

**Center for
Adaptive Behavior and Cognition**

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Introductory Overview

The Center for Adaptive Behavior and Cognition (ABC) investigates reasoning and decision making under uncertainty in both individuals and social groups. Our research group consists of psychologists, neuroscientists, computer scientists, mathematicians, economists, engineers, and researchers from other fields. Using methodologies, such as experimental methods, computer simulation, and mathematical analysis, we cooperate in solving problems from different disciplinary perspectives. The Center's program combines a strong theoretical focus with practical applications, that is, we both develop specific models and explore their applications. Applications range from helping physicians and patients understand the statistical evidence from medical research to working with the Bank of England on developing simple heuristics for a safer, more robust financial world. These practical applications are described here in two sections, one focusing on risk literacy in health (see section on the Harding Center for Risk Literacy, pp. 185–194) and the other on decision making in the wild. Our interdisciplinary approach to studying human decision making and rationality considers three aspects: bounded, ecological, and social rationality.

Bounded Rationality

Models of bounded rationality attempt to answer the question of how people with limited time, knowledge, money, and other scarce resources make decisions. With the help of such models, we study how people make—and should make—decisions in situations under “uncertainty” (where not all alternatives, consequences, and risks are known) as opposed to situations entailing known risks. This program is an alternative to the dominant optimization paradigm in cognitive science, economics, and behavioral biology, which poses the question of how a Laplacean superintelligence or near-omniscient being would behave. We study the proximal mechanisms of bounded rationality, that is, the adaptive heuristics that enable fast and frugal decisions to be made under uncertainty. This collection of heuristics and their building blocks is what we call the *adaptive toolbox*.

Ecological Rationality

Models of ecological rationality describe the structure and representation of information in actual environments and their match with mental strategies, such as boundedly rational heuristics. To the degree that such a match exists, heuristics need not trade accuracy for speed and frugality: Investing less effort can also improve accuracy. A simultaneous focus

on the mind and its environment, past and present, puts research on decision making under uncertainty into an evolutionary and ecological framework, a framework that is missing in most theories of descriptive and normative reasoning. Instead of comparing human judgments to the laws of logic and probability theory, we study the adaptation of mental and social strategies to real-world environments.

Social Rationality

Social rationality is a variant of ecological rationality, in which the environment is social rather than physical or technical. Models of social rationality describe the structure of social environments and their match with boundedly rational strategies that people might use. A variety of goals and heuristics exist that are unique to social environments. That is, in addition to the goals that define ecological rationality—to make fast, frugal, and fairly accurate decisions—social rationality is concerned with goals such as choosing an option that can be defended by argument or moral justification or creating a consensus. Whereas most research on bounded rationality maintains a cognitive focus, socially adaptive heuristics include, to a much greater extent, emotions and social norms that can act as heuristic principles for decision making.

Bounded Rationality

Humans and other animals must make inferences about unknown features of their world under constraints of time, information, and other resources, such as computational capacity. Polymath and Nobel Prize winner Herbert A. Simon called the kind of rationality inherent to these tasks *bounded rationality*. In our research, the study of bounded rationality focuses on simple models, where a few pieces of information are used and processed in straightforward ways by inspecting them one at a time or simply summing them. These models describe the cognitive processes underlying a final choice or judgment precisely enough so that they can be simulated by a computer or analyzed mathematically. Just as a mechanic uses specific wrenches, pliers, and gap gauges to maintain an automobile rather than applying a hammer indiscriminately, different tasks require different specialized tools. The notion of a toolbox lacks the beauty of Leibniz's dream of a single all-purpose decision tool. Instead, it evokes the abilities of a jack-of-all-trades who can provide serviceable solutions to almost any problem with just what is at hand. This interpretation of bounded rationality provides an alternative vision to the prevailing (and contradicting) views of bounded rationality as optimization under constraints (in economics) and as a form of irrationality (in psychology).

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Alternative Interpretations of Bounded Rationality

Paraphrasing the scientist and novelist C. P. Snow, Katsikopoulos (2014a) suggested that there are two main "cultures" of research on bounded rationality in terms of technical (e.g., data and models) and story-telling aspects (e.g., messages that can be communicated to policymakers and the public): The *idealistic culture* represents a minimal departure from the neoclassical economics framework of unbounded rationality, which assumes the ideals of omniscience and optimization of a utility function. If deviations are observed, factors such as inequity aversion or probability weighting are added to the utility function. Noble laureate Reinhard Selten has called this the "repair program." On the other hand, the *pragmatic culture* holds that people sometimes ignore information and use simple rules of thumb in order to achieve satisfactory outcomes. The story told by the idealistic culture is pessimistic: Although people should ideally be able to know what to do, they systematically fail to adhere to the supposedly normative standards of probability theory and logic. The story told by the pragmatic culture, by contrast, is more empowering: If people adaptively learn to choose the right tool from their cognitive toolbox when making decisions, they can be efficient decision makers. Gigerenzer (2016f) points out that optimization under constraints remains the dominant

interpretation of bounded rationality, even though Herbert A. Simon, who is known as the "father" of bounded rationality, explicitly dismissed this interpretation. It appears that economists and psychologists and other social scientists place a very high premium on two characteristics of optimization under constraints: (1) using all available information and (2) ensuring internal logical consistency. Without adhering to these maxims, performance will inevitably suffer in their view. Interestingly, however, recent empirical work shows that people do not conform to (1) and that not conforming to (2) is not associated with inferior performance. With respect to (1), Gigerenzer and García-Retamero (2017) used a survey instrument to test more than two thousand adults, representative of the German and Spanish population in terms of age, gender, and region. Participants were asked whether they would want to know about five negative events (e.g., "Would you want to know today when your partner will die?") and five positive ones (e.g., "Would you want to know the sex of your child before birth?"). Between 85% and 90% of people would not want to know about upcoming negative events and 40% to 70% would prefer to remain ignorant of upcoming positive events. Only 1% of participants consistently said that they wanted to know what was in store. They propose a regret theory of deliberate ignorance that covers both nega-

tive feelings that may arise from foreknowledge of negative events, such as death and divorce, and positive feelings of surprise and suspense that may arise from foreknowledge of positive events, such as knowing the sex of an unborn child. Deliberate ignorance is related to risk aversion and can be explained by avoidance of anticipatory regret.

With respect to (2), Arkes, Gigerenzer, and Hertwig (2016) reviewed thousands of articles on the Web of Science and contacted judgment and decision-making researchers to request studies indicating that decision makers who fail to conform to consistency requirements, such as transitivity, are less rich, less healthy, have less accurate beliefs, and so on. They found no evidence for a causal, or even correlational, link.

Does the fact that bounded rationality has not been found to lead to inferior outcomes mean that there is evidence that it leads to superior or at least equally good outcomes? A number of theoretical and empirical studies from our group support this hypothesis: There is evidence from mathematical analyses and computer simulations of models of bounded rationality and there is evidence from people—in fact, children—who exploit their bounded rationality. These two kinds of evidence are illustrated in the following two sections.

Bounded Rationality: From Perception to Preference and on to Inference

The choices we make can be distinguished by two types: *preferences*, where choices are largely a matter of taste and accuracy is difficult to define and *inferences*, where the correct choices can be identified and accuracy can be assessed. Luan, Schooler, and Gigerenzer (2014) developed a boundedly rational model for the latter. The model, called Δ -inference, is a generalization from a known preference model, lexicographic semiorders, to inference tasks. In a paired-comparison inference task, which entails choosing which of two objects has a larger criterion value based on a set of cues, the model can be described by the following three building blocks:

(1) *Search rule*: Examine cues in the order of their accuracy (e.g., correlation with the

criterion), where accuracy is assessed for each cue independently from the other cues.

(2) *Stopping rule*: If the difference between two objects, A and B, exceeds a threshold value Δ on a cue, then stop search.

(3) *Decision rule*: If the cue is positively related to the criterion, infer that the object with the higher cue value is the one with the higher criterion value; otherwise, infer that the object with the lower cue value is the one with the higher criterion value. If no difference exceeds Δ for all cues, then pick one object by guessing.

Key to the model and its performance is the threshold parameter Δ . Guided by Clyde Coombs' theory of single-peaked preference functions, Luan et al. (2014) showed that the accuracy of Δ -inference can be understood as an approach-avoidance conflict between the decreasing usefulness of the first cue and the increasing usefulness of subsequent cues as Δ grows larger, resulting in a single-peaked function between accuracy and Δ . The peak of this function varies with the properties of the task environment: The more redundant the cues are and the larger the differences in their information quality, the smaller is the Δ .

In well-defined simulated task environments, the Δ that leads to the highest accuracy, denoted as *Peak Δ* , is usually an intermediate value. However, when tested in 39 natural data sets, the *Peak Δ* is on average much smaller. Moreover, Δ -inference with *Peak Δ* has, on average, the same predictive accuracy as Δ -inference with $\Delta = 0$ (see Figure 1). The latter implies that the model relies almost exclusively on the best cue to make inferences and ignores all other cues, similar to the take-the-best heuristic. Finally, Luan et al. (2014) also tested how different Δ -inference models fared against other models of inference in the natural data sets. As shown in Figure 1, linear regression is more accurate in fitting, but much less accurate in prediction. Two other benchmark models, Bayesian linear regression and the general monotone model (GeMM), could not outperform the Δ -inference models unless the learning sample was comparatively large.

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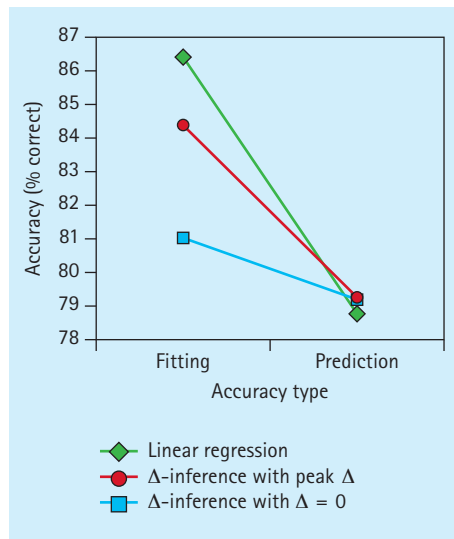


Figure 1. The fitting and predictive accuracy of linear regression and two Δ -inference models in paired-comparison inference tasks, averaged across 39 natural data sets from diverse fields, such as economics, psychology, biology, transportation, and engineering. Whereas linear regression outperforms the two Δ -inference models in fitting, the Δ -inference models perform slightly better in prediction. Note that Δ -inference with $\Delta = 0$ implies that all decisions are made by the first cue searched, except for those in which the cue values of the two objects are tied on the first cue and the search must continue to the next cue or cues (adapted from Luan, Schooler, & Gigerenzer, 2014).

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This work demonstrates that integrating and extending established concepts, models, and theories from perception and preference can improve our understanding of how the mind makes inferences. It also shows that in real-world environments, one can make good inferences by searching for very little information and spending little thought on selecting the best Δ because a Δ of 0 is generally good enough.

Children Can Perform Well By Exploiting Their Bounded Rationality

Almost by definition, children are boundedly rational. They lack many of the computational resources that adults have at their disposal and possess much less knowledge about the world. To learn about their physical and social environments, children constantly acquire new information from an early age on. Infants spontaneously grab and manipulate objects,

and approach or avoid people. As language develops, young children inquire about the meaning of words, the names of objects, and the many other new and puzzling phenomena they encounter. Research shows that children's explorative actions, question asking, and free play are crucial for learning about the world. But how effective is children's information search? And do children adapt their search behavior to the characteristics of the task at hand?

Nelson, Divjak, Gudmundsdottir, Martignon, and Meder (2014) investigated which boundedly rational strategies children use for selecting among a set of given questions. Sixty 8- to 10-year-olds played the popular *Guess Who* game, a variant of the 20-questions game. They were presented with 18 cards, each representing a person's face (Figure 2, left). Their task was to identify a target face card, randomly selected, by asking as few yes-no questions about the faces' features (e.g., gender, beard) as possible. If the children needed help formulating a question, they could refer to 20 available questions (physical features).

Figure 2 (right) shows how a simple heuristic strategy, the *split-half heuristic*, would play the game. The split-half heuristic always selects the feature that comes closest to being possessed by half of the faces remaining. For example, if the randomly selected target face is Victor's, then the split-half heuristic would first query about the feature "male" (the answer would be yes), then "beard" (the answer would be no), followed by "big mouth" (the answer would be yes), and finally "white hair" to identify him. Importantly, it can be proven that in *Guess Who* the split-half heuristic always chooses the highest information-gain question, that is, the question with the highest expected reduction in Shannon entropy. Moreover, it can be shown analytically that the split-half heuristic performs optimally in the particular environment (statistical distribution of features; see Figure 2), where the optimality criterion is to minimize the expected number of questions. Despite their young age, the children tested by Nelson et al. (2014) performed well in the game, making use of the heuristic in good measure. For

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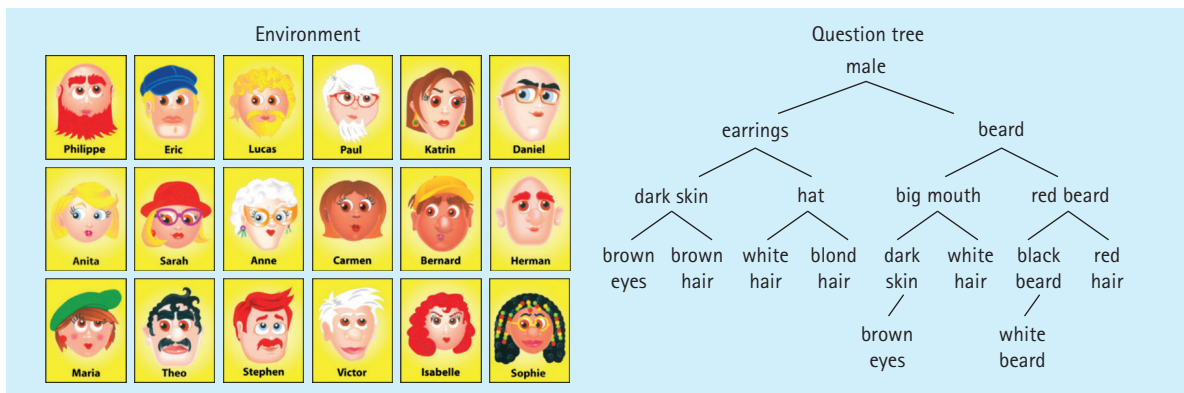


Figure 2. In the *Guess Who* game, the player is presented with a set of face cards and has to identify which of them has been selected randomly. The goal is to ask as few yes–no questions about the face's features (e.g., gender, beard) as possible. The split-half heuristic always queries about the feature that comes closest to being possessed by half of the remaining faces. In this example, if the card selected shows Victor, the heuristic would identify him by making queries about the features "male," "beard," "big mouth," and "white hair." We thank Hasbro Germany for permission to use and reproduce the stimuli from their *Wer ist es?* (*Guess Who*) game (adapted from Nelson, Divjak, Gudmundsdottir, Martignon, & Meder, 2014).

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example, the gender (male/female) question was asked first by the children in 55% of all trials. By contrast, in a different environment (different set of cards), in which gender was not the best first question, only 24% of first queries referred to that feature.

Converging findings come from Ruggeri and Lombrozo (2015), who investigated how children (7- and 10-year-olds) and young adults adapt their question-asking strategies to different characteristics of the problem at hand. Their results revealed that even young children dynamically change the types of questions they rely on in response to the information structure of the task, such as the number and a priori probability of the considered hypotheses, the difficulty of the solution to be found, and the feedback received from previous questions.

Further evidence for children's adaptive search behavior comes from developmental studies by Ruggeri, Lombrozo, Griffiths, and Xu (2016), who conducted two studies to identify potential sources of developmental change in how 7-year-olds, 10-year-olds, and adults search for information. Presented with 16 objects (e.g., animals and plants), participants could either ask questions (Study 1) or select individual

objects (Study 2) to discover which category of objects within a nested structure (e.g., animals, birds, or owls) had a novel property (e.g., is present on Planet Apres). After receiving feedback, participants could choose whether to conduct another query or to guess the solution, with the goal of finding the solution with as few queries as possible.

The results demonstrate developmental improvement in the effectiveness of information search. Importantly, the results also revealed a previously undocumented source of developmental change: Children are more likely than adults to continue their search for information beyond the point at which a single hypothesis remains and thus to ask unnecessary questions. This suggests that one crucial source of developmental change in information search effectiveness lies in children's acquisition of "stopping rules," a key building block of heuristics. Looking for confirming evidence could indeed be prudent when there is uncertainty about the hypothesis space, the obtained feedback, or the constancy of what is being learned. As novice learners in a noisy and uncertain world, children might be better to err on the side of caution by obtaining extra feedback.

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Ecological Rationality

The performance of a decision strategy, be it a simple heuristic or a complex model, depends on the structure of the environment in which it is applied. We study this relationship systematically by specifying formal models of simple and complex decision-making rules. The research program on ecological rationality aims at characterizing the structure of environments and understanding the fit between these structures and the performance of decision models. Performance is measured by external criteria, such as frugality (amount of information considered) and predictive accuracy (how well the model predicts unseen data). This approach differs strongly from the study of logical rationality, where performance is measured by internal criteria, such as consistency with mathematical axioms.

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Decision Heuristics Compete Well With Statistical Techniques

Decision heuristics use few pieces of information—sometimes only a single piece of information—and integrate these in simple ways. For example, *single-cue heuristics* use a single piece of information, *lexicographic heuristics* consider the pieces of information sequentially, and *tallying* weights the different pieces of information equally. How well can such simple methods compete with complex statistical techniques in terms of predictive accuracy? To answer this, Şimşek and Buckmann (2015) conducted an empirical analysis in a large, diverse collection of natural environments. They compared decision heuristics with two considerably more complex statistical methods: logistic regression (with elastic-net regularization) and decision trees (induced by CART). Their analysis is the most extensive evaluation of decision heuristics to date, employing 63 natural data sets on various subjects gathered from diverse sources, including online data repositories, textbooks, statistical software packages, statistics and data mining competitions, research publications, and individual scientists' collections of field data. These data sets varied in subject, size, and the amount of information available for making a decision. The decision problem was paired comparison, where the objective was to identify which of two alternatives has the higher value on a specified (unobserved) criterion: for example, to identify which of two houses currently for sale will return a higher yield on investment in 10 years, given their age, location, lot size, and sale price.

Figure 3 shows the mean learning curves for various decision methods. Each model's pa-

rameters were learned from training examples, where one training example comprised a single paired comparison between two objects in the data set. The horizontal axis shows the number of training examples used, which ranged from 1 to 100. The vertical axis shows the predictive accuracy of the various models, that is, the accuracy of the models on paired comparisons that had not been used to train the models. All training and test examples were independent of each other.

The single-cue heuristic learned the identity of the cue to be used, while the lexicographic model learned how the cues should be ordered. In addition, all three heuristics learned *cue directions*, that is, whether each piece of evidence is positively or negatively related to the criterion. As the figure shows, despite their computational simplicity, heuristics competed remarkably well with the more complex statistical models. In early parts of the learning curve, tallying was the best-performing model on average. Later on, the lexicographic decision rule either performed best or trailed the best-performing model very closely. Furthermore, the single-cue heuristic performed surprisingly well, trailing the lexicographic heuristics by 1.6 percentage points or less.

Şimşek and Buckmann (2015) also analyzed the learning rate of heuristics theoretically to discover how much computation and how many training examples were required to learn effective heuristics. Because of their simplicity, heuristics require a very small amount of computation at decision time. Like all statistical models, however, they have free parameters that are learned from training examples, such as cue directions. For that

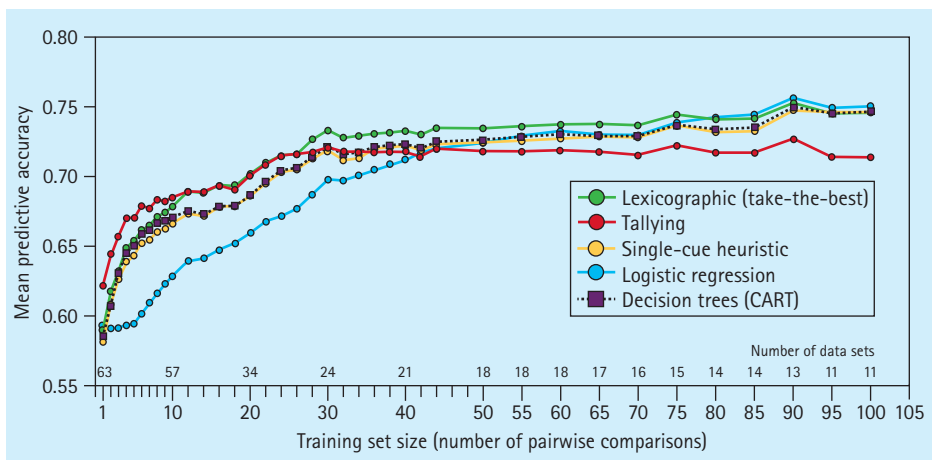


Figure 3. Performance of three decision heuristics compared to logistic regression (with elastic-net regularization) and decision trees (induced by CART) in a large, diverse collection of natural environments. Tallying predicts best with a small training set (up to 10 training examples); take-the-best predicts best with intermediate training set sizes; all models (except for tallying) predict about equally well for the largest training set sizes. Less can be more (adapted from Şimşek & Buckmann, 2015).

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reason, it was speculated in the scientific literature that the computational requirements of learning effective heuristics might in fact be high.

The authors theoretically examined two building blocks of learning heuristics: assigning cue direction (i.e., determining whether the cue is positively or negatively related to the criterion) and determining which of two cues has the higher predictive accuracy. Their analysis showed that even a few training examples lead to substantial progress in learning both building blocks. For example, if cue direction is assigned after a single training example, the expected accuracy of the cue is at least 83% of the accuracy obtained based on the true cue direction.

Statistical Properties of Natural Environments Support Decision Heuristics

How can we explain the remarkable performance of simple decision rules? For one, all decision models err when making predictions. From a statistical perspective, a model's prediction error results from bias, variance, and noise: total prediction error = (bias)² + variance + noise. The bias component reflects the inability of a model to represent the systematic patterns within the data, while the

variance component reflects the sensitivity of the model's predictions to different training examples for the same decision problem. For some time, it was believed that heuristics achieve low prediction error mainly by achieving relatively low variance, which compensates for their relatively high bias. Şimşek (2013), however, suggested that the structure of natural environments may be such that within them simple heuristics are able to achieve a level of bias comparable to that of more complex models. Recently, Gigerenzer (2016i) echoed this surprising hypothesis in his contribution to a volume commemorating the centennial of Herbert A. Simon's birth. Simple and cumulative dominance are two environmental structures that allow heuristics to achieve a level of bias equal to that of any linear model, including unit-weights regression, ordinary least-squares regression, or even state-of-the-art regularized linear regression. Consider a decision problem with three cues, C_1 , C_2 , and C_3 , where a larger value is more desirable for each of the cues. Decision alternative A with cue profile (3, 3, 4) is said to *simply dominate* decision alternative B with profile (1, 2, 0) because A has higher values than B on each of the cues. In addition, A is said to *cumulatively dominate* decision

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Şimşek, Ö., Algorta, S., & Kothiyal, A. (2016). Why most decisions are easy in Tetris—and perhaps in other sequential decision problems, as well. *Proceedings of Machine Learning Research*, 48, 1757–1765.

alternative C with cue profile (1, 4, 0) because the cumulative profile of A , (3, 3 + 3 = 6, 3 + 3 + 4 = 10) dominates the cumulative profile of C (1, 1 + 4 = 5, 1 + 4 + 0 = 5), given cue order C_1 , C_2 , and C_3 . The existence of a simply or cumulatively dominating option means that simple heuristics, such as take-the-best, can achieve equal bias with any linear model, regardless of its complexity. Şimşek (2013) has shown that both simple and cumulative dominance are prevalent in natural environments when the decision task is paired comparison. Katsikopoulos, Egozcue, and Fuentes Garcia (2014) presented a detailed analysis of the prevalence of cumulative dominance by using computer simulations, where decision problems with two options and 2 to 10 continuous cues were generated, with cue values sampled from a range of probability distributions, including uniform, normal, and skewed distributions. The prevalence of cumulative dominance was higher when the number of cues was smaller. For 10 cues, cumulative dominance occurred in 35% of the decision problems; for less than 5 cues, cumulative dominance occurred in the majority of problems, reaching 75% for 2 cues. In addition, Katsikopoulos and colleagues showed analytically that, if a dominating option exists, take-the-best and other simple heuristics achieve equal bias to that of any linear model that also includes multiplicative interactions among any subset of the available cues.

The results discussed so far relate to one-shot paired comparison problems. More recently, Şimşek, Algorta, and Kothiyal (2016) showed that the prevalence of dominance relationships is likely to extend to a much more difficult class of problems known as *sequential decision problems under uncertainty*. One example is the popular computer game Tetris. Tetris is played on a two-dimensional grid that is initially empty. Game pieces called *tetriminos* fall from the top of the grid one at a time, piling up on each other. Each tetrimino occupies four cells and is one of seven different shapes. As each tetrimino falls, the player controls where and how it lands by rotating it and moving it horizontally in either direction any number of times. Once a row has been

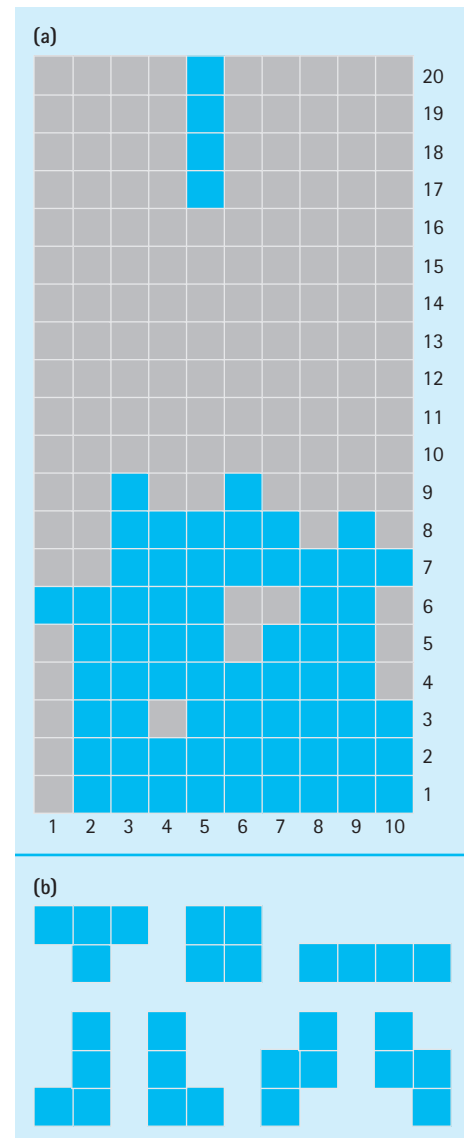


Figure 4. Sample board during a game of Tetris, showing a tetrimino falling from the top of the grid (a) and the seven possible tetriminos (b) (adapted from Şimşek, Algorta, & Kothiyal, 2016).

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filled, it is deleted, creating additional space on the grid. The game ends when there is no space remaining at the top of the grid for another tetrimino. Figure 4 shows the Tetris board during a game, with a tetrimino falling from the top of the grid (upper panel), and the seven possible tetriminos (lower panel). Artificial players can learn to play Tetris very proficiently, removing hundreds of thousands

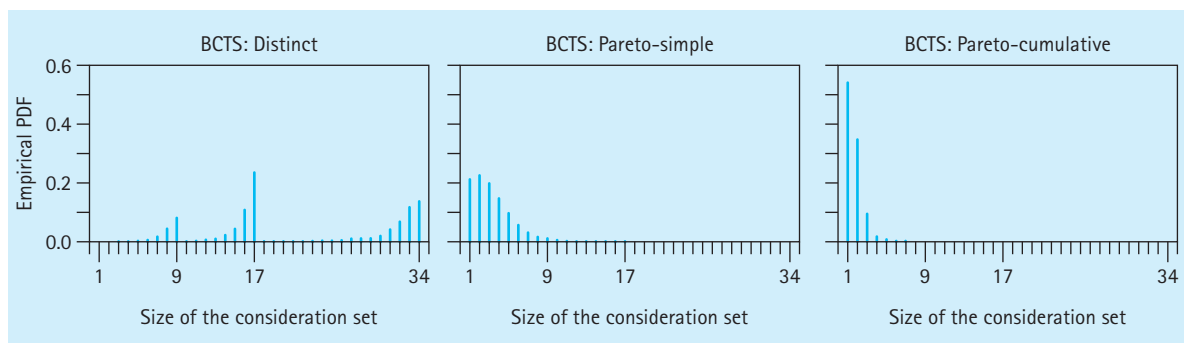


Figure 5. The empirical distribution of the number of decision alternatives (placements of the falling tetrimino) while playing Tetris: number of decision alternatives that Building Controllers for Tetris Systems (BCTS) views as distinct (left panel), number of decision alternatives remaining after filtering by simple dominance (middle panel), and number of decision alternatives remaining after filtering by cumulative dominance (right panel) (adapted from Şimşek, Algorta, & Kothiyal, 2016).

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of rows. One of the best-known artificial players is called Building Controllers for Tetris Systems (BCTS). BCTS estimates the value of each placement—defined by where and in what orientation to land the falling tetrimino—by using a linear evaluation function of eight cues. For example, one of the eight cues is the total number of holes that would be present on the board with the given placement.

Figure 5 shows the prevalence of simple and cumulative dominance in Tetris. Three empirically derived probability distributions are shown. The left panel shows the number of placements that are legal and distinct according to BCTS; that is, BCTS assigns a different evaluation score to each of these placements. The median value is 17. The middle panel shows the number of placements that are not simply dominated by one or more other placements (called *Pareto-simple*). Here, the median value is 3. Finally, the right panel shows the number of placements that are not cumulatively dominated by one or more other placements (called *Pareto-cumulative*). The median value is 1. Taking into account the mathematical truth that the best placement in the set “distinct” (according to BCTS) is also the best in Pareto-simple and Pareto-cumulative sets, one can substantially reduce the number of placements that need to be considered when filtering the action set by simple and cumulative dominance. When filtered by cumulative dominance, the median size of the

consideration set is reduced from 17 to 1. This means that, in most cases, where only one placement remains in the consideration set, the need to make a decision is eliminated. Şimşek et al. (2016) also showed how algorithms in machine learning can exploit simple and cumulative dominance to learn more efficiently, using a much smaller number of training examples. Whether dominance relationships are prevalent in sequential decision problems other than Tetris remains an open question. If so, it should be possible to train machine learning algorithms much more efficiently by taking this property into account. The research on sequential decision problems and Tetris demonstrates how ideas and concepts from research on the ecological rationality of simple heuristics can be applied to areas beyond psychology and cognitive science (see also section on “Decision making in the wild”). Thanks to the interdisciplinary background of the researchers in our group, ideas, such as the bias–variance decomposition of prediction error and dominance relationships among decision alternatives, have been discussed and applied to other fields. For instance, Katsikopoulos and Syntetos (2016) discuss the conceptual and methodological implications of the bias–variance decomposition in the context of forecasting in business. Typically, statistical methods for forecasting a quantity, say the demand of a product by a supply chain manager, are evaluated solely by their bias. Katsikopoulos and Syntetos (2016)

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- Katsikopoulos, K. V., & Syntetos, A. A. (2016). Bias-variance tradeoffs in demand forecasting. *Foresight: The International Journal of Applied Forecasting*, 40, 12–19.

highlight the importance of taking a method's variance into account as well. Interestingly, in the context of forecasting, controlling variance can be doubly important because inventory and delivery systems may be overburdened by outliers that had not been predicted. Brighton and Gigerenzer (2015) define the concept of the *bias bias*, which is the pervasive tendency to evaluate a human judgment or the output of a model, mostly based on its bias, while ignoring its variance. This tendency is exhibited by laypeople, but perhaps even more so by experts and researchers.

Key References

Meder, B., & Mayrhofer, R. (2017). Diagnostic reasoning. In M. R. Waldmann (Ed.), *Oxford handbook of causal reasoning* (pp. 433–458). New York: Oxford University Press.

Meder, B., Mayrhofer, R., & Waldmann, M. (2014). Structure induction in diagnostic causal reasoning. *Psychological Review*, 121, 277–301. doi:10.1037/a0035944

Diagnostic Reasoners Take Into Account Uncertainty About the Structure of the Environment

The previous sections discussed how the behavior of simple and complex models is contingent on environmental structures. This section considers the role of the causal structure of the environment in human reasoning and decision making.

How do people make diagnostic inferences from effect to cause? How does the mind adapt to uncertainty about the structure of the environment when reasoning diagnostically? The long-standing normative benchmark for diagnostic inferences is Bayes' rule applied to the empirical data or verbally described statistics. In an uncertain world, however, inferences often have to be made based on limited and noisy data samples from the environment. Meder, Mayrhofer, and Waldmann (2014; Meder & Mayrhofer, 2017) argue that a purely statistical norm like Bayes' rule applied to the observed data is not an adequate normative benchmark for rational inference because it neglects alternative causal structures that may have generated the data. They instead propose the *structure induction model of diagnostic reasoning*, which formalizes the intuition that diagnostic inferences should take into account whether the sample data warrant the existence of a causal relation between the candidate cause and the effect or not.

Consider the case of a possible causal relation between a binary candidate cause, such as having a particular genetic predisposition, and a potential binary effect, such as having

elevated blood pressure. A sample of data is available, that is, a joint frequency distribution that specifies for each person in the sample whether they have the condition or not (cause present vs. absent) and whether they have elevated blood pressure or not (effect present vs. absent). Examples of three data sets are shown in Figure 6a. Each sample comprises 40 people: 20 with the genetic predisposition and 20 without. In each sample, the proportion of people with elevated blood pressure varies. In Sample 1, 6 out of the 20 people with the predisposition have elevated blood pressure, whereas only 2 out of 20 people without it have elevated blood pressure. The corresponding numbers for Sample 2 are 12 out of 20 compared to 4 out of 20; for Sample 3, they are 18 out of 20 versus 6 out of 20. Importantly, the diagnostic probability of cause given effect is identical across the three data sets: In each sample, 75% of people who have elevated blood pressure possess the genetic predisposition.

Assume that a new person from the same reference class is drawn at random. This person has elevated blood pressure: What is the probability of that person also having the genetic predisposition? A purely statistical model such as Bayes' rule applied to the observed data predicts that this probability is 0.75. The structure induction model, by contrast, makes very different predictions by taking into account uncertainty about the structure of the environment. For the case of a single cause and a single effect, the model considers two alternative causal structures that may underlie the data (see Figure 6b). According to the first structure, *C* and *E* are independent events; that is, there is no causal relation between them. Although there may be a statistical dependency in the sample data (e.g., people with the predisposition are more likely to have elevated blood pressure than those without), this co-occurrence is merely accidental, and the effect is exclusively generated by unobserved (independent) background causes *A*. By contrast, the alternative environmental structure (see Figure 6b bottom) states that there is a causal relation between *C* and *E* (and also alternative background causes *A* that can

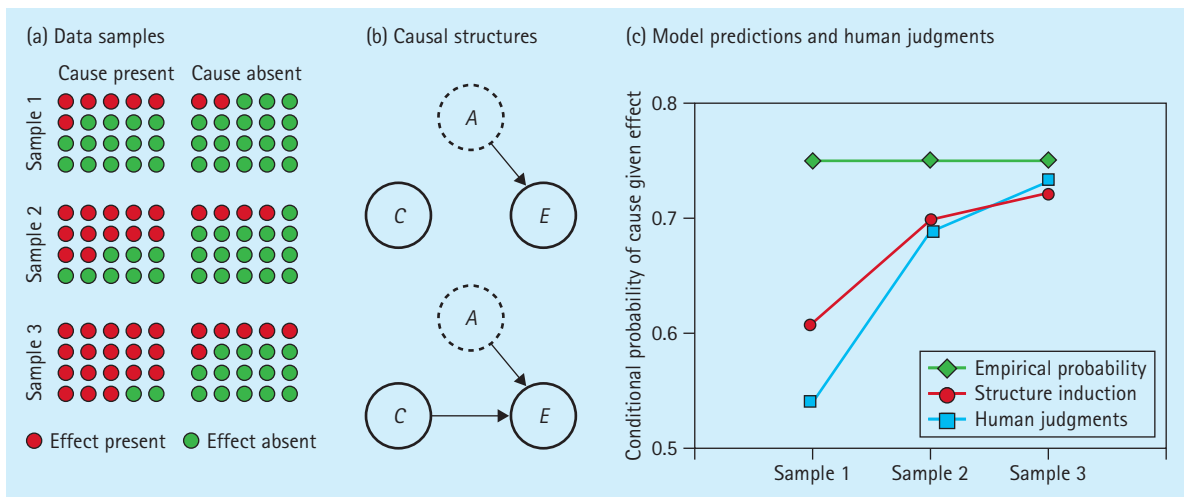


Figure 6. How the structure induction model of diagnostic reasoning works. (a) Three different data samples. In each sample, the diagnostic probability of cause given effect is 0.75. (b) Alternative environmental structures that may underlie the observed data. According to the upper structure, candidate cause *C* and effect *E* are independent; any observed empirical contingency is merely coincidental. According to the alternative structure (bottom) there is a causal relation between *C* and *E*. (c) Model predictions and empirical results. Because the empirical probability of cause given effect is 0.75 in all three data samples, a purely statistical account predicts the same judgment for each data set. The structure induction model makes very different predictions by taking into account uncertainty about environmental structure. It predicts higher judgments as it becomes more likely that the data warrant the existence of a causal relation. Mean human judgments are not invariant across the three data sets, showing that people are sensitive to uncertainty about environmental structure (adapted from Meder, Mayrhofer, & Waldmann, 2014).

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independently generate the effect when *C* is absent).

The structure induction model predicts that the observation of the effect should lead to higher diagnostic inferences the stronger the belief is in the existence of a causal relation between the candidate cause and effect. Thus, even if an identical probability of the disease given the symptom is observed in different data sets, this does not necessarily mean that the diagnostic judgments are invariant. Figure 6c illustrates these predictions for the three data sets shown in Figure 6a. Because the empirical probability of cause given effect is identical across all data sets, a purely statistical account predicts that diagnostic judgments are invariant. The structure induction mode, however, predicts diagnostic probabilities that systematically deviate from the observed probabilities. For instance, for Sample 1, the empirical probability of cause given effect is 0.75, whereas the structure induction model predicts a conditional prob-

ability of 0.61. This prediction arises from the fact that the contingency between cause and effect is relatively weak, so that either of the two structures has equally likely generated the data.

Is human diagnostic reasoning sensitive to uncertainty about the structure of the environment? Meder et al. (2014) presented participants with different data samples in which the empirical diagnostic probability was invariant (as in the three data sets in Figure 6a, where the diagnostic probability was always 0.75) and asked them to make a diagnostic judgment from effect to cause. The key finding was that human diagnostic judgments systematically varied (see Figure 6c). Although such an inference pattern appears flawed and biased from the perspective of a purely statistical account, the analyses show that the judgment patterns should instead be considered as resulting from a causal inference strategy that is well adapted to the uncertainties of the world.

Social Rationality

How do humans cope with a world full of uncertainty? One way is to apply mental tools that are boundedly and ecologically rational, such as simple heuristics; another is to exploit the collective wisdom arising through communication and social interactions. Understanding how humans make judgments and decisions in interactive, social environments has always been a key goal of the Center. In line with our work on other research topics, we study social rationality by focusing on the interplay of the mind—or a group of minds—and the environment, exploring how simple strategies help us solve difficult social problems and investigating the conditions under which collective decisions succeed or fail. The research reported here covers recent work in the areas of crowd wisdom, creativity, moral judgment, cooperation, and social cognition and learning.

Key Reference

Barkoczi, D., & Galesic, M. (2016). Social learning strategies modify the effect of network structure on group performance. *Nature Communications*, 7:13109. doi:10.1038/ncomms13109

How Do Social Networks Influence Group Performance?

The structure of social networks is an important factor determining the problem-solving capacity of teams, organizations, and societies. However, previous studies yielded contradictory results regarding the relationship between network structure and group performance: Some showed support for the superior performance of well-connected, efficient network structures, whereas others showed support for that of poorly connected, inefficient network structures. Barkoczi and Galesic (2016) hypothesized that the influence of social networks on group performance depends on both the network structure and

the social learning strategies used by individual team members. Consequently, reliance on different social learning strategies can lead to the superiority of either well-connected or poorly connected network structures. To test this hypothesis, the authors conducted a simulation study in which a group of agents performed a problem-solving task. To obtain good solutions, the group had to strike a balance between exploration (i.e., searching for new solutions through trial and error) and exploitation (i.e., imitating existing solutions that work well). The authors varied a number of factors, including task difficulty, individuals' social learning strategies, and network structures. As Figure 7 shows, well-connected

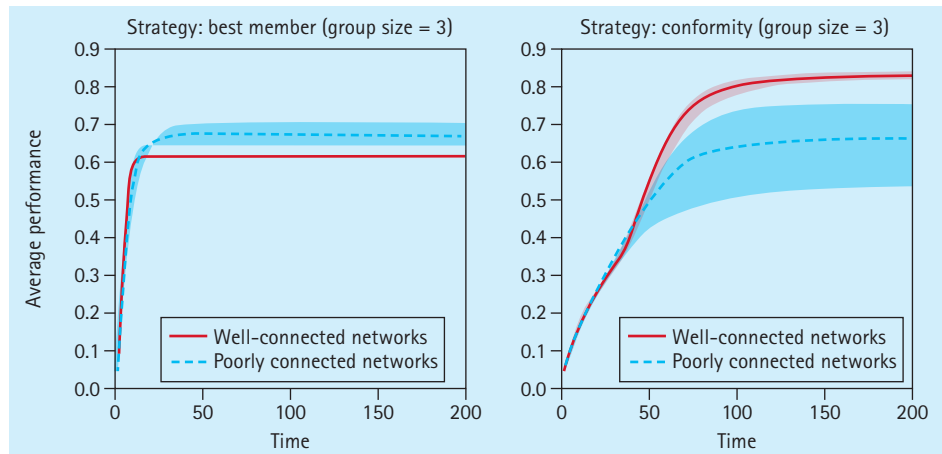


Figure 7. Group performance over time. Group performance is the average performance over either 10 well-connected (red solid lines) or 10 poorly connected (blue dashed lines) networks. Left panel: groups relying on the best member strategy (i.e., copying the solution from the highest payoff member); right panel: groups relying on the conformity strategy (i.e., copying the most frequent solution within the group). Shadings around the lines show the region between the best and worst performing network in each category at each point in time. The results demonstrate that well-connected networks are superior when individuals rely on the conformity learning strategy, whereas poorly connected networks are superior when individuals copy the best member (adapted from Barkoczi & Galesic, 2016).

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networks were found to outperform poorly connected networks when individuals relied on conformity by copying the most frequent solution among their social contacts. However, poorly connected networks were superior when individuals copied the group member with the highest payoff. The intuition underlying these results is that both network structure and social learning strategy affect the balance of exploration and exploitation and that a group needs to find a good match between the two to perform well. Overall, their findings reconcile contradictory results in the literature and highlight the importance of studying the match between

cognition (social learning strategy) and the environment (social network structure) in group decision research.

Smaller Crowds Can Be Wiser

Decisions about political, economic, legal, and health issues are often made via simple majority voting by groups that rarely exceed 30 to 40 members and are typically much smaller. Given that wisdom is usually attributed to large crowds, should committees not be larger? Galesic, Barkoczi, and Katsikopoulos (2016) studied this question using a simple mathematical model. They assumed that, over the course of their

Key Reference

Galesic, M., Barkoczi, D., & Katsikopoulos, K. V. (2016). Smaller crowds outperform larger crowds and individuals in realistic task conditions. *Decision*. Advance online publication. doi:10.1037/dec0000059

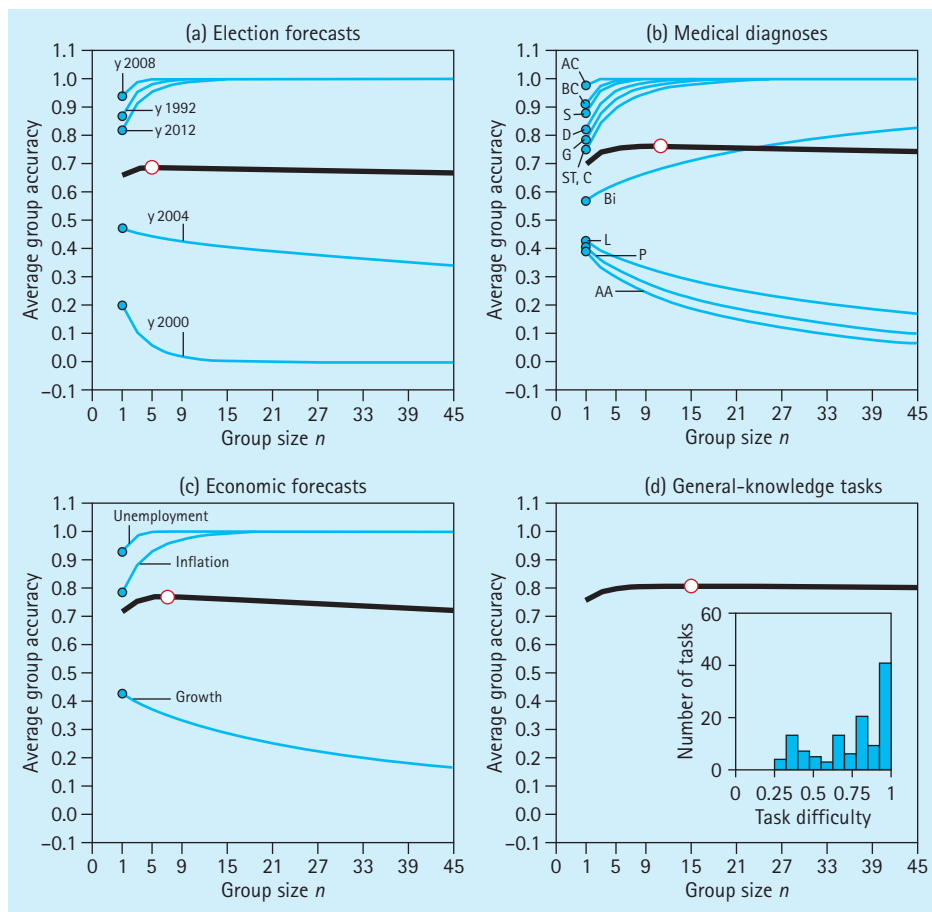


Figure 8. Average group accuracy depends on the combination of task difficulties and the proportion of easy tasks a group encounters. Using data on expert forecasting accuracies for different events in four different domains (panels a–d), the authors derive the best group size. Blue lines show extrapolated accuracy for each task, assuming different group sizes; black lines show average group accuracy across all tasks. Given the large number of trials available in panel d, the blue lines are replaced by a histogram showing the distribution of task difficulties. In all four domains, small to moderate-sized groups achieve greatest accuracy (adapted from Galesic, Barkoczi, & Katsikopoulos, 2016).

Key Reference

Fific, M., & Gigerenzer, G. (2014). Are two interviewers better than one? *Journal of Business Research*, 67, 1771–1779. doi:10.1016/j.jbusres.2014.03.003

existence, groups can encounter a number of different tasks. Most tasks are easy, where average individual accuracy is above chance (i.e., most individuals are more likely to be correct than incorrect), but some are surprisingly difficult, where most group members decide wrongly. Examples of such tasks are elections with surprising outcomes, sudden turns in financial trends, or tricky knowledge questions. It is difficult, if not impossible, for groups to predict in advance whether the next task will be easy or difficult. The authors show that, under these circumstances, moderately sized groups, whose members are selected randomly from a larger group, can achieve higher average accuracy across all tasks than can either larger groups or individuals. This occurs because an increase in group size can lead to a decrease in group accuracy for difficult tasks that is larger than the corresponding increase in accuracy for easy tasks. The authors derive this nonmonotonic relationship between group size and accuracy from the Condorcet jury theorem and use simulations and further analyses to show that it holds under a variety of assumptions. They further show that situations favoring moderately sized groups occur in a variety of real-life situations, including political, medical, financial decisions, and general knowledge tests (see Figure 8). These results have implications for the design of decision-making bodies at all levels of policy.

Are Two Interviewers Better Than One?

When firms hire candidates for job positions, the final decision is often based on a series of interviews. How many interviewers should be used for each candidate to achieve the best results? Condorcet's jury theorem and the "wisdom of the crowd" suggest that more is better. In fact, a survey showed that large consulting firms use between 5 to 11 different interviewers per candidate, depending on the level of the position. Questioning this practice, Fific and Gigerenzer (2014) show that—under quite general conditions—two interviewers are on average not superior to the best interviewer. Nor will adding further interviewers increase the expected collective hit rate when interviewers are homogeneous (i.e., their hits are nested), but only when interviewers are heterogeneous (i.e., their hits are not nested).

Consider a company that wants to identify the 10 best applicants ("targets") out of a pool of 100. The interviewers are called "Interviewer 1, 2, ..., " where "1" stands for the interviewer with the best hit rate, "2" for the second best, and so on. All decisions are made by the majority rule. Under these conditions, Fific and Gigerenzer (2014) showed that using Interviewer 1 alone is always better than adding Interviewer 2; that is, one interviewer is better than two. For instance, if Interviewer 1 has a hit rate of 0.80 and gets to pick 10 out of a pool of 100 applicants, we expect that interviewer to pick 8 of the 10 targets. Adding

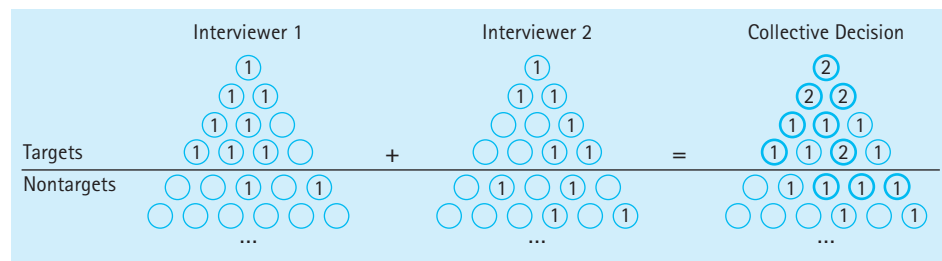


Figure 9. Does it help to add Interviewer 2, who is able to identify all targets that Interviewer 1 missed? The 10 target candidates (circles) are placed at the pyramid's top. The best interviewer, Interviewer 1, has a hit rate of 0.80 (i.e., selecting 8 of the top 10 candidates ["targets"] correctly). Interviewer 2 has a lower hit rate of 0.60, but picks the two targets that the other interviewer misses. The two interviewers' collective decision is made by the majority rule; that is, they choose the ones who receive two votes and randomly select the ones who receive one vote (the number of votes is noted in the circles). The expected collective decision is shown on the right side of the figure with the selected candidates in bold circles. The hit rate of the collective decisions is only 0.70, lower than when relying on the best interviewer alone (adapted from Fific & Gigerenzer, 2014).

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another interviewer with a lower hit rate (e.g., 0.60) will, on average, result in a lower hit rate than using Interviewer 1 alone. This holds even if Interviewer 2 can correctly identify all targets that Interviewer 1 missed, as illustrated and explained in Figure 9.

What happens if the company wants to use a team of interviewers with $n > 2$ members? Fific and Gigerenzer (2014) showed that a homogeneous set of n interviewers will never be better than the best interviewer alone nor will there be any improvement by having "mirror" interviewers who can identify the targets missed by the best interviewer. If the best interviewer is not known, it will be better for a company to hire a team of heterogeneous interviewers. The size of this team depends on the range of individual hit rates: The closer the hit rates to that of the best (unknown) interviewer and the smaller their variability, the fewer additional interviewers are needed.

This analysis has significant implications on hiring practice. First, it suggests that the best policy is to invest resources in improving the quality of the best interviewer rather than

distributing these to improve the quality of many interviewers. Second, in cases where it is unclear who the best interviewers are, companies should increase the size of the interviewing team and draw on heterogeneous interviewers with diverse backgrounds.

The Power of Groups in Developing Good Ideas

Research on brainstorming has repeatedly claimed that individuals are more creative than groups. However, these conclusions are largely based on measuring creativity by the quantity of ideas generated. Other important components of creativity, such as the development of initial ideas, are often ignored. Given the topic's great practical relevance, there is a need for more empirical studies that can capture the complexity of the entire creative process and investigate whether the development of an idea is best achieved in a group setting or individually.

McMahon, Ruggeri, Kämmer, and Katsikopoulos (2016) compared group performance with individual performance in creative tasks beyond the idea generation phase,

Key Reference

McMahon, K., Ruggeri, A., Kämmer, J. E., & Katsikopoulos, K. V. (2016). There is more to creativity than generating ideas: The power of groups in developing ideas. *Creativity Research Journal*, 28, 247–257. doi:10.1080/10400419.2016.1195637

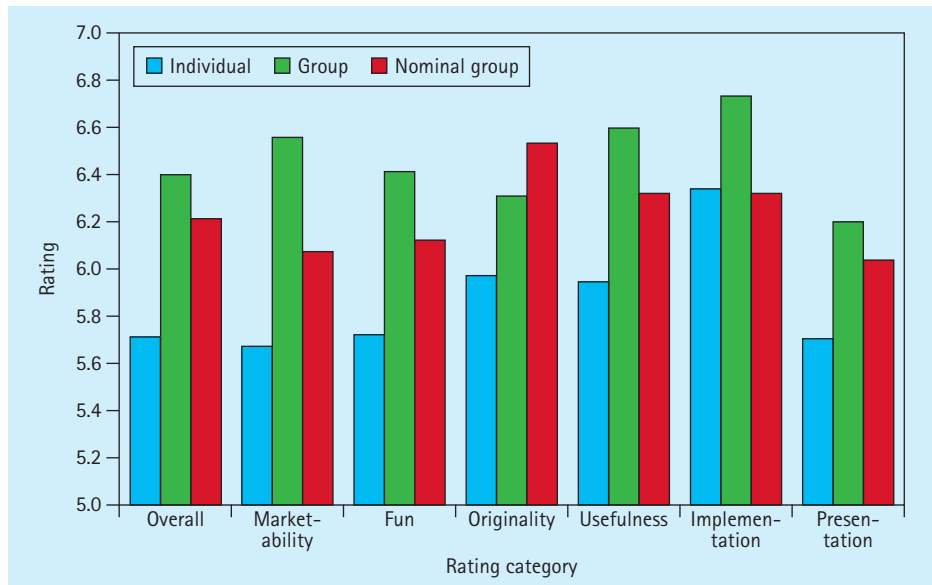


Figure 10. Average ratings of individuals, groups, and nominal groups in different evaluation categories for the language-learning games they developed. In the overall category, both types of groups received higher ratings than individuals; in the marketability category, groups received higher ratings than those of nominal groups, which were in turn higher than those of individuals; in the fun category, groups received higher ratings than individuals. All categories were rated on a scale of 1 (low) to 10 (high) (adapted from McMahon, Ruggeri, Kämmer, & Katsikopoulos, 2016).

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experimentally exploring the phase of developing an idea into a product. In the first study, they compared the performance of groups (i.e., participants working together), nominal groups (i.e., groups composed of individuals working separately, with their performances aggregated for analysis), and individuals in selecting and developing an original design for a language-learning game. They found that all three performed equally well. In the second study, one idea was preselected and given to the participants for further development. Creative processes were compared in terms of both quantitative measures of the final outcome and qualitative measures of the development phases. As Figure 10 shows, groups received higher overall ratings and higher ratings in the marketability category than both nominal groups and individuals, and higher ratings in the fun category than individuals. The qualitative data demonstrate that groups discussed a wider range of topics,

including the topic of marketability, than individuals.

Altogether, the results from this research indicate that there may be benefits in developing ideas in a collaborative group rather than individually. Hence, it is not accurate to say that groups are inferior to individuals with respect to creativity.

Key Reference

Kämmer, J. E., Gaissmaier, W., Reimer, T., & Schermuly, C. C. (2014). The adaptive use of recognition in group decision making. *Cognitive Science*, 38, 911–942. doi:10.1111/cogs.12110

The Adaptivity of Group Decision Making

How do groups and individuals make decisions, and what factors influence their decision processes? Both the social psychology literature on group decision making and the cognitive psychology literature on individual decision making have addressed very similar questions, yet they remain largely unconnected. Kämmer, Gaissmaier, Reimer, and Schermuly (2014) combined the two literatures to investigate an important aspect of group decision making: Do groups select decision strategies adaptively? And if so, how?

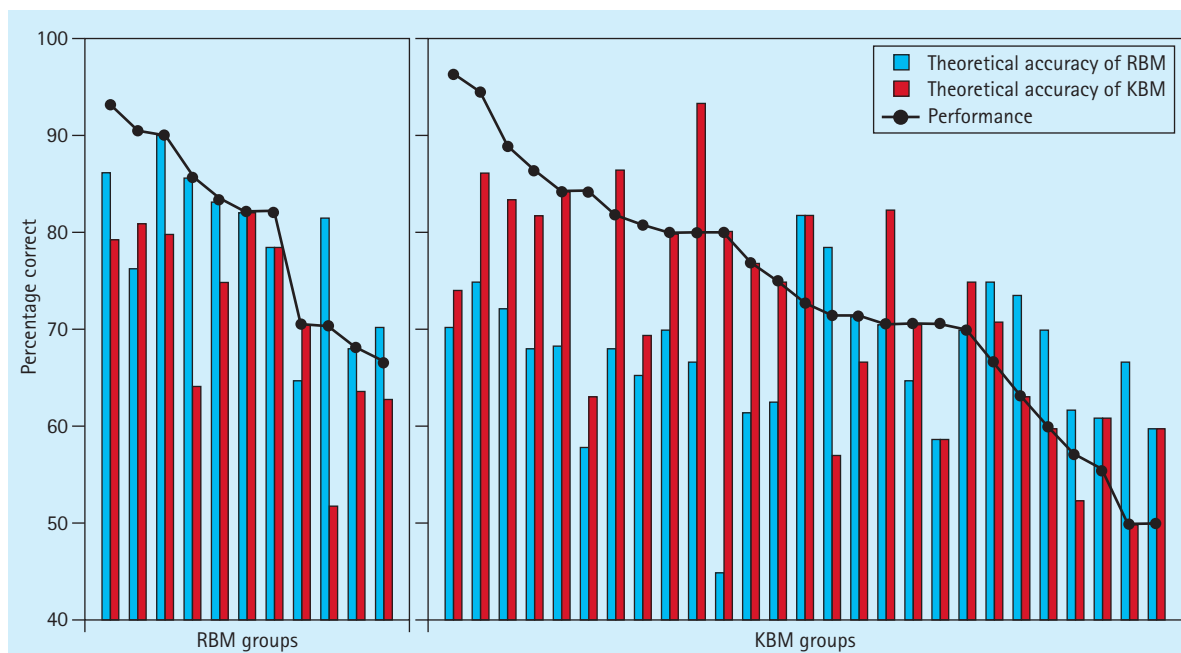


Figure 11. Group performance in a paired comparison task in which groups judged which of two companies had a higher market capitalization. Two models were tested on their ability to describe group choices: (1) a recognition-based model (RBM), which assumes that group members who could use the recognition heuristic determined the group choice and (2) a knowledge-based model (KBM), which assumes that members who could use their knowledge determined the group choice. This figure shows the achieved and theoretical accuracy of the KBM and of the RBM in situations where both models were applicable. It can be seen that, for the RBM groups, the theoretical accuracy of RBM was higher and closer to the observed accuracy than that of the KBM (left panel) and vice versa for the KBM groups (right panel). These results suggest that groups behaved adaptively, adopting strategies that helped them achieve higher accuracy (adapted from Kämmer, Gaissmaier, Reimer, & Schermuly, 2014).

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The study focused on the recognition heuristic, which predicts that if only one of two alternatives is recognized and the other is not, the recognized one is inferred to have the higher value on the target criterion. Here, the task-relevant features were the validities of group members' recognition and knowledge that influenced the potential performance of group strategies. Forty-three groups consisting of three people each had to infer which of two German companies had a higher market capitalization. Results support the hypothesis that groups adaptively apply the strategy that leads to the highest theoretically achievable performance (see Figure 11). In other words, performance of a group is not necessarily improved by increasing the quantity of information exchanged; rather, the *adaptive* selection of group decision strategies determines the success of a group. Under some circumstances, this means that groups rely on the less knowledgeable members who happen to possess the more valid cue (i.e., recognition). The results of this study show that, in order to be successful, a group must select a strategy that fits to the structure of the task environ-

ment *and* the features and composition of its members.

Moral Hindsight: Moral Judgments Under Certainty Versus Uncertainty

Uncertainty is a key feature of many situations in which moral judgments are made. Is it morally permissible to threaten a kidnapper with torture to find the victim, even if this risks the kidnapper's acquittal due to violation of procedural rules? Should a government cultivate genetically modified crops that could ensure food availability, even if it is uncertain whether these may cause severe allergies and the destruction of ecosystems and food chains? Although uncertainty is ubiquitous, most research on moral judgments has focused on problems in which all consequences are presented as certain (e.g., the famous "trolley dilemma"). By contrast, Fleischhut, Meder, and Gigerenzer (in press) investigated moral reasoning under uncertainty. Adopting a classic hindsight paradigm from the judgment and decision-making literature, they tested the predictions of two types of moral theories on how judgments should vary under un-

Key Reference

Fleischhut, N., Meder, B., & Gigerenzer, G. (in press). Moral hindsight. *Experimental Psychology*.

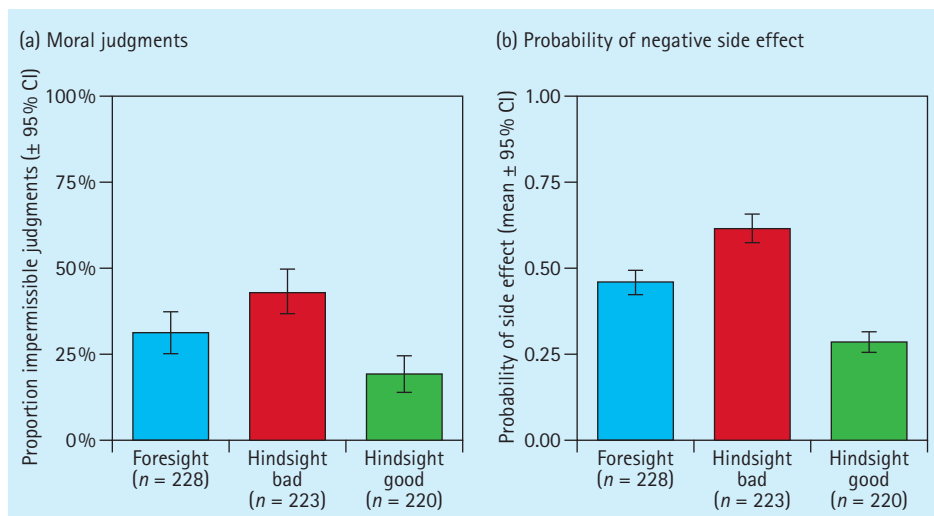


Figure 12. Moral judgments and probability estimates for the negative side effects aggregated across six moral dilemmas. In the foresight condition, it was uncertain whether the side effect would occur; in the hindsight bad condition, it was known that the negative side did occur; and in the hindsight good condition, it was known that the side effect did not occur. (a) The way moral judgments vary across conditions reflects participants' inability to disregard outcomes, even though they remained uncertain when the decision had to be made: a moral hindsight effect. (b) A corresponding hindsight effect for probability estimates of the negative side effect. Importantly, the hindsight effect in probability estimates carried over to moral judgment solely for participants who indicated a cost-benefit trade-off as most important for their moral evaluation (adapted from Fleischhut, Meder, & Gigerenzer, in press).

certainty and certainty across six real-world dilemmas. Specifically, in foresight, it was uncertain whether the cultivation of genetically modified crop would lead to severe allergies and destruction of eco systems, whereas in hindsight, it was known that these adverse side effects either occurred or did not. The key result was a hindsight effect in moral judgment (see Figure 12a). Participants in the foresight condition judged actions to be more morally permissible than participants in the *hindsight bad* condition, who knew that the negative side effects did occur. Conversely, foresight participants judged actions to be less permissible than participants in the *hindsight good* condition, who knew that negative side effects did not occur. The second finding was a classical hindsight effect when participants judged the likelihood of negative side effects: Although instructed to ignore the outcome of the decision, their probability judgments in hindsight mirrored their knowledge of the actual course of events (see Figure 12b). There was also a systematic relation between moral judgments and probability estimates: Participants who considered the action to be morally impermissible gave on average higher probability estimates for the negative side effect than participants who considered the action to be permissible. However, the hindsight effect on probability estimates corresponded to the hindsight effect on moral judgments solely for “consequentialist” participants who reported a cost-benefit trade-off as most important for their moral evaluation. Among participants who did not report a trade-off as the most important reason, a hindsight effect in probability judgments was observed, but did not carry over to the moral judgments.

This work highlights the importance of investigating moral reasoning under conditions that more closely resemble real-world dilemmas. It also provides new pathways for investigating how people make moral judgments in a fundamentally uncertain world.

An Evolutionary Approach to the Influences of Social Contact on Cognition

In 2016, more than 80 million Twitter users followed the President of the United States

Barack Obama and he, in turn, followed over 600,000 users. How did Obama remember all of these people? Of course, he did not have personal relationships with all of them, and likely had aides manage his account. But the scope of modern social networks raises interesting questions about how our cognition copes with the demands of our social world. To maintain relationships, it is critical to remember information about our social partners. In general, we are more likely to reencounter individuals whom we have encountered frequently and recently in the past. Our memory, therefore, might make a bet about needing information on social partners based on the pattern of past encounters: We should better remember more frequently and recently encountered partners. In fact, there are clear (power-law) patterns in how we encounter individuals in our social networks (see Figure 13a), and our memory shows the same pattern (see Figure 13c). However, the origin of this relationship is not clear. Does memory reflect patterns of social contact because memory has adapted over our lifetimes to how we encounter other individuals? Or is the connection between social contact patterns and memory important enough that it has been passed down evolutionarily? Stevens, Marewski, Schooler, and Gilby (2016) tested this question by investigating social contact patterns and memory in a phylogenetically closely related species—the chimpanzee (*Pan troglodytes*). They tested whether (1) chimpanzees show the same patterns of social contact as those observed in humans and (2) chimpanzee memory performance matches their social contact patterns. Analyzing 19 years of social contact data from the chimpanzees at Kibale National Park, Uganda, they found that chimpanzee social contact data in fact mirrored the human data, with a power-law relationship between past and future contact (see Figure 13b). Moreover, chimpanzee memory performance showed the same kind of pattern as in their social contact data (see Figure 13d). These findings suggest that human and chimpanzee memory have evolved to solve similar information-processing problems faced in their social networks. Discovering how human cognition

Key Reference

Stevens, J. R., Marewski, J. N., Schooler, L. J., & Gilby, I. C. (2016). Reflections of the social environment in chimpanzee memory: Applying rational analysis beyond humans. *Royal Society Open Science*, 3(8):16029314. doi:10.1098/rsos.160293

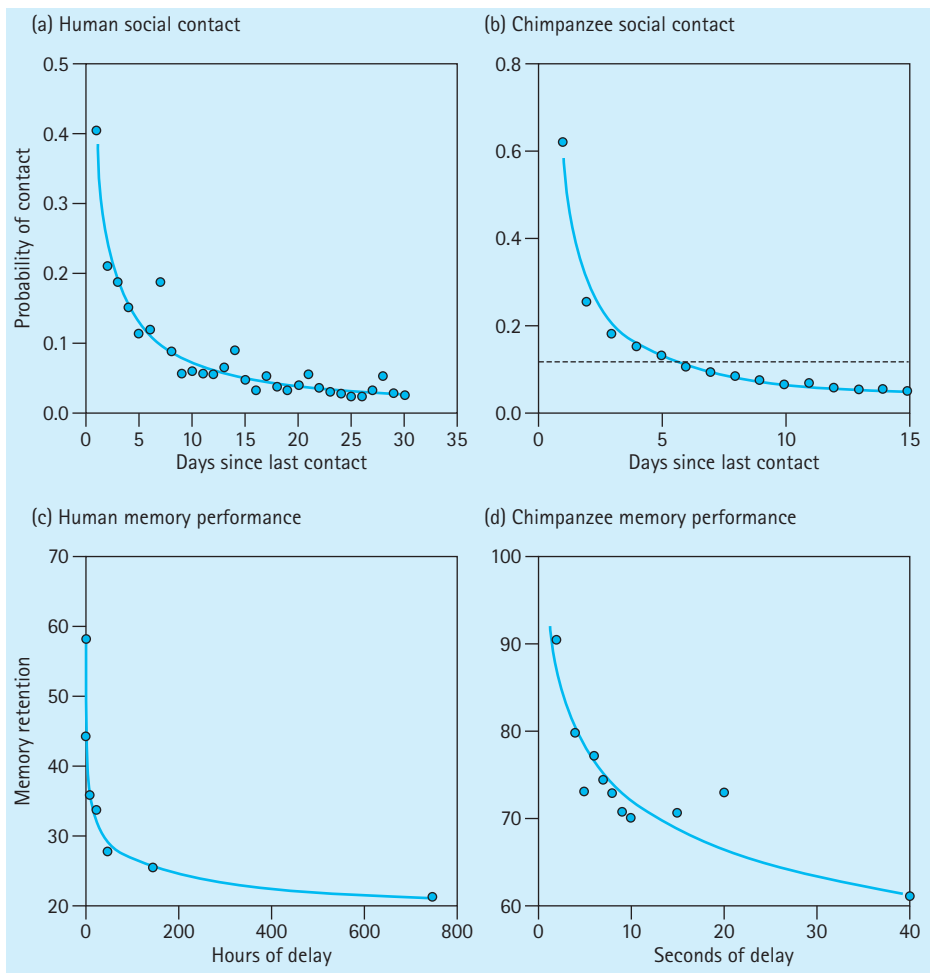


Figure 13. How does recency of encounter influence future social contact and memory performance in humans and chimpanzees? Previous work has shown that human memory performance reflects patterns of social contact. For example, both (a) the probability of future social contact and (c) memory performance decrease as a power function of the recency since encountering social partners and the objects to be remembered. Stevens, Marewski, Schooler, & Gilby (2016) searched for similar patterns in chimpanzees (*Pan troglodytes*) by measuring social contact patterns in wild chimpanzees and analyzing memory data from captive chimpanzees. They found that chimpanzees, like humans, also showed power-law relationships with recency for both (b) social contact and (d) memory performance, suggesting that human and chimpanzee memory have evolved to solve similar information-processing problems faced in their social networks (adapted from Stevens, Marewski, Schooler, & Gilby 2016).

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reflects and diverges from those of other species offers a promising route for better understanding how the social world shapes our cognition.

Understanding the Process of How We Decide to Forgive

Cooperation among nonkin has received significant attention in the last decades. Although advances have been made in

understanding why performing costly actions for another's benefit can be adaptive, less is known about the computational processes used to make such decisions.

Tan, Luan, and Katsikopoulos (2016) studied forgiveness decisions, which are a key type of decision supporting recurrent cooperation. They argued that deciding whether to forgive someone can be viewed as a signal detection task: Forgiving is adaptive if a continued rela-

Key Reference

Tan, J. H., Luan, S., & Katsikopoulos, K. V. (2017). A signal-detection approach to modeling forgiveness decisions. *Evolution and Human Behavior*, 38, 27–38. doi:10.1016/j.evolhumbehav.2016.06.004

tionship with the person is fitness enhancing and not adaptive if the relationship is fitness reducing. As a consequence, the decision to forgive should be biased toward lowering the likelihood of the more costly error, which, depending on the context, may be either erroneously not forgiving or erroneously forgiving. Building on this conceptualization, the study examined two cognitive models that implement signal detection principles: fast-and-frugal trees (see Figure 14 for what they are and how they might be implemented in making forgiveness decisions) and Franklin's rule, a linear model. Tan et al. (2017) tested whether these models could describe forgiveness decisions in hypothetical scenarios and predict decisions in recalled real-life incidents.

The study found that the models performed similarly and generally well—around 80%

accuracy in description and 70% in prediction. Moreover, this modeling approach enabled the decision bias of each participant to be estimated. The estimated biases were generally consistent with the prescriptions of signal detection theory and were directed at reducing the more costly error.

In addition to testing cognitive models of forgiveness decisions, this study also contributes to forgiveness research by empirically demonstrating that people adopt reasonable decision biases in forgiving. Finally, although this study focused on forgiveness decisions, many other social decisions can also be understood from the perspective of signal detection theory and be investigated using the same methodology. This research is thus a demonstration of how cognitive models can be used to investigate the processes of social decisions.

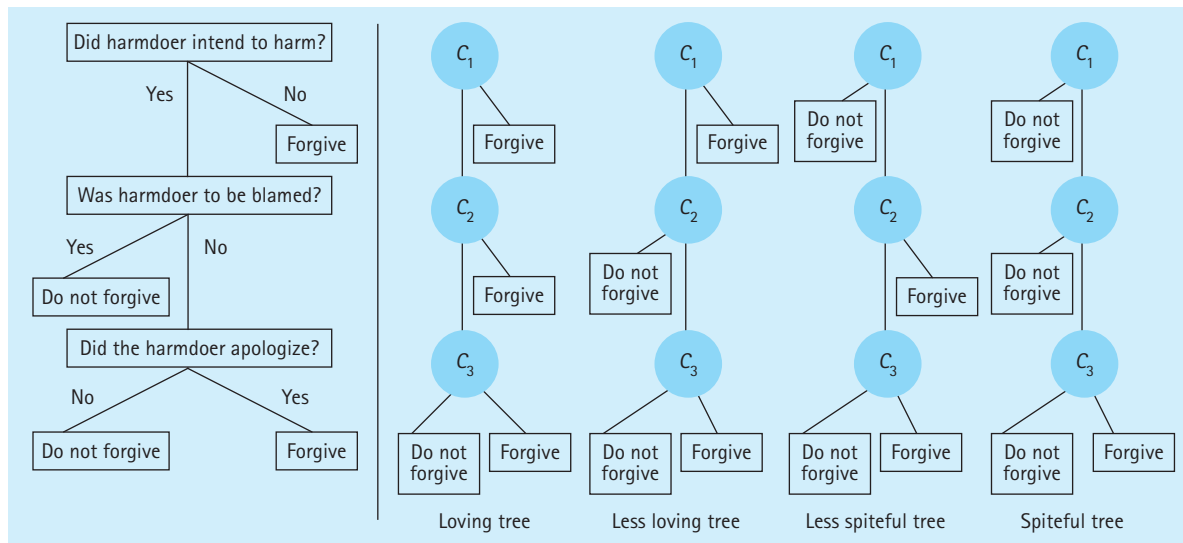


Figure 14. Fast-and-frugal trees in forgiveness decisions. In fast-and-frugal trees, cues are looked up sequentially and a decision can be made after each cue, without considering all subsequent cues. The left panel illustrates how an offended individual might make a forgiveness decision using a fast-and-frugal tree with three cues: intention, blame, and apology. The individual might first consider whether the harmdoer intended to harm. If there was no intent to harm, then the decision would be to forgive; otherwise, the next cue (blame) would be considered. Finally, the agent may consider whether the harmdoer apologized. The right panel shows the four exit structures of a fast-and-frugal tree, with C_1 , C_2 , and C_3 representing three cues in a fixed order. From left to right, the trees become more and more biased against forgiving; they are named according to their overall decision biases. The illustration on the left panel has the exit structure of a less loving tree (adapted from Tan, Luan, & Katsikopoulos, 2017).

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Decision Making in the Wild

The study of bounded, ecological, and social rationality conceives behavior as the result of an interaction between cognition and environment. It investigates the conditions under which simple heuristics can both lead to faster, more accurate predictions and increase the transparency of the decision process. In this section, we present a selection of our work outside the laboratory: an analysis of how car dealers price used BMWs, a project with the Bank of England, a study on checkpoint decision making in the age of terrorism, and one on governmental paternalism ("nudging").

Heuristic Pricing of Used Cars

When economists build models of markets, they assume the ability to fully capture all relevant aspects of the decision situation, which would enable deducing the market equilibrium and the optimal strategy agents should employ. However, unlike rational choice models, firms compete in dynamic and complex environments and thus often have only limited information at their disposal. Under these conditions, how do firms set prices? Artinger and Gigerenzer (2016) tested whether firms employ an aspiration level heuristic for price setting as first proposed by Herbert A. Simon in 1955 for such situations.

Analyzing the pricing strategies of 745 used-car dealers on the basis of online market data and interviews, they found that virtually all dealers employ a form of aspiration level pricing, depicted in Figure 15. The heuristic

used by the dealers is to start off with a high initial price and sequentially lower it in fixed time intervals until the car sells. The heuristic explains the counterintuitive "cheap twin paradox," where two identical cars at the very same dealership are often priced thousands of euros apart. This occurs when the twin cars differ in terms of the time that they have been at the dealer, so that the price of the "older twin" has already been lowered more than the price of its "younger twin." In Figure 15, this corresponds to different points on the x-axis with one or more "steps" in-between. The heuristic also generates an aggregate pattern that is well described by a model of equilibrium price dispersion. However, unlike the equilibrium model, the aspiration level heuristic correctly predicts systematic pricing characteristics, such as high initial price, price stickiness, and the cheap twin paradox.

Key Reference

Artinger, F., & Gigerenzer, G. (2016). Adaptive heuristic pricing. In J. Humphreys (Ed.), *Proceedings of the Seventy-Sixth Annual Meeting of the Academy of Management*. Advance online publication. Online ISSN: 2151-6561.

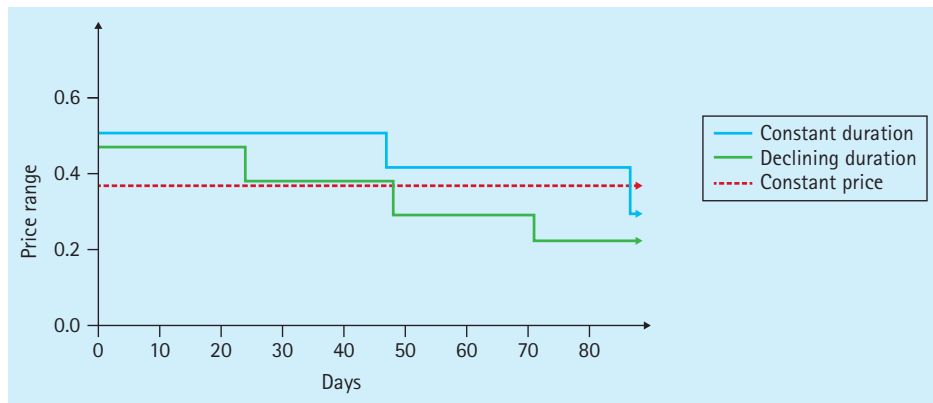


Figure 15. How do car dealers price used cars? Virtually all 745 dealers used one of three variants of the aspiration level heuristic: All dealers started at a fixed percentile of the price range. Then 51% of dealers used the "constant duration," strategy, where they kept the price constant for the same fixed interval across time for 24 days on average; 27% used "decreasing duration," where dealers sequentially lower the price, but decrease the duration for which consecutive prices are held constant from 48 days on average in the first step to 40 days in the second step; and 19% employed a "constant price," a special case of the aspiration level heuristic, where the initial price does not change (adapted from Artinger & Gigerenzer, 2016).

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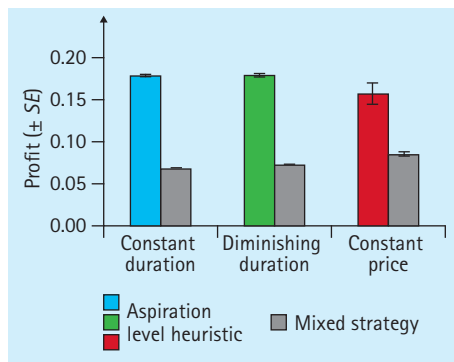


Figure 16. Simple adaptation heuristics can be more profitable than complex economic equilibrium pricing models (mixed strategy) (adapted from Artinger & Gigerenzer, 2016).

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Indeed about 14% of cars have a twin at the very same dealership. This analysis also provides first evidence that heuristic pricing can generate higher profits than the optimization strategy underlying the equilibrium model (see Figure 16).

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Aikman, D., Galesic, M., Gigerenzer, G., Kapadia, S., Katsikopoulos, K. V., Kothiyal, A., Murphy, E., & Neumann, T. (2014). *Taking uncertainty seriously: Simplicity versus complexity in financial regulation* (Bank of England Financial Stability Paper No. 28). London: Bank of England.

Gigerenzer, G., & Brighton, H. (2009). Homo heuristics: Why biased minds make better inferences. *Topics in Cognitive Science*, 1, 107–143. doi:10.1093/acprof:oso/9780199744282.003.0001

The Bank of England Project: Simple Heuristics for a Safer World of Finance

Since 2012, members of the Center have been meeting regularly with economists of the Bank of England to investigate alternatives to the present encumbrance of overly complex risk models and regulations. Both the private sector and public authorities have responded

to the growing complexity of the financial system with more complexity, whether through increasingly elaborate modeling and risk management or ever-lengthening regulatory rulebooks. But this helped neither to predict nor to prevent the most recent global financial crisis. In fact, financial models predicted that such a crisis was virtually impossible. For instance, in 2003, Robert Lucas, one of the most distinguished macroeconomists, declared that economic theory would protect us from future disaster: "Its central problem of depression-prevention has been solved, for all practical purposes, and has in fact been solved for many decades." Five years later, the greatest crisis since the Great Depression hit. The project is led by Andrew G. Haldane, Bank of England's Chief Economist and Executive Director of Monetary Analysis and Statistics, and Gerd Gigerenzer. Its goal is to combine the economic competencies of the bank with the research on simple heuristics from our group. The main question is whether heuristics can provide more robust and accurate tools for estimating key safety factors of the financial system, such as capital requirement and bank vulnerability. Heuristics can reduce estimation error and overfitting by virtue of estimating fewer parameters, as formally described in the bias-variance decomposition (Gigerenzer & Brighton, 2009). Figure 17 shows an example of a fast-and-frugal tree for assessing bank vulnerability. A

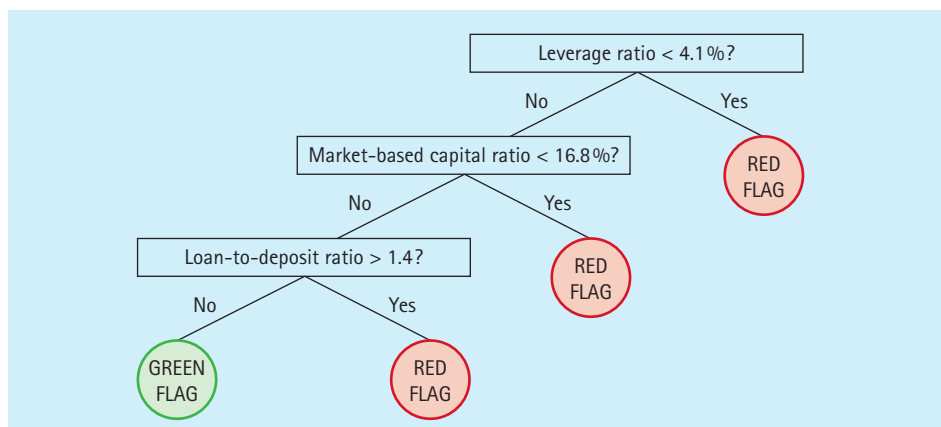


Figure 17. A fast-and-frugal tree for assessing bank vulnerability (Aikman et al., 2014). The tree was constructed using a combination of expert intuition (for selecting the three variables) and a statistical analysis for estimating the thresholds for each variable (adapted from Aikman et al., 2014).

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fast-and-frugal tree with n variables (or questions) has $n + 1$ exits, one at each variable and two at the end, compared to 2^n exits in a complete tree. The tree was constructed on the basis of data from before the global financial crisis and tested on data during the crisis. For an idea of how this tree works in practice, consider the case of UBS, which required significant financial support from the Swiss authorities during the crisis. Given its leverage ratio of 1.7 at the end of 2006, it is automatically red flagged on the first cue in the tree. This completely ignores the fact that the bank had a market-based capital ratio significantly exceeding 16.8% and a loan-to-deposit ratio well below 1.4 (the tree has a "noncompensatory" structure). By contrast, a regression model would balance UBS's low leverage ratio with its high market-based capital ratio and low loan-to-deposit ratio, and as a result might not give a strong warning signal. Figure 18 shows that the accuracy of the fast-and-frugal tree, as measured by the actual vulnerability during the crisis, compares favorably with standard logit models used in finance. These general results may have lessons for the design of regulatory standards. They high-

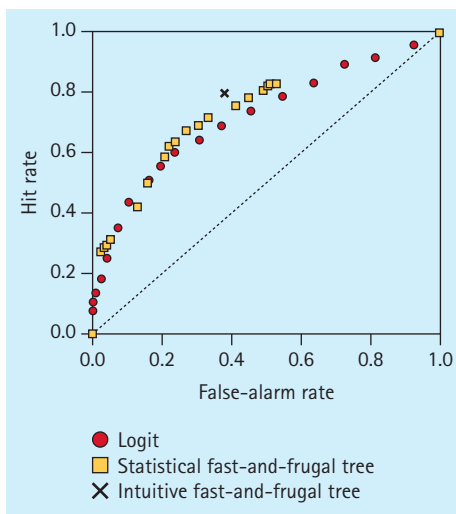


Figure 18. Less can be more in predicting bank vulnerability. The fast-and-frugal tree in Figure 17 performs as well as or better than standard logit models. Also shown are fast-and-frugal trees that are based purely on a statistical analysis of past data (without adding expert intuition to select the variables) (adapted from Aikman et al., 2014).

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light the importance of imposing a leverage ratio standard to complement risk-based capital requirements. And they suggest the usefulness of simple, high-level indicators to complement more complex metrics and other sources of information for assessing macroprudential risks. Moreover, simplicity in macroprudential policy may also facilitate transparency, communicability, and accountability, thus potentially leading to a greater understanding of the intent of policy actions, which could in turn help increase trust in such policies. Simple approaches are also likely to have wider benefits by being easier to understand and communicate to key stakeholders. For example, if senior management and investors have a better understanding of the risks that financial institutions face, internal governance and market discipline may both improve. Simple rules are not a panacea, especially in the face of regulatory arbitrage and an ever-changing financial system. But in a world characterized by Knightian uncertainty, tilting the balance away from ever-greater complexity and toward simplicity may lead to better outcomes for society.

Unrealistic Assumptions About Perfect Information Flow May Underestimate Bank Vulnerability

Although financial theory typically assumes a perfect flow of information among financial agents, in reality, financial reporting is not real-time, reports are not always reliable (as in the case of Lehman Brothers), and some information is exclusively shared between business partners. The study by Davidovic, Galesic, Katsikopoulos, and Arinaminpathy (2014) adds realism to a model of interbank markets by introducing uncertainty into what banks know about other banks. In their model, information spreads through the lending network established among banks, and the quality of information depends on the proximity of the information source in the network—information is more accurate and up-to-date between direct partners than between banks connected via other banks. Instead of having complete information, the latter receive information that is delayed, noisy, or local. For instance, in one of their

Key Reference

Davidovic, S., Galesic, M., Katsikopoulos, K. V., & Arinaminpathy, N. (2014). Modeling uncertainty in banking networks. In S. Omatu, H. Bersini, J. M. Corchado, S. Rodriguez, P. Pawlewski, & G. Buccarelli (Eds.), *Distributed computing and intelligence: 11th International Conference (Advances in Intelligent Systems and Computing No. 290)* (pp. 107–114). Berlin: Springer. doi:10.1007/978-3-319-07593-8_14

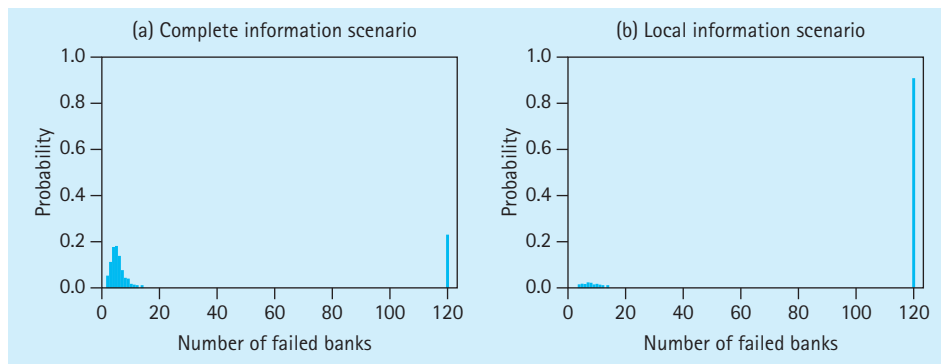


Figure 19. Probability distributions of the number of failed banks after a strong, externally applied financial shock to a banking system with 120 banks when (a) banks have perfect information about the lending network and (b) banks have reliable access to information from their direct neighbors only. When the information flow is uncertain as opposed to perfect, the probability that all 120 banks fail increases significantly (adapted from Davidovic, Galesic, Katsikopoulos, & Arinaminpathy, 2014).

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uncertainty scenarios, the authors introduce the concept of “locally perceived” confidence, where banks exclusively rely on information from the neighboring banks. As a result, the local impact of a financial shock is more intense, but initially limited to the neighborhood of banks directly affected. This local impact, however, is subsequently transmitted through the system (analogous to the dynamics of crack propagation in a solid medium), resulting overall in a significantly higher risk of system collapse than if complete information is assumed (see Figure 19).

academics working in fields that overlap with economics.

Classic decision theory is based on rules of consistency (such as transitivity or Bayes’ rule), and its implicit assumption is that consistency leads to more accuracy or to better health or wealth. The authors could not find any evidence linking belief inconsistency to belief inaccuracy or economic loss (see

Key Reference

Berg, N., Biele, G., & Gigerenzer, G. (2016). Consistent Bayesians are no more accurate than non-Bayesians: Economists surveyed about PSA. *Review of Behavioral Economics*, 3, 189–219. doi:10.1561/105.00000034

The White-Coat Heuristic, Consistency, and Prostate Cancer Screening

Berg, Biele, and Gigerenzer (2016) studied decision making about whether or not to participate in prostate cancer screening using Prostate Specific Antigen (PSA) tests. They asked two questions. First, does consistency correlate with accuracy in judgments? Second, do economists follow their own logic of rational choice by weighting the pros and cons and, if not, what is the process of their decision making?

The authors conducted face-to-face interviews with attendees of the annual meeting of the American Economic Association (attended by more than 10,000 registered conference participants). Of 133 respondents, 123 (92%) identified themselves as economists; the others were political scientists and

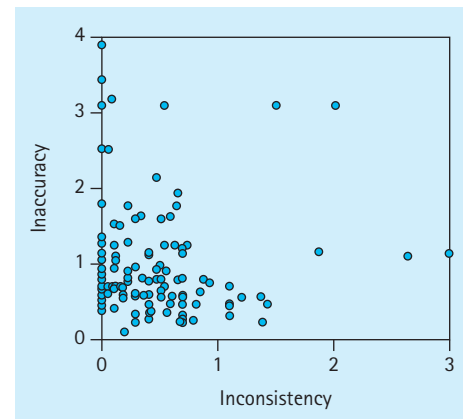


Figure 20. Inconsistency is not positively correlated with inaccuracy ($r = -0.04$). Inconsistency is measured by Bayesian consistency between estimated sensitivity, specificity, and other “elicited frequencies”; accuracy was measured by the discrepancy between estimated values and published estimates. For instance, the two persons with the most inaccurate beliefs (highest values on the y-axis) were perfect Bayesians, whereas the two most inconsistent persons (highest values on the x-axis) had below-average inaccuracy (adapted from Berg, Biele, & Gigerenzer, 2016).

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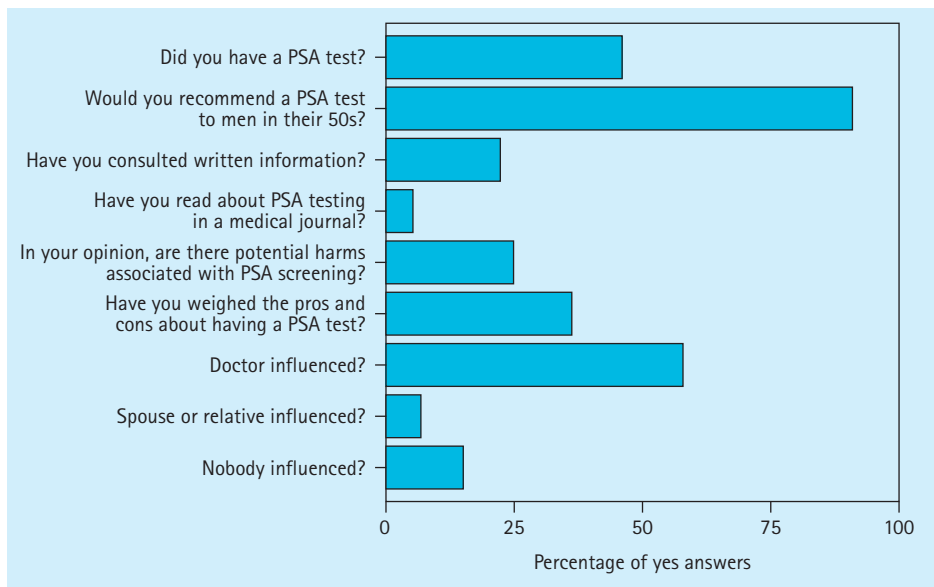


Figure 21. A survey of economists' knowledge and decision making with regard to prostate cancer screening (PSA tests). For instance, only 36% said that they had weighed the pros and cons of screening before deciding whether to take the PSA test. In contrast, 65% said that their doctor (58%) or their spouse (7%) had influenced their decision (adapted from Berg, Biele, & Gigerenzer, 2016).

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Figure 20). The correlation between consistency and accuracy was basically zero, even slightly negative. Economists with consistent (i.e., Bayesian) conditional beliefs about the sensitivity and positive predictive value of the PSA test had unconditional beliefs about the risk of prostate cancer that are, if anything, less accurate than the beliefs of inconsistent non-Bayesians. This lack of correlation between consistency and accuracy mirrors the lack of evidence that violations of coherence are costly in terms of health, wealth, or happiness (Arkes, Gigerenzer, & Hertwig, 2016).

How do economists make decisions about PSA screening? Keeping in mind the usual caveats about interpreting self-reports on issues as personal as medical decision making, Berg et al. (2016) asked respondents whether they had acquired written information on the PSA test, the sources of that information, and whether or not they had weighed the pros and cons when deciding whether to be tested. More than half said that they had not weighed pros and cons (see Figure 21). Yet about two thirds said they had followed

doctors' recommendations—a heuristic sometimes referred to as the white-coat heuristic—or their spouses' advice. The influential role of social heuristics is well-documented (e.g., having the PSA test because a spouse or doctor or another familiar person recommended it), yet it is nevertheless surprising in the context of PSA testing, given that medical organizations such as the U.S. Preventive Services Task Force (USPSTF) recommend against routine PSA testing. Because there is proof of severe harms (such as incontinence and impotence from surgery), but no proof that lives are saved, medical organizations tell every man to weigh the benefits carefully. Yet the present study indicates that PSA decisions depend more on social heuristics than on weighing the pros and cons; that is, they rely mostly on the white-coat heuristic.

Saving Civilian Life in the Age of Terrorism

Reducing civilian casualties in stability operations, such as the NATO mission to Afghanistan (ISAF), is not only a moral but also a political and strategic imperative. Several strategic directives aimed at minimiz-

Key Reference

Arkes, H. R., Gigerenzer, G., & Hertwig, R. (2016). How bad is incoherence? *Decision*, 3, 20–39. doi:10.1037/dec0000043

Key Reference

Keller, N., & Katsikopoulos, K. V. (2016). On the role of psychological heuristics in operational research; and a demonstration in military stability operations. *European Journal of Operations Research*, 249, 1063–1073. doi:10.1016/j.ejor.2015.07.023

ing civilian casualties have been issued by ISAF commanders, such as Petraeus in 2009. These, however, have failed to reduce civilian casualties in “force protection” situations—situations in which a military presence out in the field feels itself under threat and engages in signaling or self-defensive measures. The greatest threat for these troops is that of a vehicle-borne suicide attack: cars laden with explosives driven to a checkpoint or patrol and detonated.

On the basis of a goal-directed task analysis (analysis of classified documents, pre-deployment training observations, and expert interviews), Keller and Katsikopoulos (2016) constructed a fast-and-frugal tree (FFT) to assist soldiers in differentiating suicide attacker vehicles from civilian vehicles (see Figure 22). This FFT contains three binary cues:

- whether the vehicle contains one or more than one occupants;
- whether the approaching vehicle complies with military signals (slows down or stops) or not;
- whether any additional threat cues are present or not.

After construction of the FFT, a database of 1,060 ISAF reports of force protection incidents (January 2004 – December 2009) became available. These reports include 7 suicide attacks and 204 civilians erroneously injured or killed by ISAF forces. Because the FFT was not fitted to these reports, we can estimate its performance if it had been used instead.

Testing the FFT on the ISAF reports revealed that using it would have reduced civilian casualties by over 60%: from 204 to 78 civilians killed or injured. The FFT would also have enabled fast decisions: Across all 1,053 incidents where no suicide attacker was present, the FFT would have used on average only 1.2 cues, and 84% of the cases would have been categorized after looking up the first cue only. Finally, the FFT may improve soldier safety; while all 7 recorded suicide attacks were successful, the FFT could have identified all those attackers displaying noncompliant behavior.

The FFT, together with guidelines on action selection, was published in a classified

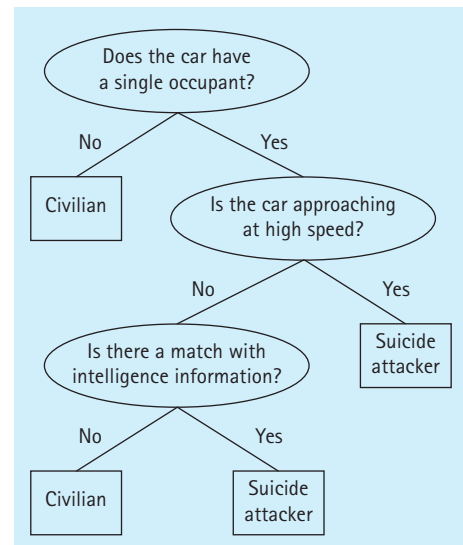


Figure 22. A fast-and-frugal tree to reduce civilian casualties in stability operations, such as checkpoints or patrols. The tree asks (at most) three questions, and a test on 1,060 critical incidents in ISAF reports shows that using it would have reduced the number of civilians killed or injured from 204 to 78 (adapted from Keller & Katsikopoulos, 2016).

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German Federal Armed Forces information leaflet and distributed to all troops (Aus dem Einsatz lernen, 02–2013). It also featured in *Science News* (10 August 2015) and a *ZEIT* Interview (17 September 2014).

Governmental Paternalism: On the Supposed Evidence for the Need to “Nudge” the People

Can the general public learn to deal with risk and uncertainty, or do authorities need to steer people’s choices in the right direction? In their book *Nudge*, Richard Thaler and Cass Sunstein (2008) argue that psychological research has shown people’s reasoning to be systematically flawed, more in line with Homer Simpson than *Homo economicus*. In addition, they find little evidence that people can be de-biased from their cognitive illusions, which they liken to stable visual illusions and the “reptilian brain,” known as “System 1.” Pessimistically, the authors conclude that governments need to step in and steer their citizens in the right direction. This philosophy of nudging is called “libertarian

Key Reference

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. New Haven, CT: Yale University Press.

paternalism," and governments in the United States, the United Kingdom, and elsewhere have been quick to assemble nudging teams to influence the public for their benefit. Nudges are nothing new, being the bread-and-butter of marketing and persuasion. But what is new is justifying them on the basis of people's irrationality. Libertarian paternalism's justification for governmental intervention deviates greatly from that of neoclassical economic theory, where intervention may be deemed necessary to correct imperfections of the market, such as when a firm has a monopoly. If, however, the imperfections are engraved in our brains rather than in the market, as libertarian paternalists assume, there is little hope of redressing them. In this very sense, libertarian paternalism is more "red-blooded" than some forms of hard paternalism, even if it does not endorse coercion (Rebonato, 2012).

Gigerenzer (2015c) analyzes the scientific evidence underlying the justification of libertarian paternalism through psychological research, focusing on three so-called systematic deviations from rationality presented by Thaler and Sunstein: framing effects, violations of Bayesian inference, and heuristics.

- (1) People "make different choices depending on the wording of the problem," which is known as the *framing effect*.
- (2) People "fail to make forecasts that are consistent with Bayes' rule."
- (3) People "use heuristics that lead them to make systematic blunders," which is part of the postulate that using statistics and logic always leads to more accurate judgments than when relying on heuristics and intuition.

(1) *Framing*. A framing effect occurs when people's choices differ depending on how two "logically equivalent" statements are framed. This behavior is said to be inconsistent with rational behavior because it violates the principle of "description invariance." As Thaler and Sunstein put it, the fact that people are influenced by framing demonstrates that humans are "mindless, passive decision makers" (2008, p. 40).

Libertarian paternalists, including some behavioral economists, may be among the

last professionals who cherish the ideal that logic *alone* provides a universal yardstick for intelligent choice. By contrast, psychological research by Craig McKenzie, Anton Kühberger, and others has shown that logically equivalent frames are not necessarily informationally equivalent. People (such as health-care providers) use framing to signal recommended options and listeners (such as patients) tend to understand the message between the lines. All in all, the principle of descriptive invariance is, by itself, an inappropriate general yardstick of rationality. Framing effects, defined as the violation of this principle, can be the result of strategic interaction, signaling of recommended options, and other forms of social intelligence. These frequently intuitive forms of intelligence have been misinterpreted in the behavioral economic literature as cognitive errors that are hard to unlearn. What this literature overlooks is that when intuition is more ecologically rational than logic, there is little need for governments to educate people out of their "logical errors."

(2) *Bayesian Inference*. Psychological research on Bayes' rule is conducted within two separate research programs. The first is the Bayesian rationality program, spearheaded by researchers, such as Ward Edwards, Nick Chater, and Josh Tenenbaum, who all conclude that cognitive functions, such as memory or perception, can typically be described as Bayesian inference. Note that behavioral economists routinely claim that these fast, unconscious, and automatic judgments (the so-called "System 1") do not work according to the rules of probability. According to the cognitive scientists just mentioned, however, they do.

The second paradigm does not involve probability learning, but instead considers textbook problems in which the probabilities are already numerically stated. These tasks are called *decisions from description* as opposed to *decisions from experience* (Hertwig & Erev 2009). In contrast to the early work by Kahneman and Tversky, which concluded that people systematically violate Bayesian rationality, research beginning with Gigerenzer and Hoffrage (1995) has shown that using *natural frequencies* instead of *conditional*

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Bauer, T. K., Gigerenzer, G., & Krämer, W. (2014). *Warum dick nicht doof macht und Genmais nicht tötet: Über Risiken und Nebenwirkungen der Unstatistik*. Frankfurt a.M.: Campus. (e-book www.campus.de) (Special edition, Bundeszentrale für politische Bildung: *Wahr oder wahrscheinlich: Über Risiken und Nebenwirkungen der Unstatistik*. Bonn: Bundeszentrale für politische Bildung, 2015; Korean translation: Ulysses Publishing, in press; Reprinted in: Goldmann Verlag, 2016)



Gigerenzer, G. (2014c). *Risk savvy: How to make good decisions*. New York: Viking.

probabilities facilitates Bayesian reasoning. This technique has since been tested in a large number of contexts and successfully applied in the fields of law and medicine. Moreover, it was shown that even fourth-graders can make consistently Bayesian inferences when probabilities are formulated as natural frequencies (Gigerenzer, 2014c).

(3) *Heuristics*. Since the 1990s, our research has shown that, in situations of uncertainty (as opposed to fully known risks), heuristics can often outperform more complex strategies. One formal way to understand why and when this occurs is the bias-variance dilemma (Gigerenzer & Brighton, 2009). Thus, relying on heuristics is second-best only in situations where the risks are known for certain, not under uncertainty.

The article also discusses libertarian paternalists' problematic ideal of benevolent choice architects who want only the best for the people, while also knowing exactly what the public wants. Flaws in this idealistic assumption have been highlighted for one by the 2011 Report of the House of Lords on nudging, which suggested that the Cameron Government, who implemented a nudge team, used nudging in part to avoid cracking down on regulating industry. Rather than banning advertisement of unhealthy food targeted at children and risking conflict with the food industry, for instance, governments may welcome soft strategies, such as a program that places apples rather than chocolate within eyesight of children in school cafeterias. The article concludes that evidence is lacking for the claim that we are hardly educable and that nudging is not the solution. Even a well-intending government will not stay in power forever; when a less benevolent person

takes over, they may well nudge people in a different direction. A more enduring solution would be to invest in public risk literacy. To be effective, education should start early, before young people are seduced into smoking, eating unhealthy food, and similar behaviors. A modern technological democracy needs less paternalism and more critical citizens.

The Monthly "Unstatistik"

Together with economist Thomas Bauer and statistician Walter Krämer, Gerd Gigerenzer writes a monthly column called the "Unstatistik des Monats," that is, the misleading statistic of the month. Selecting a media report that cites misleading statistics, the authors explain what has been claimed, why it is wrong, and what is the general principle that the reader needs to become aware of—such as, that a correlation is not a causation or that *relative* risk increases are often used to frighten people while *absolute* risk increases are more transparent. Topics range from reports about studies on genetically modified food to claims that Microsoft's search machine can detect pancreas cancer and increase survival to what Berlin's former mayor Klaus Wowereit meant when stating that the new Berlin airport is "98%" finished. The Unstatistik is a nonprofit service to the public and available at www.unstatistik.de. It is copublished by the magazine Capital and reported each month by dozens of newspapers and other media. A collection of the columns appeared in Bauer, Gigerenzer, and Krämer (2014), and the German Bundeszentrale für politische Bildung (Federal Agency for Civic Education) has reissued the book in their own series. A Korean translation is in press.

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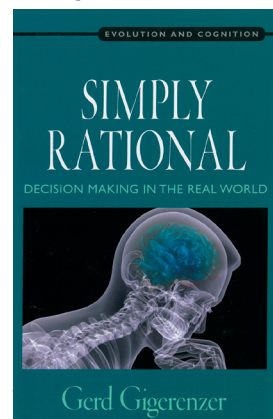
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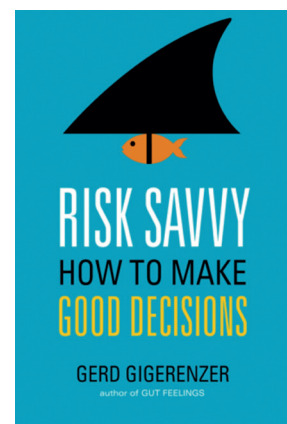
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