (1990) objective be reframed as follows:

> In order to describe, predict, and explain the behavior of a system of bounded rationality, one must construct theories of the system's processes as well as *theories of the mechanisms behind the environmental structur*es to which the system is adapting (p. 326, emphasis added).

What would such a theory look like? Focusing again on the family of risk–reward structures, Pleskac et al. (2021) proposed the *competitive risk–reward ecology theory* (CET) to derive a set of boundary conditions for this structure in contexts in which humans compete over limited resources. CET builds on a formal framework from behavioral ecology, the ideal free distribution (IFD) principle (Fretwell & Lucas, 1969). In modern human-made environments, including those analyzed by Pleskac and Hertwig (2014), the driving forces between risk–reward structures can typically be traced back to the marketplace. Buyers want high rewards with minimal risks (at low costs), and sellers want the opposite. It is not only in institutionalized markets that agents have competing interests and compete over limited resources, however. Both of these features characterize many formal and informal choice environments.

The IFD principle predicts on the level of the population how competitors distribute themselves in such choice environments to optimize their chances of success. Competitors in this process are assumed to be ideal and free, meaning that they are capable of detecting the patches with the highest rate of consumption and are free to move between patches. This, in turn, means that they will move to patches that promise a higher consumption rate and that, given time, the entire system will reach an equilibrium. At this point, the number of competitors n_y is proportional to the amount of resource r_y in that patch:

$$n_y \propto r_y. \tag{1}$$

As shown by Pleskac et al. (2021), based on two reasonable assumptions, this property of the IFD specified in Eq. 1 can imply a risk–reward structure. The first assumption is that the total amount of a resource is proportional to the size s_y and number of resources m_y:

$$n_y \propto s_y m_y \tag{2}$$

The second is that the probability that a competitor is able to obtain a resource p_y is related to both the number of resources and the number of other competitors such that

$$p_y \propto m_y / n_y \tag{3}$$

Substituting Eq. 2 into Eq. 3 reveals that the probability of successfully obtaining a resource (or "success probability") is inversely proportional to the size of the resource in a patch:

$$p_y \propto 1/s_y$$

That is, if there is variation in the size of each resource between patches but not within patches (e.g., because different patches consist of different habitat types), then individual competitors will face a choice between patches that trades off resource size for the probability of obtaining an item: a risk–reward structure.

Having established this link between the risk–reward structure and the IFD principle, Pleskac et al. (2021) then employed the CET framework to identify conditions under which the coupling of risk and rewards will change, or not emerge at all. For example, let us consider, one by one, the boundary conditions of a state of equilibrium, unlimited resources, and ideal competitors. An IFD of competitors can be expected when the average consumption of resources is equal across patches, that is, when the system is in equilibrium. If the system cannot reach this state, or has yet to reach it, the distribution of competitors cannot be expected to conform to an IFD, and a reliable inverse relationship between risk and reward should not be assumed. This means, for instance, that a newly forming competitive market will not have a risk–reward structure. The same holds when resources are unlimited. When a resource is unbounded (e.g., air), there is no need to compete over it. Ergo, no risk–reward structure should be expected.

The third boundary condition refers to the competitor's ability to discriminate between the quality of the patches. The IFD assumes that ideal competitors are perfectly sensitive to the patches' rate of consumption and are able to move to patches that maximize their success rate. This assumption bears an uncanny similarity to the idea that *homo economicus* has unlimited cognitive resources to maximize expected utility (Simon, 1955). What happens if we temper competitors' ability to detect differences in the quality of a patch, such that they overuse poor patches and underuse rich patches? Fig. 6 shows how the risk–reward structure changes when the number of resources is fixed between patches. As sensitivity to patch quality lessens, the risk–reward structure flattens. A similar pattern occurs when there is variability in the number of resources between patches, with the added characteristic that there is greater variability in the success probabilities for lower-quality patches. Overall, this pattern of a flattening of the risk–reward structure and increased variability in the success probability for smaller resources (i.e., rewards) is also consistent with people's empirical intuitions of the risk–reward structure in Pleskac et al. (2021) experimental studies. This mapping suggests that key aspects of an ecology of competition shape people's representation of the risk–reward structure.

To conclude, CET enables researchers to go beyond blanket statements such as "the risk–reward heuristic fits a risk–reward environment." Analyzing the dynamics behind the evolution of an environmental structure reveals conditions that make it possible to predict when the risk–reward heuristic will be less or not at all successful. On this basis, it is possible to empirically test if and to what extent people employ the heuristic or suspend its use when they encounter specific boundary conditions. Pleskac et al. (2021) conducted a set of empirical tests and found that people's beliefs about the probabilities of diverse set of rewards (e.g., money, rental apartment) map onto the properties predicted by CET, and that beliefs change systematically as a function of the experienced environment. CET affords the opportunity not

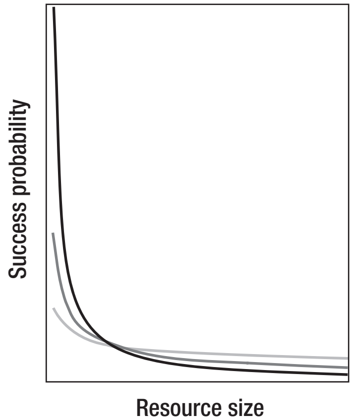

Fig. 6. Success probability as function of resource size for different levels of sensitivity to patch quality. As sensitivity to patch quality lessens and competitors become less ideal (indicated by lighter lines), success probabilities become less extreme for small resources and more extreme for large resources. From Pleskac et al. (2021). Copyright 2021 by American Psychological Association. Reproduced with permission.

only to explain human behavior, but also to identify a priori conditions in which a particular strategy or heuristic should or should not be used. It can thus serve as a key component, we contend, in extending notions of rationality.

More generally, the vision of ecological rationality, with its core assumption of fit between a decision making process (e.g., heuristic) and a particular environment—be it physical, biological, social, or cultural—requires theories about the environment. In our view, such theories can originate in a wide range of disciplines, including behavioral ecology (as in the case of the IFD), economics, sociology, and physics. These theories will not be ready to use but represent starting points for the cognitive modeler. Returning to the example of CET, Pleskac et al. (2021) identified eight ecological conditions that directly impact whether or not and to what extent a risk–reward structure is to be expected in a given environment. Only then was it possible to investigate to what extent people's cognition is indeed adapted to the risk–reward structure as well as to these conditions. Another question when enlisting theories from other fields is whether the environmental structure in question is part of the individual's subjective ecology, that is, the ecology that emerges through the interaction of the individual's cognitive, sensory, and body systems with the physical environment (akin to von Uexküll's, 1957, notion of *Umwelt*). In other words, taking an ecological rationality perspective does not mean that psychological research will be reduced to those disciplines from which theories of the environment can be sourced.

8. Ecological rationality and other approaches to bounded rationality: How do they relate?

The progress that has been achieved in the study of ecological rationality does not mean that no challenges remain. One important challenge resides in the notion of "fit" between cognition and environment. Is the required fit best understood in terms of a lock-and-key relationship in which a small mismatch disables the function? This is unlikely, not least because environmental structures are subject to perturbation and because the perception and learning of structures are imprecise. One avenue for future research is to characterize or even quantify the necessary and sufficient degree of fit for a heuristic to succeed. Another key question is how the mind selects a heuristic from the adaptive toolbox. As the analysis by Spiliopoulos and Hertwig (2020) as well as other analyses (see, e.g., Gigerenzer & Brighton, 2009; Hertwig et al., 2019) have shown, there is typically great variability in the performance of heuristics in a given environment. Choosing the wrong heuristic may prove costly. How then do individuals learn which heuristics to select? Various answers have been proposed, including individual reinforcement learning (Rieskamp & Otto, 2006), social learning (Hertwig, Hoffrage, & the ABC Research Group, 2013), ecological niches that do some of the work in strategy selection (Marewski & Schooler, 2011), and meta-inductive strategies that consider heuristics' past success (Schurz & Thorn, 2016). Recent work on resource rationality represents another important approach to analyzing and modeling the issue of strategy selection.

Before we turn to the other approaches of (bounded) rationality presented in this special issue, let us mention another insight relevant to strategy selection. In a simulation of preferential choice heuristics, Hertwig et al. (2019) observed that a simple heuristic, the equiprobable heuristic, on average performed very well relative to competitor strategies when knowledge about the kind of environment faced was very limited. Similarly, its strategic counterpart, the L1 heuristic, exhibits significant robustness to high levels of payoff uncertainty and strategic uncertainty (Spiliopoulos & Hertwig, 2020). Resigning oneself to the existence of irreducible uncertainty by adopting the principle of indifference is often better than denying its existence and engaging in a futile attempt to attach highly specific probabilities to events. It thus seems possible that some heuristics may offer good fallback options when an informed strategy selection is not possible.

8.1. Resource rationality

Like the ecological rationality program, the resource rationality program (e.g., Lieder & Griffiths, 2020; Prystawski & Lieder, 2022) models the operation of simple cognitive processes as an adaptive response to cognitive and external constraints, and acknowledges the key role of environmental structures for behavior. How do these two approaches relate? To a large extent, they make complementary contributions. For instance, resource rationality analysis provides a computationally fleshed-out framework for modeling cognitive strategies and the mind's natural constraints as well as processes of strategy selection. The study of ecological rationality, in turn, pinpoints the specific properties of the environment that permit information processes to be simplified while maintaining accuracy.

There are also important differences between the two programs. First, although both programs would predict that the mind will choose a simple heuristic that works well in a particular environment, the study of ecological rationality also emphasizes the importance of theorizing and modeling the structure of the environment. This has led, for instance, to insights on how risks and rewards are associated in many environments shaped by competition (Pleskac

& Hertwig, 2014; Pleskac et al., 2021). In contrast, the study of resource rationality focuses on the problem of strategy selection, based on an accuracy–effort trade off. In addition, whereas resource rationality assumes that strategy selection is based on the mind "trad[ing] off accuracy against effort in an adaptive, nearly optimal manner" (Lieder & Griffiths, 2020, p. 5), ecological rationality does not assume such optimality. Rooted in Simon's notion of satisficing, strategy selection will be ecologically rational even if the strategy is merely "good enough" in the given context.

8.2. Quantum models of cognition

Another approach that can be understood as reflecting Simon's bounded rationality, but less so ecological rationality, is that of quantum cognitive models (Busemeyer & Bruza, 2012; Pothos & Busemeyer, 2013). These models are constructed not on the basis of classical probability theory, as is the conventional approach, but on the basis of quantum probability theory (e.g., Anderson et al., 2004; Gershman, Horvitz, & Tenenbaum, 2015; Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010). This approach permits the models to better respect the mind's computational limits. Consider, for illustration, Tversky and Kahneman's (1983) studies on the conjunction fallacy. Participants were told about a woman, Linda, who majored in philosophy and was concerned with issues of discrimination and social justice. They were then asked to judge the probability that Linda was, among other options, a bank teller or a feminist bank teller. Classical theory assumes that this narrative generates a sample space for all possible combinations of characteristics for Linda, including unfamiliar ones such as feminist bank teller (Pothos & Busemeyer, 2013). In contrast, quantum probability and, by extension, quantum models of cognition only require a representation for each question or trait under consideration, a property that would seem to become more cognitively significant as additional questions are considered (other interpretations of the Linda task challenge the assumption of a probability judgment altogether; see, e.g., Hertwig & Gigerenzer, 1999). Thus, in this sense, quantum models of cognition are concerned with and aim to respect the mind's computational constraints, a concern they share with models of ecological rationality.

However, there are also differences. One is that the adaptive toolbox of ecological rationality is largely composed of distinct and independent tools (Hertwig, Pleskac, & Pachur, 2019), even if respective heuristics are constructed from the same cognitive building blocks. Quantum models of cognition as well as models grounded in classical probability theories, in contrast, are woven around a coherent set of axioms (Busemeyer & Bruza, 2012). Such an approach can be advantageous as it makes it possible to show how quantum models of cognition can meet coherence criteria of rationality like the Dutch Book Theorem (Pothos, Busemeyer, Shiffrin, & Yearsley, 2017). A future challenge for the heuristics of the adaptive toolbox is whether a core set of principles or building blocks can be identified. There have been some suggestions (Gigerenzer & Gaissmaier, 2011), but more work is needed to establish how heuristics are derived from those building blocks. Quantum information theory may provide such a starting place (Kvam & Pleskac, 2017). At the same time, ecologically rational heuristics are clearly more process-oriented, specifying *how* search for information unfolds, *when* search is stopped, and *how* people integrate the information into a response (Gigerenzer & Gaissmaier, 2011). A challenge is for quantum models of cognition will be to be more explicit about such elementary processes (see, e.g., Busemeyer, Kvam, & Pleskac, 2020; Kvam, Busemeyer, & Pleskac, 2021; Kvam, Pleskac, Yu, & Busemeyer, 2015).

8.3. What about alternative standards of rationality?

Let us conclude this comparative discussion with a final remark. The concept of rationality appears to imply a single universal standard against which it is possible to assess rationality. Almost by definition, it is therefore impossible to endorse alternative standards of rationality, because of the conundrum of potentially being rational according to one standard but deviating from rationality according to the other. Does the ecological rationality framework, like rationality concepts with a universality ambition, imply that alternative notions of rationality must be abandoned? Our answer is no for at least three reasons. First, the notion of ecological rationality builds on the assumption of different ecological niches and structures in the world. This implicates, by definition, distinct benchmarks of adaptive behavior and, by extension, rationality. Take, for instance, the notion of coherence. Undoubtedly, the ecological rationality framework strongly challenges the assumption that coherence is a universal, domain-general criterion of rationality; and yet there are, of course, environments in which reasoning in accordance with norms of coherence is absolutely crucial *in the service of an organism's goals*—for example, in the exercise of transitive inference to infer status hierarchies or coherence in the service of safeguarding equal protection of the law (see the discussion on the "ecological rationality of coherence" in Arkes et al., 2016). Second, the ecological rationality framework acknowledges the major distinction between risk and (numerically immeasurable) uncertainty (Keynes, 1937; Kozyreva et al., 2019), with the former permitting optimization frameworks and the latter rendering optimization impossible. Third, the ecological rationality framework challenges any notion of a universal, domain-general criterion of rationality. Therefore, its solution to the apparent conundrum of potentially being rational according to one standard but not another is that there is not or need not be any such conundrum. It is quite possible that one framework is best suited for one class of environments and misaligns with another. The putative conundrum originates in the claim of universality. Once this claim is suspended, conflicts can be resolved by identifying the environments in which a given standard is the most "fitting" and those in which it is misplaced.

One future challenge for the ecological rationality framework is to investigate its utility and its implications in domains in which relevant cognitive strategies and the texture of the environment are still relatively little understood. Recently, for instance, the process of language understanding has been interpreted as a process of Bayesian inference and a special case of social cognition in which listeners assume that speakers choose their utterances in an approximately optimal way; listeners, in turn, interpret an utterance by using Bayesian inference to "invert" the speaker's model (e.g., Goodman & Frank, 2016; Goodman & Stuhlmüller, 2013). An alternative view would be to think of the process of utterance production and understanding as a heuristic process. For instance, in Wilson and Sperber's (2004) theory, the "relevance-theoretic comprehension procedure" (a) follows the "path of least effort in computing cognitive effects"—that it, it tests interpretive hypotheses "in order of accessibility" and (b) stops "when expectations of relevance are satisfied" (p. 613). It can be seen as "a 'fast and frugal heuristic,' which automatically computes a hypothesis about the speaker's meaning on the basis of the linguistic and other evidence provided" (p. 625).

From this perspective on heuristic strategies for inferential comprehension, an important next step would be to identify relevant environmental structures and to model the fit of the strategies (or lack thereof) to those structures.

9. Conclusion

We are not advocating for a theory of rationality to be grounded *solely* in the structure of the environment. Our emphasis lies in the study of the cognition–environment system. Clearly, studying the environment can be immensely important. When trying to predict the shape gelatin will take when it solidifies, "…we do not study the gelatin; we study the shape of the mold in which we are going to pour it" (Simon, 1990, p. 6). This is true enough, but the shape of the mold does not explain why gelatin can take the shape of the container, nor does it explain why gelatin wiggles when shaken. It was only by examining gelatin in depth that chemists discovered that a netting formation of protein chains allows the gelatin to hold the shape of the mold. Investigating the mold and the gelatin in tandem helped chemists to understand its behavior. In the same way, the mind is shaped not only by the environment in which it is placed, but also by the neural and cognitive structures of which it is composed. Let us study them in tandem.

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Notes

1 Lévi-Strauss (1962) described the "bricoleur" as follows: They are "adept at performing a large number of diverse tasks; but, unlike the engineer, [they do] not subordinate each of them to the availability of raw materials and tools conceived and procured for the purpose of the project" (p. 11). A similar image was proposed by Wimsatt (2007), who characterized the mind and its competences as akin to that of a "parts dealer and crafty backwoods mechanic, constantly fixing and redesigning old machines and fashioning new ones out of whatever comes easily to hand" (p. 10). Neither the bricoleur nor the crafty backwoods mechanic fit the assumption of a single universal decision policy that determines the best course of action as implied by, for instance, expected utility theory.

2 By abandoning the ideal of a universal framework of rationality such as expected utility theory, the ecological rationality framework faces the question of how to define the success of a heuristic or of any cognitive strategy. Clearly, this framework no longer assumes a single success criterion or even a family of criteria such as internal consistency standards that concern purely syntactical relations between behaviors (e.g., property α; Sen, 1993). More generally, the ecological rationality framework focuses on correspondence criteria (Hammond, 1996) that concern relations between behavior and the environment, using measures such as how healthy, rich, successful in school, happy in marriage, or accurate, frugal, or fast a behavior such as a choice, judgment, or inference is (see Arkes, Gigerenzer, & Hertwig, 2016; Schurz & Hertwig, 2019). One important methodological imperative when testing the success of cognitive strategies is comparative testing, that is, testing simpler processes against computationally more complex alternatives and competitors and, ideally, using multiple success criteria to examine the extent to which results converge. This imperative also guided Spiliopoulos and Hertwig's (2020) analysis.

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