Center for Adaptive Behavior and Cognition

The Center for Adaptive Behavior and Cognition

The **Center for Adaptive Behavior and Cognition** (ABC) (Director: Gerd Gigerenzer) investigates human rationality, in particular decision making and risk perception in an uncertain world. Current research focuses on (1) adaptive and ecological rationality, that is, heuristic decision making by experts and laypeople in situations under uncertainty as opposed to known risks; (2) social intelligence in cooperation and competition; and (3) risk understanding and uncertainty management in everyday life, including applications in medicine, law, education, and financial regulation. Each of these research areas emphasizes the evolutionary foundations of behavior and cognition, in particular their domain specificity and functional adaptiveness.

Research Team 2011–2013

Henry Brighton, Uwe Czienskowski, Flavia Filimon, Wolfgang Gaissmaier, Mirta Galesic, **Gerd Gigerenzer,** Konstantinos V. Katsikopoulos, Monika Keller, Shenghua Luan, Julian N. Marewski (as of 08/2011: University of Lausanne, Switzerland), Björn Meder, Jonathan D. Nelson, Hansjörg Neth, Henrik Olsson (until 07/2012), José Quesada (until 09/2011), Lael J. Schooler, Özgür Şimşek, Jeffrey R. Stevens (as of 09/2011: University of Nebraska-Lincoln, USA), Odette Wegwarth, Anja Westram (until 03/2013)

Postdoctoral Fellows
Florian Artinger (as of 02/2013: University of Warwick, UK), Sabrina Artinger, Bryan Bergert (until 11/2012), Nicolai Bodemer (until 11/2013), Markus A. Feufel (as of 07/2012: Charité Universitätsmedizin Berlin, Germany), Mario Fific (as of 09/2011: Grand Valley State University Michigan, USA), Wasilios Hariskos, Juliane E. Kämmer (as of 12/2013: Center for Adaptive Rationality), Amit Kothiyal, Michelle McDowell, Mehdi Moussaïd (as of 10/2013: Center for Adaptive Rationality), Azzurra Ruggeri, Laurianne Vagharchakian

Predoctoral Fellows
Daniel Barkoczi (IMPRS Uncertainty), Stojan Davidovic (IMPRS Uncertainty), Hanna Bettine Fechner (MaxNetAging Research School), Nadine Fleischhut (until 10/2011), Perke Jacobs, Jana Jarecki (IMPRS Uncertainty), Astrid Kause, Niklas Keller (as of 07/2013: Charité Universitätsmedizin Berlin, Germany), Jan Multmeier (as of 01/2012: National Association of Statutory Health Insurance Physicians, Berlin, Germany), Malte Petersen, Pantelis Pipergias Analytis (IMPRS Uncertainty), Roman Prinz, Martin Rosenauer (until 10/2013), Hagen Sinodoru, Jolene H. Tan (IMPRS Uncertainty), John Wong (MaxNetAging Research School)

Adjunct Researchers

Florian Artinger (Warwick Business School, University of Warwick, UK), Ana Paula Bortoleto (University of Sheffield, UK), Edward T. Cokely (Michigan Technological University, USA), Markus A. Feufel (Charité Universitätsmedizin Berlin, Germany), Rocio García-Retamero (Universidad de Granada, Spain), Julian N. Marewski (University of Lausanne, Switzerland), Laura Martignon (Ludwigsburg University of Education, Germany), Shabnam Mousavi (John Hopkins Carey Business School, Baltimore, USA), Jan Multmeier (National Association of Statutory Health Insurance Physicians, Berlin, Germany), Robin Pope, Jan Gerrit Schuurman (Foundation Inspire2Live, Amersfoort, Netherlands), Jeffrey R. Stevens (University of Nebraska-Lincoln, USA), Nassim N. Taleb (New York University's Polytechnic Institute, USA), Peter M. Todd (Indiana University, Bloomington, USA), Gregory Wheeler (Carnegie Mellon University, Pittsburgh, USA)

Visiting Researchers

Susanne Abele (Miami University, Oxford, USA), Hal R. Arkes (Ohio State University, Columbus, USA), Uljana Feest (Technische Universität Berlin, Germany), Adam Feltz (Schreiner University, Kerrville, USA), Kevin A. Gluck (Air Force Research Laboratory, Ohio, USA), Wayne D. Gray (Rensselaer Polytechnic Institute, Troy, USA), Till Grüne-Yanoff (Royal Institute of Technology KTH, Stockholm, Sweden), Simone Guercini (Università degli Studi di Firenze, Italy), Bonnie L. Halpern-Felsher (University of California, San Francisco, USA), Niklas Keller (Charité Universitätsmedizin Berlin, Germany), Kevin McConway (The Open University, Open Keynes, UK), Henrik Olsson (Berlin), Garold Stasser (Miami University, Oxford, USA), Danilo Streck (Universidade do Vale do Rios dos Sinos, São Leopoldo, Brasil), Brian Taylor (University of Ulster, Londonderry, UK), Gregory Wheeler (New University of Lisbon, Caparica, Portugal), Wei Zhu (Tongji University, Shanghai, China)

Introductory Overview

The Center for Adaptive Behavior and Cognition investigates reasoning and decision making under uncertainty at the levels of both individuals and social groups. The research group consists of psychologists, neuroscientists, computer scientists, economists, and researchers from other fields. Using a range of methodologies, such as experimental methods, computer simulation, and mathematical analysis, we cooperate in solving the same problems. The Center's program combines a strong theoretical focus with practical applications, that is, the research group both develops specific models and explores their applications. Applications range from helping physicians and patients understand the statistical evidence arising from medical research to working with the Bank of England to develop simple heuristics for a safer, more robust financial world. These practical applications are divided into two sections, one focusing on risk literacy in health and the other on decision making in the wild. Our interdisciplinary approach to studying rationality also stresses the critical role of theory integration in the advancement of psychological theory, a topic which we will detail in a separate section. The Center's main theoretical focus on rationality can be, albeit artificially, divided into 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. Specifically, 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 with "known risks." This program is an alternative to the dominant optimization paradigm in cognitive science, economics, and behavioral biology that poses the question of how Laplacean superintelligences or near omniscient beings would behave. We study the proximal mechanisms of bounded rationality, that is, the adaptive heuristics that enable quick and frugal decisions 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. The 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 reasoning, both descriptive and normative. In short, we study the adaptation of mental and social strategies to real-world environments rather than compare human judgments to the laws of logic and probability theory.

Social Rationality

Social rationality is a variant of ecological rationality, one for 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. There is a variety of goals and heuristics 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 one can defend with argument or moral justification or that can create a consensus. To a much greater extent than the cognitive focus of most research on bounded rationality, socially adaptive heuristics include 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 limited time, knowledge, and computational capacities. We do not conceive bounded rationality as optimization under constraints nor do we think of bounded rationality as the study of how people fail to meet normative ideals. Rather, bounded rationality is the key to understanding how people make decisions in an uncertain world, without utilities and probabilities. Bounded rationality consists of simple step-by-step rules that function well under the constraints of limited search, knowledge, and time—whether an optimal procedure is available or not. Just as a mechanic will pull out specific wrenches, pliers, and gap gauges to maintain an engine rather than just hit everything with a hammer, different tasks require different specialized tools. The notion of a toolbox lacks the beauty of Leibniz' dream of a single all-purpose inferential tool. Instead, it evokes the abilities of a craftsman, who can provide serviceable solutions to almost any problem with just what is at hand.

Key Reference

Helversen, B. von, Wilke, A., Johnson, T., Schmid, G., & Klapp, B. (2011). Performance benefits of depression: Sequential decision making in a healthy sample and a clinically depressed sample. *Journal of Abnormal Psychology, 120,* 962–968. doi:10.1037/a0023238

The Adaptive Toolbox

This repertoire of specialized cognitive mechanisms, which include fast and frugal heuristics, are shaped by evolution, learning, and culture for specific domains of inference and reasoning. We call this collection of mechanisms the "adaptive toolbox." We clarify the concept of an adaptive toolbox as follows:

- It refers to a specific group of rules or heuristics rather than to a general-purpose decision-making algorithm.
- These heuristics are fast, frugal, and computationally cheap rather than consistent, coherent, and general.
- These heuristics are adapted to particular environments, past or present, physical or social.
- The heuristics in the adaptive toolbox are orchestrated by some mechanism reflecting the importance of conflicting motivations and goals.

Fast and frugal heuristics generally consist of three building blocks: simple rules for guiding search for information (in memory or in the environment), for stopping search, and for decision making. They are effective when they exploit the structure of the information in the environment and basic cognitive capacities, such as memory and perception. That is, their rationality is a form of "ecological rationality" rather than one of consistency and coherence. We continue to explore fast and frugal heuristics and their importance in diverse disciplines, such as biology, economics, and cognitive psychology. In what follows, we describe some examples of research into the adaptive toolbox. Here, we focus on how depression influences how people search the environment and how the world is represented in memory, and how these memory representations can help solve the problem of how to select heuristics from the adaptive toolbox.

Performance Benefits of Depression in Sequential Decision Making

Sadness, apathy, and preoccupation are traits that come to mind when people think about depression, the world's most frequently diagnosed mental disorder. Yet, according to a study by von Helversen, Wilke, Johnson, Schmid, and Klapp (2011), depressed individuals perform better than their nondepressed peers in sequential decision tasks. In their study, participants—who were healthy, clinically depressed, or recovering from depression—played a computer game designed to resemble everyday decision problems, such as household shopping and dating. In the game, the participants could earn money by hiring an applicant in a simulated job search. Each applicant was assigned a monetary value and applicants encountered applicants one after the other. Participants faced the challenge of determining when to halt search and select the current applicant. As von Helversen and colleagues report, while healthy participants searched through relatively few candidates before selecting an applicant, depressed participants searched more thoroughly and made choices that resulted in higher payoffs.

For decades, psychologists have debated whether depression has positive side effects. While researchers have recognized that most symptoms of depression impede cognitive functioning, some have proposed that depression may promote analytical reasoning and persistence—that is, qualities useful in complex tasks. Past research provides some evidence that supports this possibility, but it focused on individuals with low levels of nonclinical depression. Von Helversen and colleagues demonstrate that even severe depression might benefit decision making.

The Cognitive Niche Framework for Strategy Selection

Most theories of strategy selection assume the existence of an effort-accuracy trade-off: Expending more effort leads to greater accuracy. Marewski and Schooler (2011) proposed a complementary approach that asks how the interplay of the cognitive system and the environment creates *cognitive niches* that restrict the range of strategies that are applicable at any given moment in time. Marewski and Schooler (2011) used computer simulations to model how the environment shapes a person's representation of the environment in memory. These representations define cognitive niches, where some heuristic strategies operate better than others. To illustrate, consider the situation in which a customer asks a bartender what kinds of beer are available. The bartender mentions two beers that the customer has never tried, so the customer now must infer which of two beers they will prefer. The customer may recognize both brands of beer, just one of them, or neither of them. For a brand they recognize, they may, in addition, know something about it. What a person knows about these beers depends on their past experience and how memory represents this experience. It is this interplay between the cognitive system and the environment that carves out a cognitive niche for each strategy, or to put it in other words, a limited number of situations in which the strategy can be applied. For instance, using the recognition heuristic requires that the decision maker recognizes just one of the two brands. Here, a straightforward application of the recognition heuristic would lead to the inference that the recognized brand is better. Importantly, these niches may not overlap, alleviating the problem of strategy selection. For instance, the fluency heuristic, which depends on discerning how quickly the brands were recognized, will most likely be applicable when a person is familiar with the brands, but knows nothing else about them. In such situations, knowledge-based strategies cannot compete because the requisite knowledge is unavailable. Overlapping niches would arise when, for example, abundant knowledge about the alternatives is available. Where different strategies' niches overlap, the selection could be guided by the traditional selection mechanisms that depend on effort-accuracy trade-offs. In short, for those situations where two or more strategies do not overlap, the cognitive niche framework provides an account of how strategy selection can emerge as a bottom-up process—in the absence of feedback and learning—solely through the interplay between the cognitive system and the environment.

Mapping the Structure of Semantic Memory

The cognitive niche framework illustrates that the more we know about how the environment is represented in memory, the better we can understand the heuristics that depend on knowledge retrieved from memory. A limitation of Marewski and Schooler's (2011) analysis is that it did not take into account the semantic associations that guide what knowledge is likely to be retrieved from memory when a person is using any given heuristic. To reveal these associations, Morais, Olsson, and Schooler (2013) mapped the structure of individuals' semantic memory with a new snowball sampling paradigm, illustrated in Figure 1. To start, participants were asked to generate associates to cue words. During approximately 6 weeks of 1-hour daily sessions, the responses to a cue generated by an individual on one day were used as cues for eliciting their semantic associates on a subsequent day. In the map of an individual's semantic network, depicted in Figure 1, words are represented as nodes joined by links that

Key Reference

Marewski, J. N., & **Schooler, L. J.** (2011). Cognitive niches: An ecological model of strategy selection. *Psychological Review, 118*(3), 393–437. doi:10.1037/a0024143

Key Reference

Morais, A. S., Olsson, H., & Schooler, L. J. (2013). Mapping the structure of semantic memory. *Cognitive Science, 37,* 125–145. doi:10.1111/cogs.12013

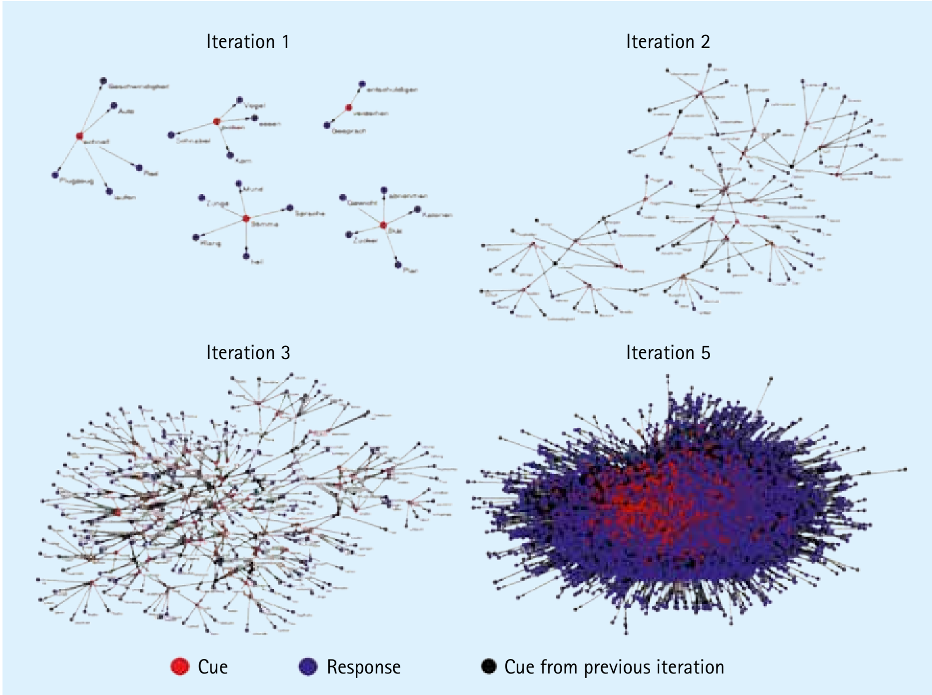


Figure 1. Five iterations of the snowball sampling paradigm. For example, on day 1, the individual was given cue words, such as *schnell* and *picken*. In response, the individual generated the words *Rad* and *Vogel,* among others. *Rad* and *Vogel,* in turn, were used as cues on day 2. After 54 days and 5 iterations, the original set of cues had snowballed in to a network of 9,129 interconnected words (adapted from Morais, Olsson, & Schooler, 2013).

represent whether a word was named as an associate by that individual in response to a cue word. Computer simulations suggest that these network maps of semantic structure constructed using the snowball sampling paradigm reliably depict the structure of semantic memory. Statistical analyses of the semantic networks of individuals showed that they have, among other distinctive features, distributions of links across nodes that indicate that most words are poorly connected and a minority of words have a high number of links. This type of distribution arises naturally when a memory system incurs costs for learning and maintaining connections between concepts. From a functional standpoint, connections between concepts reflect statistical associations that can be used to retrieve information that is likely to be useful in heuristic inference.

Ecological Rationality

The performance of a decision rule will depend on the structure of the environment in which it is applied. The ABC Research Group studies this relationship systematically by specifying formal models of heuristics and other decision rules. The research program on ecological rationality aims to characterize the structure of environments and understand the fit between these structural characteristics and the performance of decision rules. Performance is measured by external criteria, such as speed, frugality, and accuracy. Notice how this objective differs to the study of logical rationality, where performance is measured by internal criteria, such as consistency. Here, we present a sample of recent research on the ecological rationality of simple heuristics.

The Importance of Noncompensatory Processing

An intriguing finding in the study of ecological rationality is that simple heuristics which ignore information can often match or exceed the accuracy of the linear decision rule. Our recent research has focused on understanding why. To take an illustrative example, consider the problem of deciding which one of two cities, such as Berkeley and Chicago, has a higher value on a numerical criterion, such as a city's homelessness rate. The inference is made using cues (e. g., one city, in this case Chicago, has a basketball team, while the other city, in this case Berkeley, does not) which correlate to some degree with the criterion. The linear rule uses all cues to make an inference. It estimates the criterion by calculating a weighted sum of all the cue values and then decides on the city with the greater estimated criterion value. For example, standard multiple regression is a special case of the linear rule, where the weights of the cues minimize the sum of squared errors.

There are two ways to simplify the linear rule: First, the cues are not added, but are simply inspected one-by-one based in a prespecified order; as soon as a cue is found which discriminates between the two cities (e. g., the basketball-team cue), a decision is made based on that cue alone, ignoring the remaining cues. Such heuristics are *noncompensatory;* the decision made based on the first discriminating cue cannot be compensated by the remaining cues, even if those cues would, if considered, lead to an alternative decision. Elimination by aspects and take-the-best are examples of noncompensatory heuristics. These heuristics weight, but do not add, cues. The second way of simplifying the linear rule is to ignore weights and simply add cues. This heuristic is called tallying.

Because they use less information and computation relative to the general linear model, are noncompensatory decision rules and tallying necessarily less accurate? In previous work, it is has been shown that the noncompensatory heuristic take-the-best achieves perfect accuracy if the true cue weights are noncompensatory (i. e., the weight of the first cue is greater than the sum of all other cue weights and so on; e. g., for four cues, the weights 4, 2, 1, and 0.5 are noncompensatory) and these weights are known. Tallying achieves perfect accuracy if the true cue weights are equal, in which case the cue weights are termed fully compensatory. More generally, the space of true cue weights is populated by sets of weights that are neither noncompensatory nor fully compensatory. In such cases, which decision rule is most accurate? One possibility is that take-the-best and tallying perform much worse than, say, the perfect benchmark of the linear rule which uses the true cue weights.

This turns out not to be the case. Enumerating all possible data sets comprised of binary cues, previous research has found that, for a wide range of compensatory cue weights and across different sizes of the consideration set (i. e., the set of decision alternatives, e. g., the cities that are compared according to homelessness rate), take-the-best and tallying achieve near-perfect performance. For example, if there are three or four binary-valued cues, one of take-the-best, tallying, or both, achieve at least 96 % accuracy for each combination of cue weights and consideration set size. Two of our recent studies have provided explanations for this intriguing finding.

Key References

Katsikopoulos, K. V. (2013). Why do simple heuristics perform well in choices with binary attributes? *Decision Analysis, 10,* 327–340. doi:10.1287/deca.2013.0281

Şimşek, Ö. (2013). Linear decision rule as aspiration for simple decision heuristics. *Advances in neural information processing systems: Vol. 26. Proceedings of the 27th Annual Conference on Neural Information Processing Systems, December 5–8, 2013, Lake Tahoe, Nevada, USA.* Red Hook, NY: Curran Associates.

Table 1
Are Noncompensatory Cue Weights Necessary for Noncompensatory Decision Rules to Perform Well?

(a)															
Consideration set size	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Take-the-best accuracy	98	98	97	96	96	96	96	97	98	99	99	100	100	100	100
Tallying accuracy	94	91	91	92	94	96	97	99	99	100	100	100	100	100	100
(b)															
Consideration set size	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Take-the-best accuracy	92	88	87	88	90	92	94	96	97	98	99	100	100	100	100
Tallying accuracy	99	99	99	99	100	100	100	100	100	100	100	100	100	100	100

Note. In (a), the accuracy of take-the-best and tallying (in % of correct inferences) are shown as a function of the size of the consideration set for four cues and with cue weights that are the least compensatory. Both take-the-best and tallying reach 100 % accuracy when the size of the consideration set increases. Are compensatory cue weights necessary for compensatory decision rules to perform well? In (b), the accuracy of take-the-best and tallying (in % of correct inferences) are shown as a function of the size of the consideration set for four cues and with cue weights that are most compensatory. Again, both take-the-best and tallying reach 100 % accuracy when the size of the consideration set increases.

Katsikopoulos (2013) derived expressions for the accuracy of take-the-best and tallying as a function of the cue weights, the size of the consideration set, and the number of binary cues. For four cues, with cue weights that are the least compensatory (e. g., cue weights of 4, 1, 0.75, and 0.5), Table 1a compares the accuracy of take-the-best and tallying as function of size of the consideration set. Table 1b compares the decision rules for the most compensatory weights (e. g., cue weights 3, 2.5, 2, and 1.25). These results confirm that heuristics are, under some conditions, robust to apparently unfavorable cue weights. As can be seen in Table 1a, although cue weights which are highly noncompensatory do not in general favor tallying, this simple strategy achieves 100 % accuracy when considering 10 or more alternatives. As can be seen in Table 1b, although highly compensatory cue weights do in general favor take-the-best, this compensatory strategy achieves perfect accuracy when considering 13 or more alternatives.

In a related study, Şimşek (2013) considered the degree to which natural environments have a noncompensatory structure. For a large number of environments, the most predictive linear rule was identified for each environment using statistical and machine learning techniques, including regularized linear models. The resulting cue weights were, by and large, compensatory (in 83 % of the data sets). However, as Figure 2 shows, the corresponding noncompensatory decision rule, which uses substantially less information than the linear rule, competed very well with the linear rule and could, in some data sets, achieve higher predictive accuracy. Thus, we again see a noncompensatory decision rule performing very well even though the environments are largely compensatory. Why is this? Şimşek pointed out that even if the environment is compensatory, the cue values might be such that cues with smaller weights do not in fact compensate for the cues with larger weights. In 51 data sets, this property—termed noncompensation—

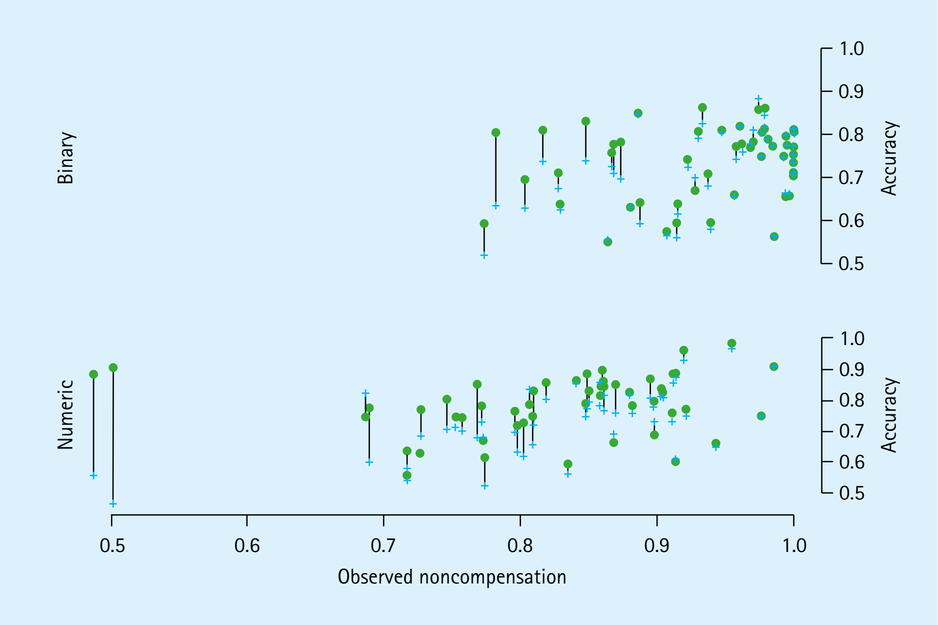


Figure 2. Relative to the best-predicting linear model for a given environment, does predictive accuracy increase or decrease when the cues are processed using a noncompensatory decision rule? Plotted as a function of the degree of noncompensation, this figure depicts the change in predictive accuracy in 51 natural environments. Environments are categorized as either containing numeric or binary cues. The accuracy of the best-predicting linear rule is shown by a green circle and the accuracy of the corresponding noncompensatory decision rule is displayed by a blue plus sign. Accuracies on the same data set are connected by a straight line.

was observed quite frequently, as shown in Figure 2.

Intelligence in the World

In 2012, the ABC Research Group published *Ecological Rationality: Intelligence in the World,* a book detailing new contributions to the study of ecological rationality (Todd et al., 2012; see Box 1). Much of the book focuses on understanding the adaptive fit between simple heuristics and the structure of natural environments. A key step toward understanding this fit is to explain why simple heuristics—such as take-the-best—can, in many natural environments, outperform more familiar cognitive models. Taking a slightly different perspective from the work detailed above, Brighton and Gigerenzer (2012) examined the ability of simple heuristics to achieve high predictive accuracy under uncertainty, where the weights of environmental cues are not known, but have to be inferred from observations. They argue that a more thorough understanding of heuristic performance is gained by viewing strategies as addressing what is termed *the bias-variance dilemma.*

Simple Heuristics and the Bias-Variance Dilemma

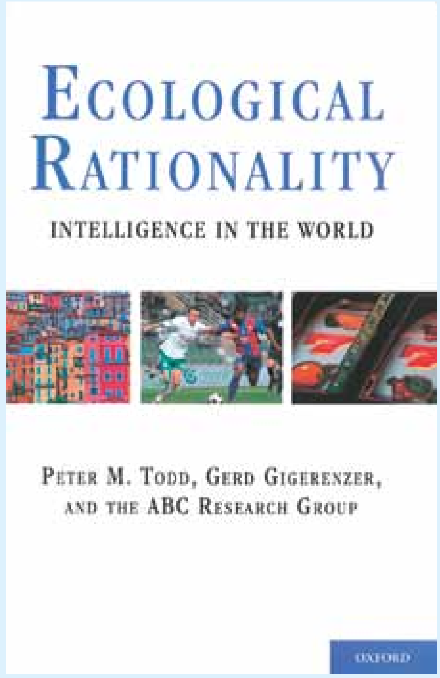
All statistical models, including heuristics, err when making predictions. In a given task environment, a model's prediction error can be decomposed into bias, variance, and noise. The bias component of prediction error reflects the inability of a model to represent the systematic patterns that govern the observations. The variance component of prediction error reflects the sensitivity of the model's predictions to different observations of the same problem, such as a different sample from the same population. Together, bias and variance additively contribute to the total prediction error as follows: Total error = $(\text{bias})^2$ + variance + noise. To achieve low bias, models should be capable of fitting diverse patterns of data. To achieve low variance, models need to restrict the range of patterns they consider in order to limit the

Key References

Brighton, H., & **Gigerenzer, G.** (2012d). How heuristics handle uncertainty. In P. M. Todd, G. Gigerenzer, & the ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world* (pp. 33–60). Oxford: Oxford University Press.

Todd, P. M., Gigerenzer, G., & the ABC Research Group. (2012). *Ecological rationality: Intelligence in the world.* Oxford: Oxford University Press.

Ecological Rationality: Intelligence in the World (Todd, Gigerenzer, & the ABC Research Group, 2012) details the recent advances in the study of ecological rationality. The idea that more information and more computation yield better decisions has long shaped our vision of rationality. Yet humans and other animals typically rely on simple heuristics or rules of thumb to solve adaptive problems, focusing on one or a few important cues and ignoring the rest, and shortcutting computation rather than striving for as much as possible. In this book, the authors argue that, in an uncertain world, more information and computation are not always better and instead ask when, and why, less can be more. The answers to these questions constitute the idea of ecological rationality, as explored in the chapters in this book: how people can be effective decision makers by using simple heuristics that fit well to the structure of their environment. When people wield the right tool from the mind's adaptive toolbox for a particular situation, they can make good choices with little information or computation—enabling simple strategies to excel by exploiting the reliable patterns in the world to do some of the work. Heuristics are not good or bad, "biased" or "unbiased," on their own, but only in relation to the setting in which they are used. The authors show heuristics and environments fitting together to produce good decisions in domains including sports competitions, the search for a parking space, business group meetings, and doctor/patient interactions. The message of *Ecological Rationality* is to study mind and environment in tandem. Intelligence is not only in the mind but also in the world, captured in the structures of information inherent in our physical, biological, social, and cultural surroundings.



Box 1.

model's sensitivity. Under uncertainty, a model cannot do both simultaneously, and this is why all models must strike a balance between limiting bias and variance—all models face a bias-variance dilemma.

Brighton and Gigerenzer (2012) first showed that, when cue weights are not known, but must be inferred from observations, take-the-best will often outperform more sophisticated models such as the decision tree induction algorithms C4.5 and CART, the nearest neighbor classifier, and a version of take-the-best which takes into account conditional dependencies between cues (known as greed take-the-best). Figure 3 compares, in two natural environments, the performance of take-the-best and these alternative models: Take-the-best outperforms the four alternative models, all of which expend additional effort in searching for conditional dependencies between the cues. Why is this? To answer this question, Brighton and Gigerenzer analyzed the relative ability of take-the-best and its sophisticated counterpart, greedy take-the-best, to reduce bias and variance. In two artificial environments designed to elicit extreme performance differences between the two models, Figure 4 details the predictive accuracies of the two models but also decomposes their prediction error into bias and variance. The performance differences arise due to differences in variance, crucially, because both models are noncompensatory. The performance differences cannot be explained by an appeal to properties of the decision rule: The extreme performance differences arise due to the assumptions made when inferring cue weights rather than how these weights are used once they have been inferred.

These findings have significant implications. First, they provide a statistical explanation for why ignoring information can improve performance—one cannot assume that more effort will lead to better inferences, less effort can have a dramatic and positive effect on predictive accuracy by reducing variance.

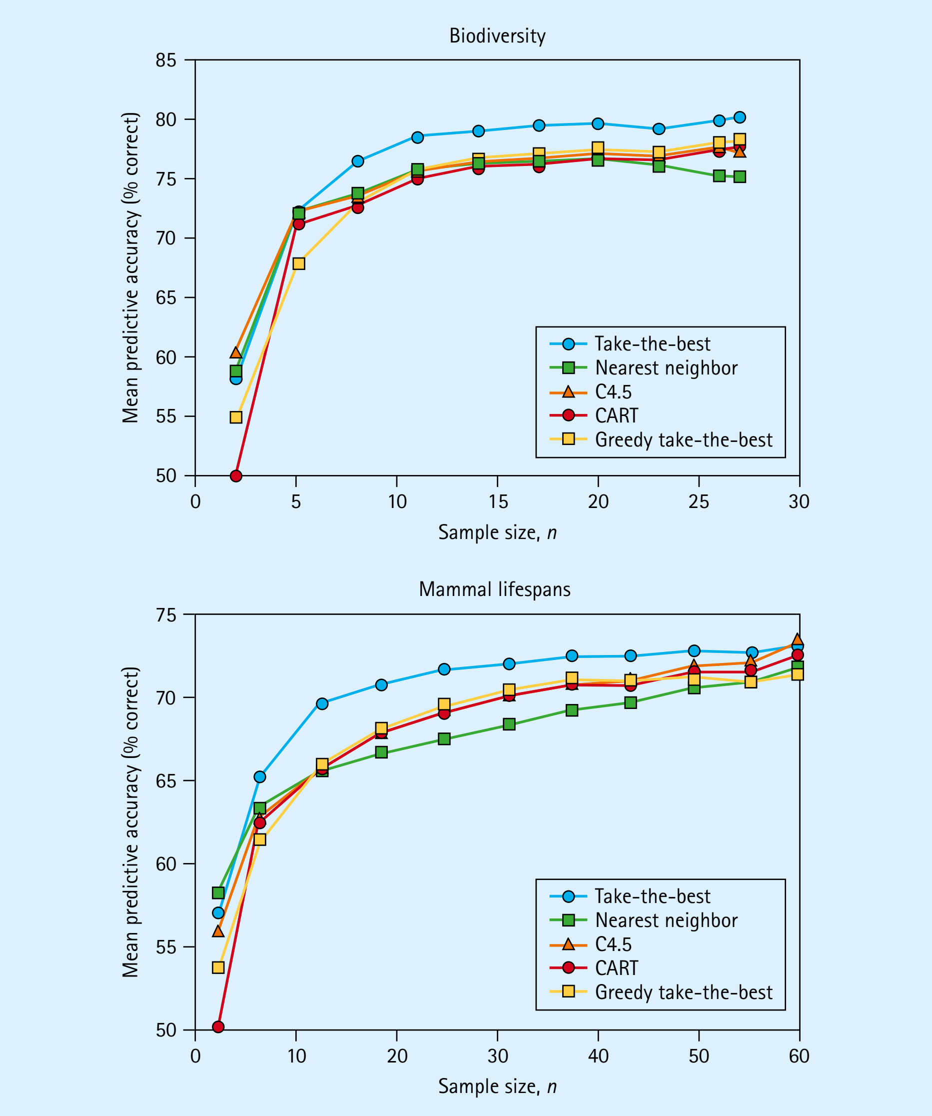


Figure 3. How well does the simple heuristic take-the-best perform in comparison to sophisticated tree induction algorithms C4.5 and CART, the nearest neighbor classifier, and a variant of take-the-best which searches for conditional dependencies between environmental cues? Here, in two natural environments, the predictive accuracies of the models are plotted as a function of the size of the sample used to estimate the model parameters. In this first environment, the task is to predict which of two Galapagos islands has greater biodiversity. In the second environment, the task is to predict which two mammals is likely to live longer. In both cases, take-the-best achieves a higher predictive accuracy than the alternative models for the majority of sample sizes.

Second, these results suggest that improved performance is not always due to the ability of a model to accurately model the environment—variance reduction is often achieved by making simplifying assumptions when inferring properties of the environment, even though these assumptions are known not to hold true in practice.

Naïveté: The Good and The Bad

Complementing the study of the relationship between environmental conditions and the performance of cognitive models, Jarecki, Meder and Nelson (2013) investigated the relationship between environmental conditions and human behavior. Focusing on a categorization task, they considered an artificial

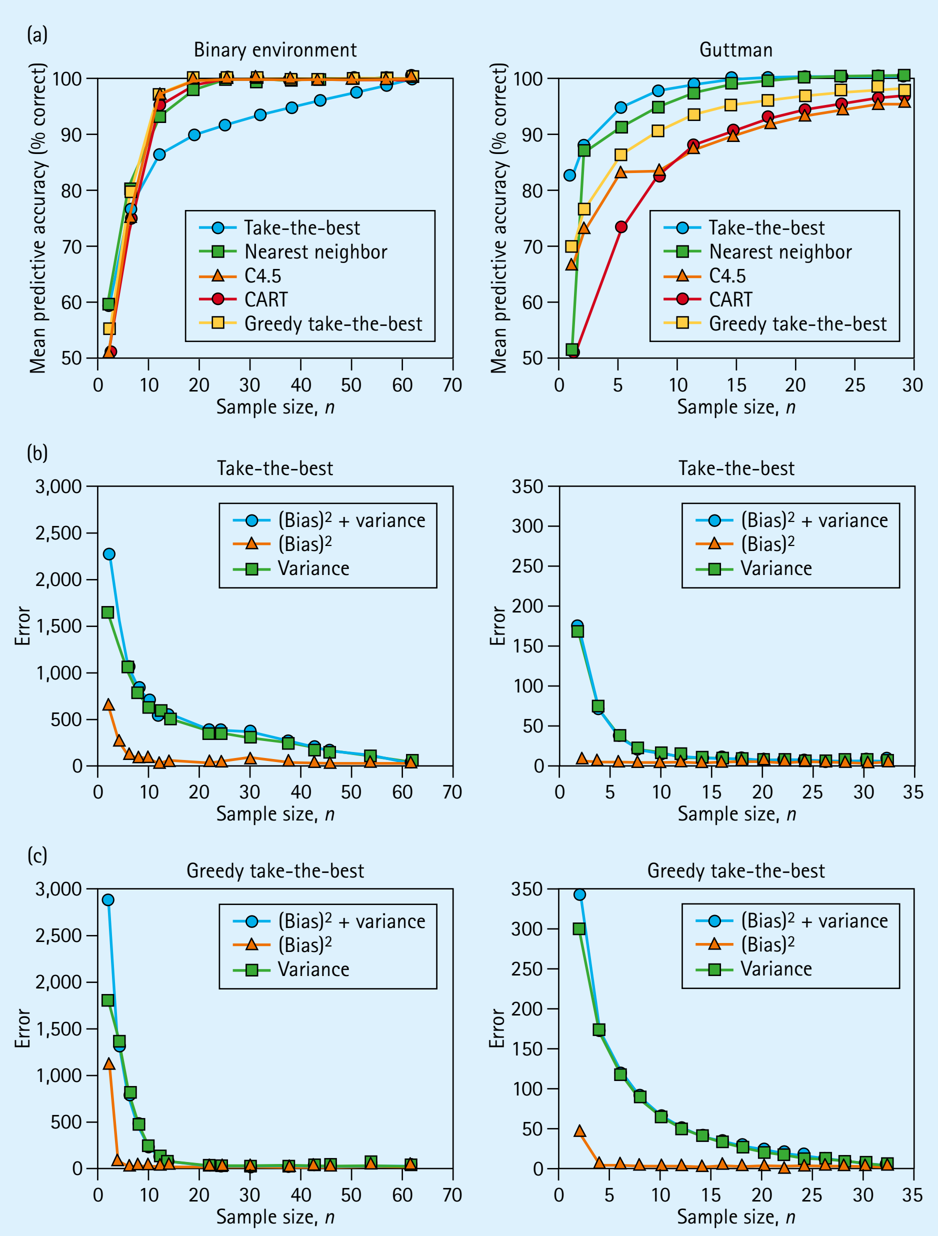


Figure 4. Why does ignoring information benefit performance? Here, the performance of take-the-best and its sophisticated counterpart, greedy take-the-best (which searches for conditional dependencies between cues) are compared in a critical test. In the left-hand column, the models are compared in a "binary" environment designed to elicit poor performance in take-the-best (top-most plots). Take-the-best performs poorly due to its relative inability to reduce variance (shown in the middle and lower plots). In the right-hand column, the models are compared in a "Guttman" environment designed to favor take-the-best (top-most plots). Here, take-the-best performs well due to its relative ability to reduce variance. In both cases, variance explains the performance differences. Note that, because both take-the-best and greedy take-the-best use a noncompensatory decision rule, these performance differences are unrelated to the distinction between compensatory and noncompensatory processing.

environment where the cues are independent of each other, conditional on the category. For instance, if the two categories in question are "has breast cancer" and "does not have breast cancer," and two available cues are the results of a mammography and the person's family history, the cues are conditionally independent if the probability of cancer given the result of the mammography would not change if family history also became known. The label "naïve" is often used to describe the assumption of class-conditional independence.

In previous work, it has been shown that the environmental condition of conditional independence is favorable to the accuracy of heuristics such as take-the-best. Thus, to the extent that people use take-the-best, it should be the case that people believe in conditional independence. Jarecki et al. (2013) tested this hypothesis. They asked participants to play biologist and classify plankton specimens to one of two possible categories, labeled "A" and "B." The planktons had three binary cues, "eye," "tail," and "claw." Figure 5 provides an example illustration of a plankton provided to the participants.

Jarecki et al. (2013) designed statistical environments in which learners who presume class-conditional independence would make particular kinds of errors, especially early in learning. This is because, for certain configurations of features, the true category (species) and the predictions of the naïve model strongly diverge. Interestingly, the configuration for which the naïve model and the true probabilities most strongly diverge is also the configuration that required the greatest number of learning trials for the participants. This provides evidence for the hypothesis that people may presume class-conditional independence early in the learning process. Class-conditional independence or related assumptions provide one way that learners could make inferences early in the learning process, before accumulating enough evidence to learn the actual class-conditional dependencies among features that may apply in a particular environment.

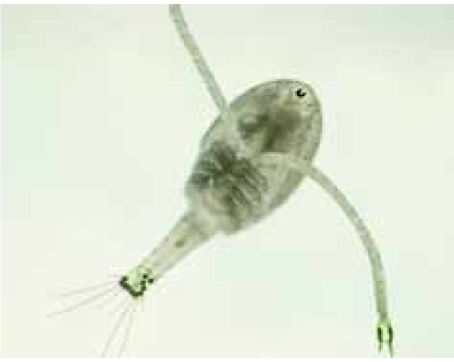


Figure 5. Image of a plankton shown to participants for categorization. Three cues were used to classify plankton: eye (located in the top right), tail (located in the bottom left), and claw (bottom right). The images were based on pictures from the Florida Medical Entomology Laboratory.

Source. Florida Medical Entomology Laboratory (with special thank to Prof. Jorge Rey and Prof. Sheila O'Connel).

Key Reference

Jarecki, J., Meder, B., & **Nelson, J. D.** (2013). The assumption of class-conditional independence in category learning. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 2650–2655). Austin, TX: Cognitive Science Society.

Social Rationality

Humans are remarkably social. No other species has such elaborate cooperative practices, exhibits so much empathy toward others, or relies so much on social learning and the cultural transmission of knowledge and values. Decades of research on social cognition seem to suggest that people suffer from a number of biases in their social judgments and behaviors. Studies of different aspects of social rationality conducted by the ABC Research Group focus on the interplay of human minds and their social environments and show that many seemingly irrational behaviors can be explained by simple rules adapted to particular environmental structures. Here, we present such recent work in the areas of cooperation, social cognition and learning, group decision making, and crowd behavior.

Key Reference

Zhu, L., **Gigerenzer, G.,** & Huangfu, G. (2013). Psychological traces of China's socio-economic reforms in the ultimatum and dictator games. *PLoS ONE, 8*(8)*:* e70769. doi:10.1371/journal.pone.0070769

Cooperation

Do Socio-Economic Changes Within a Society Affect Altruistic Sharing?

Zhu, Gigerenzer, and Huangfu (2013) took advantage of a natural quasi-experiment provided by post-Mao reforms in China to study people from the same society who were raised with radically different values about distribution of wealth and altruistic behavior. A main moral principle in the Mao era (1949–1976) was equal allocation, which meant state-owned productive sources, equal distribution of wealth and welfare, and no difference in workers' socioeconomic status (Figure 6). In 1978, China launched its economic reform led by Deng Xiaoping, which has resulted in enormous economic growth accompanied by changes in social values. Equal allocation gave way to allocation in terms of contribution, where the absolute level of common prosperity takes priority over equality (Figure 7).

Zhu et al. (2013) studied behavior in ultimatum and dictator games of 248 Chinese citizens from three cohorts: people born before Mao's regime (Cohort I), during the regime (Cohort II), and after it (Cohort III). They predicted and found that altruistic sharing, that is, the size of offers in the games, increased with the number of years lived in the Mao era. Cohort I, which spent the maximum time possible under Mao's regime, provided the highest offers in the games (Table 2). Also as predicted, older members of Cohort II offered more than the younger ones, while there was no correlation between age and offers in the other two cohorts, in each of which all members spent equal time under Mao. This result provides additional support that selfishness was influenced by the number of years under Mao's regime and not by age. Taken together, these results suggest that people's behavior in laboratory experimental games is strongly affected by socioeconomic values they experienced in their social environment over

Figure 6. In Mao's era, people lived in collectives and took all their meals together in a public dining room. The characters mean: "Eating costs nothing, but we need to work hard."

Source. Wikimedia Commons/Public Domain.

Figure 7. Under Deng's leadership, social-economic reforms led to modernization and changes in social values. The characters mean: "Development is the last word."

Source. Bernd Gross/Wikimedia Commons/Public Domain.

Table 2
Socioeconomic Changes Affect Sharing in Laboratory Games

	Size of offers as % of total sum		*Correlation of age and offers*	
	Ultimatum game Mean (SE)	*Dictator game Mean (SE)*	*Ultimatum game r (SE)*	*Dictator game r (SE)*
Cohort I: Born ≤ 1950	53.8 (2.3)	44.0 (3.1)	–.08 (.12)	–.30 (.12)
Cohort II: Born 1951–1975	46.0 (1.9)	38.5 (2.6)	.14 (.10)	.38 (.10)
Cohort III: Born ≥ 1976	46.1 (2.1)	35.4 (2.8)	–.06 (.11)	–.18 (.11)

Note. The table shows participants' offers and their correlations with age in the ultimatum game and the dictator game, by cohorts. Cohort I, which spent the maximum time possible under Mao's regime provided the highest offers in the games (second and third columns). Older members of Cohort II offered more than the younger ones, while there was no correlation between age and offers in the other two cohorts, in each of which all members spent equal time under Mao (fourth and fifth column) (Zhu et al., 2013).

their lifetime and, in particular, during their formative years.

Do Social Emotions Make Us Altruistic?

In the 18th century, the philosopher David Hume argued that moral judgments evolve from sentiment and immediate feelings instead of reasoning. However, existing psychological and economic research has mostly focused on the cognitive antecedents of other-regarding preferences, such as theory of mind. Developmental studies are particularly rare, and those that do exist are mostly cross-sectional rather than longitudinal. Filling this gap, our research has used longitudinal and cross-sectional designs to investigate how social emotions influence altruistic behavior in children, adolescents, and adults. Malti, Gummerum, Keller, Chaparro, and Buchmann (2012) followed a sample of 175 six-year-old children, their primary caregivers, and their teachers over a 3-year period. They show that sharing resources developmentally increased in children from 6 to 9 years of age. Sympathy toward anonymous others and feelings of social acceptance strongly predicted sharing with anonymous others in later years, even after controlling for earlier sharing, intelligence, and socioeconomic status.

Malti, Keller, and Buchmann (2013) report the data from a representative two-wave longitudinal study of 995 fifteen-year-old adolescents followed for a period of 3 years in Switzerland. The adolescents reported their decisions and emotions regarding hypothetical moral conflicts in close friendships. Adolescents predominantly made moral decisions and reported feeling good following these decisions. However, a small number of adolescents made selfish decisions and consistently reported feeling good about these decisions.

Edele, Dziobek, and Keller (2013) continued the exploration of individual differences by investigating emotional precursors of altruistic behavior in adults. Their participants first made sharing decisions in dictator games. After 5 to 7 months they were reinvited (for the second part of the study) to assess two kinds of empathic abilities: cognitive empathy (ability to understand what another person is feeling) and affective empathy (ability to experience feelings congruent with another's emotional situation). Figure 8 shows one of the items used to measure affective empathy. Affective empathy emerged as the strongest predictor for the size of offers in the previously played dictator games, while cognitive empathy did not explain the offers. This suggests that altruistic sharing is strongly shaped by affective reaction tendencies rather than by reasoning about others' reactions.

These findings fit well with Hume's contention that affect rather than reason is critical both for moral behavior and reasoning, which

Key References

Edele, A., Dziobek, I., & **Keller, M.** (2013). Explaining altruistic sharing in the dictator game: The role of affective empathy, cognitive empathy, and justice sensitivity. *Learning and Individual Differences, 24,* 96–102. doi:10.1016/j.lindif.2012.12.020

Malti, T., Gummerum, M., **Keller, M.,** Chaparro, M. P., & Buchmann, M. (2012). Early sympathy and social acceptance predict the development of sharing in children. *PLoS ONE, 7*(12): e52017. doi:10.1371/journal.pone.0052017

Malti, T., **Keller, M.,** & Buchmann, M. (2013). Do moral choices make us feel good? The development of adolescents' emotions following moral decision making. *Journal of Research on Adolescence, 23,* 389–397. doi:10.1111/jora.12005

Key References

Fleischhut, N., & **Gigerenzer, G.** (2013a). Can simple heuristics explain moral inconsistencies? In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 459–485). New York: Oxford University Press.

Galesic, M., Olsson, H., & Rieskamp, J. (2012). Social sampling explains apparent biases in judgments of social environments. *Psychological Science, 23,* 1515–1523. doi:10.1177/0956797612445313

has implications for educational settings. Cognitive interventions could be supplemented with interventions aimed at supporting emotional reactions of sympathy and care, thus increasing orientation toward others and decreasing antisocial behaviors.

Do Simple Heuristics Make Us Good?

Recognizing that behavior in moral situations is a form of decision making under uncertainty, Fleischhut and Gigerenzer (2013) argue that the study of simple heuristics provides a valuable perspective for understanding moral behavior. They argue that (a) moral actions are typically guided by heuristics, and (b) these heuristics are not moral rules, but social rules that are also applied outside of moral domains. They show that these two assumptions imply inconsistencies in moral behavior across situations, inconsistencies between moral judgment and reasoning, and between moral judgment and behavior. These inconsistencies have been a problem for "rational" moral theories that attribute the cause of moral behavior to some internal disposition instead of to an interaction between social heuristics and the structure of the environment.

It has been shown that simple heuristics can make us smart. In the context of moral situations, however, the question is: Do simple heuristics make us good? The answer is no. Just as simple heuristics only perform well in some environments, the same holds true for heuristics in the moral domain. The study of bounded and ecological morality does not suggest that simple heuristics make us good. But the more we know about the heuristics in the adaptive toolbox, including what triggers their use, the greater the prospects for designing environments which can make us behave better.

Social Cognition and Learning

How Do People Make Judgments About Their Social World?

Research on social cognition is dominated by demonstrations of biases in our judgments of other people. The list of biases is long and includes opposite effects such as findings of both self-enhancement and self-depreciation relative to other people. Galesic, Olsson, and Rieskamp (2012) proposed a simple social sampling model that explains these biases without assuming faulty minds. According to their model, people make inferences about

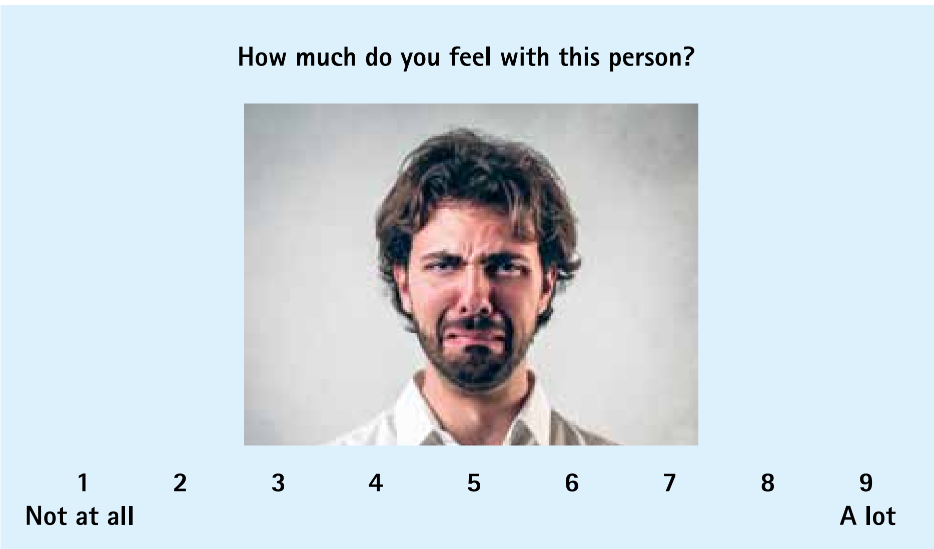


Figure 8. The face represented here is a photo analogous to the items of the MET (Multifaceted Empathy Test) used by Edele et al. (2013) to assess affective empathy. Participants with stronger affective empathy showed more altruistic sharing with anonymous others.

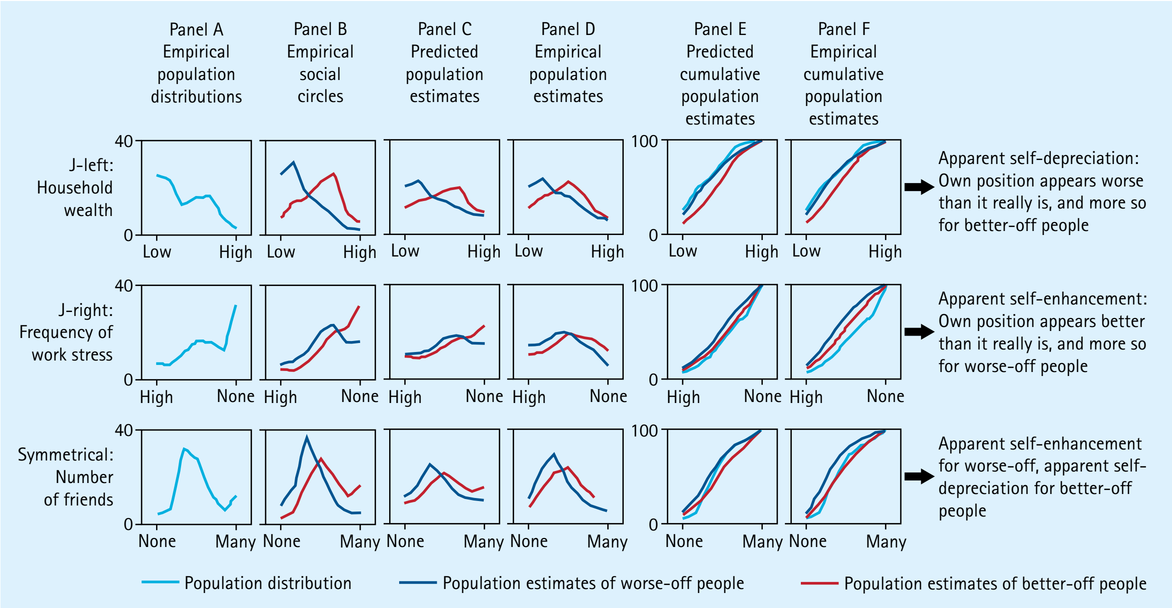


Figure 9. People make inferences about broader populations by sampling from their immediate social environments (Galesic et al., 2012). Empirical data and predictions of the social-sampling model for 3 of 10 studied characteristics of the Dutch population. The x-axes show levels of each characteristic and the y-axes show percent of people at each level. Panel A: Different characteristics have different shapes of population distributions (J-left most people doing badly, J-right most people doing well, or symmetrical). Panel B: Social environments are clustered people tend to know more people similar to themselves. "Worse-off" people are those positioned at one of the three lowest levels of a particular characteristic, while "better-off" people are those positioned at one of the three highest levels. Panel C: The social-sampling model predicts that people use their social circles to estimate population distributions, which is supported by empirical data in Panel D. Panel E: The model predicts apparent self-depreciation and self-enhancement effects that are supported by empirical data in Panel F. The social-sampling model makes two predictions about people's estimates of their social environments. First, because of the interplay of the shapes of population distributions and the sampling process, apparent self-enhancement will occur when the underlying distribution of the general population is J-right shaped (i. e., when most people are doing well) and apparent self-depreciation when the underlying distribution is J-left shaped (when most people are doing badly). Second, because of the interplay of spatial clustering of social environments and people's reliance on social circles when estimating population distributions, worse-off people will appear to make larger errors in their estimates when the underlying distribution is J-right shaped, but smaller when the underlying distribution is J-left shaped. All of these patterns of results occurred in previous studies, but so far no single model was able to explain them.

broader populations by sampling from their immediate social environments. Interplay of these sampling processes and the specific structure of social environments leads to apparent biases in social perception. As shown in Figure 9, Galesic et al. (2012) tested the predictions of the social-sampling model on a large probabilistic national sample of Dutch participants who evaluated their own and others' life circumstances. The social-sampling model better predicted the findings than existing accounts based on motivated reasoning, cognitive incompetence, egocentric focus, or simple regression effects. This work highlights the importance of studying both people's inference processes and their environments to obtain a deeper understanding of human behavior.

What Are the Building Blocks of Social Learning Strategies?

Humans and other animals often rely on social learning when solving problems. Most studies of social learning focus only on the decision phase of social learning strategies (e. g., imitate-the-majority), disregarding the interaction between information sampling and the structure of the social environment. To begin filling this gap, Barkoczi and Galesic (2013) model social learning strategies in terms of three basic building blocks, specifying how people search for social information (e. g., by searching randomly from the whole population or only among contacts), when they stop the search (e. g., after sampling a small or large number of social contacts), and how the decision is made (e. g., by imitate-

Key Reference

Barkoczi, D., & **Galesic, M.** (2013). Social learning in complex networks: The role of building blocks and environmental change. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 1821–1826). Austin, TX: Cognitive Science Society.

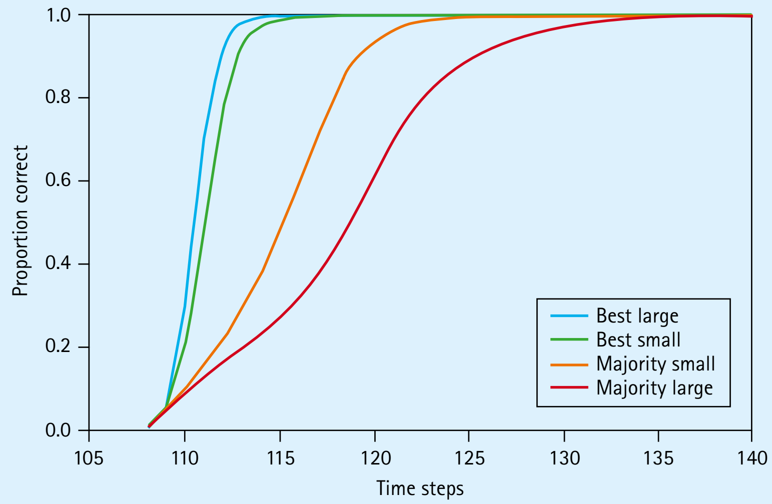


Figure 10. Smaller samples can trump larger samples (Barkoczy & Galesic, 2013). Here, the task was to make repeated decisions between two options where one option was correct and the other incorrect and, over time, the environment may change, rendering previously learned information obsolete. After environmental change, when most agents possess outdated information, imitate-the-majority benefits from smaller rather than larger samples.

the-majority or imitate-the-best). Their results revealed that, under the assumption that the best member can be reliably identified, imitate-the-best almost always outperforms imitate-the-majority because it is faster to respond to environmental change. However, while searching for more agents always benefits imitate-the-best, less exhaustive search helps imitate-the-majority after environmental change, when most agents possess outdated information (see Figure 10). This counterintuitive result occurs for three reasons: (1) a smaller sample is more likely to include a majority of agents with the correct option; (2) while the correct option is in minority, a smaller sample keeps the overall accuracy of the group higher compared to a larger sample; and (3) smaller samples require fewer instances of correct behavior to reach a decision in favor of the correct option, allowing for faster learning.

Group Decision Making

When Can Diversity Trump Ability in Group Decision Making?

In decision-making tasks, it is often unclear what is more important for group performance: diversity among its members or their individual abilities. Luan, Katsikopoulos, and Reimer (2012) addressed this issue in a simulation study in which they manipulated agents' individual accuracy and group diversity. As Figure 11 illustrates, Luan et al. (2012) compared performance of groups with members using these two heuristics while varying several external factors, including differences between cue validities and errors in information that agents had about cue values. They found that individual accuracy was more important than diversity when cue validities differed substantially. In contrast, when all cues had similar validities, diversity was more important than accuracy. Surprisingly, Luan et al. (2012) also found that erroneous information agents had about cue values had a nonlinear effect on group accuracy, as shown in Figure 11. With a larger error magnitude, group performance started to get better, reached its best at some intermediate error level, and only got worse slowly afterward. In other words, the right magnitude of information errors could actually help a group make better decisions than when there was no error. This

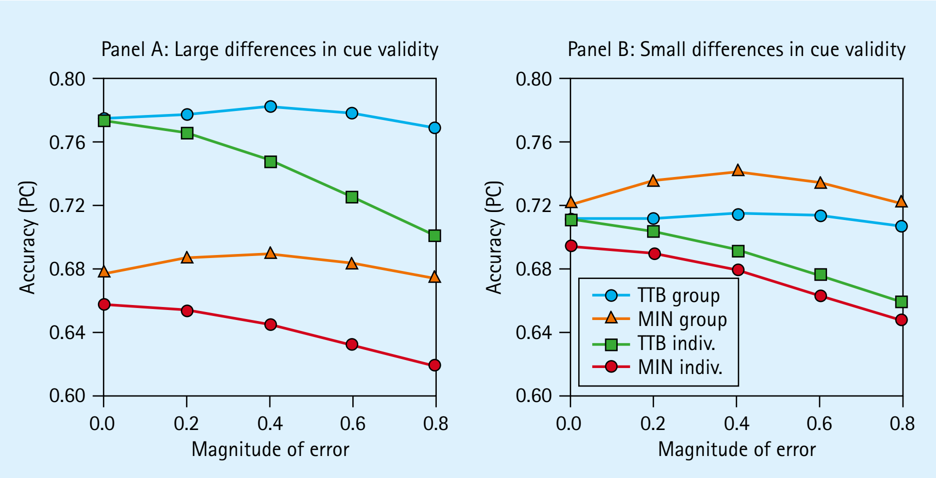


Figure 11. Errors in information have a nonlinear effect on group decision accuracy (Luan et al, 2012). When choosing between two options described by a number of cues, individuals and groups used either take-the-best ("TTB indiv." and "TTB group") or minimalist heuristic ("MIN indiv." and "MIN group"). Agents using take-the-best tended to be more accurate, but their decisions less diverse than those using minimalist. Agents were embedded in groups of five and a simple majority rule was applied to determine the group decision. Panel A shows results in an environment where there are large differences in validity, a measure for information quality, among the cues, and Panel B shows results in another environment where the validity differences among the cues are small. The magnitude of information error is measured as the standard deviation of a normal distribution from which random errors are generated and then added to true cue values.

Key Reference

Luan, S., Katsikopoulos, K. V., & Reimer, T. (2012). When does diversity trump ability (and vice versa) in group decision making? A simulation study. *PLoS ONE, 7*(2): e31043. doi:10.1371/journal.pone.0031043

rather counterintuitive result was observed no matter which strategy, take-the-best or minimalist, agents were using and how cue validities were distributed. How can this be explained?

Luan et al. (2012) speculated that the answer lies in the opposing effects that information errors have on group decisions. On the one hand, the information errors undermine individual agents' performances and drag the group's performance down. On the other hand, those errors diversify the information searched by a group of agents and their individual decisions, and this increased diversity increases the group's performance. These two opposing effects are always present, but do not always cancel each other out perfectly. With smaller magnitudes of errors, the gain of group accuracy due to added diversity compensates for the loss due to reduced individual accuracy, resulting in a net accuracy gain. As the magnitude of errors increases, the gain reaches its maximum at some intermediate level, with its exact value depending on factors such as the strategy used, the cue validity distribution, and the size of the group. Finally, when there is too much error, the group accuracy gain disappears, and groups perform below the level they could have achieved with no information error. These results demonstrate that "flawed" individuals may rely on groups to achieve levels of performance that they cannot reach alone and imply that groups should be tolerant of, and even welcome, occasional errors made by its members.

How Do Groups Make Decisions Under Uncertainty?

In two projects, Kämmer and her collaborators apply the framework of ecological rationality to the group level in order to explain some of the heterogeneous findings of research on group decision making. The ecological rationality perspective assumes that no decision strategy is good or bad per se; rather, its success depends on the structure of the environment and on the composition of the group. Kämmer, Gaissmaier, and Czienskowski (2013) compare the learning success of individuals and dyads in a multi-attribute paired-comparison task, where

Key References

Kämmer, J. E., Gaissmaier, W., & **Czienskowski, U.** (2013). The environment matters: Comparing individuals and dyads in their adaptive use of decision strategies. *Judgment and Decision Making, 8,* 299–329.

Kämmer, J. E., Gaissmaier, W., Reimer, T., & Schermuly, C. C. (in press). The adaptive use of recognition in group decision making. *Cognitive Science.*

participants had to learn the most adaptive strategy in an unknown task environment. They found that dyads were better able to adapt to the (changing) environment than individuals, but only when successful learning required ignoring less valid information. These results suggest that groups are superior when the environment structure requires replacing a default strategy by a more appropriate strategy. Small group research often implicitly or explicitly suggests that groups perform best if they pool all information that is available to their single group members and that their larger knowledge base makes them superior to individual decision makers. Kämmer, Gaissmaier, Reimer, and Schermuly (in press) show that this is not always the case. They examined a paired-comparison task in which the recognition heuristic can play an important role (e. g., "Which of two German companies has the higher market capitalization?"). In line with the ecological rationality perspective, they find that some groups perform—in a theoretically predictable way—better if they bet on group members who lack some knowledge, namely, those who do not recognize an object. Both of these projects show that individuals as well as small groups are able to intuitively use the most adaptive decision strategies in different choice tasks. They also reveal that group level regularities are similar to those that have been extensively studied on the individual level and thus extend the decision-making research to the practically relevant domain of groups.

Crowd Behavior

Can Complex Crowd Behavior Be Predicted by Simple Heuristics?

Understanding and modeling the behavior of pedestrians and the collective dynamics of crowd movements is a critical issue for the safe management people in urban environments and during mass events. Moussaïd and Nelson (in press) compare two approaches to simulating crowd dynamics: outcome models that describe the behavior of pedestrians by means of analogies with physical systems and process models that describe the cognitive process underlying the behavior by means of navigation heuristics. An example of process models is the study of heuristics described by Moussaïd, Helbing, and Theraulaz (2011). They suggest that the movements of a pedestrian can be described by the interplay of two simple navigation heuristics: The first describes how pedestrians choose a walking direction by searching for deep empty spaces in their field of vision. The second rule describes how pedestrians adapt their walking speed by keeping the time to collision with surrounding obstacles above a certain threshold time. The combination of these two heuristics predicts the emergence of many self-organized crowd patterns, such as the highway formation, stop-and-go waves, and the sudden transition to crowd chaos at extreme densities—a phenomenon that has been observed during recent crowd disasters. Moussaïd and Nelson (in press) show that process models constitute a simpler and more realistic description of crowd movements compared to sophisticated and idealized outcome models. This research could help urban planners to design better exit routes for evacuation of large crowds from buildings and to adapt the environment for a safe planning of mass events.

How Do Ideas Spread in Large Groups?

The dynamics of collective opinion formation has important implications for understanding a range of social phenomena. Based on the results of laboratory experiments, Moussaïd, Kämmer, Pipergias Analytis, and Neth (2013) show how participants answering factual questions revise their initial judgment after being exposed to the opinion of others. By means of a simple model derived from empirical observations, they have studied how the collective opinion changes in a large group of people repeatedly, influencing one another. The results, detailed in Figure 12, show that two major mechanisms determine the collective opinion: (1) the expert effect, induced by the presence of a few highly confident individuals in the group and (2) the majority effect, caused by the presence of a critical mass of laypeople sharing a similar opinion. This work opens practical applications for the management of conflicting situations in

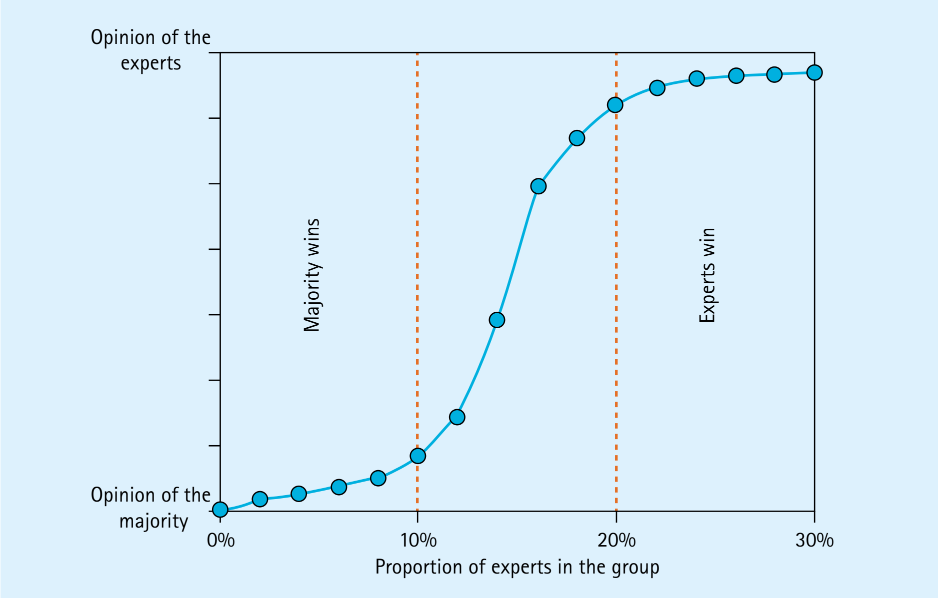


Figure 12. Computer simulations indicating the collective opinion of a population in which a large majority of laypeople interact with a small minority of highly confident experts (Moussaïd et al., 2013). At least 20 % of highly confident experts are needed to counterbalance the strength of the majority.

which well-informed minorities challenge the views of a large majority of laypeople, such as helping doctors convince a population of laypeople to adopt certain disease prevention methods or preventing extremist groups from taking control of a large population of people.

Can Election Results Be Predicted From Small, Lousy Samples?

"The trouble with free elections is, you never know who is going to win," former political leader of the Soviet Union, Leonid Brezhnev, supposedly said. Polling agencies try to solve this problem by interviewing large representative samples of citizens to forecast elections. Gaissmaier and Marewski (2011) demonstrated that very simple forecasting models based on small unrepresentative samples can provide a surprisingly accurate alternative. They aggregated judgments on (1) which of the parties participants recognized (recognition-based forecasts) and (2) how participants think the parties will fare in the elections (wisdom of crowds). Gaissmaier and Marewski compared these forecasts to simulated polls in four major German elections and found that recognition-based forecasts were particularly competitive when forecasting the success of smaller parties. In polls, very few people (if any) declare they will vote for smaller parties, resulting in too few observations. Wisdom-of-crowds forecasts were even more successful by drawing on the benefits of recognition while avoiding its downsides – recognition cannot discriminate among major parties and is sometimes caused by factors unrelated to success. As shown in Figure 13, a simple extension of recognition-based forecasts—asking participants what proportion of the population would recognize a party instead of whether they themselves recognize it—eliminated these downsides.

Key References

Moussaïd, M., Helbing, D., & Theraulaz, G. (2011). How simple rules determine pedestrian behavior and crowd disasters. *Proceedings of the National Academy of Sciences, USA, 108,* 6884–6888.

Moussaïd, M., Kämmer, J. E., Pipergias Analytis, P., & **Neth, H.** (2013). Social influence and the collective dynamics of opinion formation. *PLoS ONE, 8*(11): e78433. doi:10.1371/journal.pone.0078433

Moussaïd, M., & **Nelson, J. D.** (in press). Simple heuristics and the modeling of crowd behavior. *Pedestrian and Evacuation Dynamics.*

Key Reference

Gaissmaier, W., & **Marewski, J. N.** (2011). Forecasting elections with mere recognition from small, lousy samples: A comparison of collective recognition, wisdom of crowds, and representative polls. *Judgment and Decision Making, 6,* 73–88.

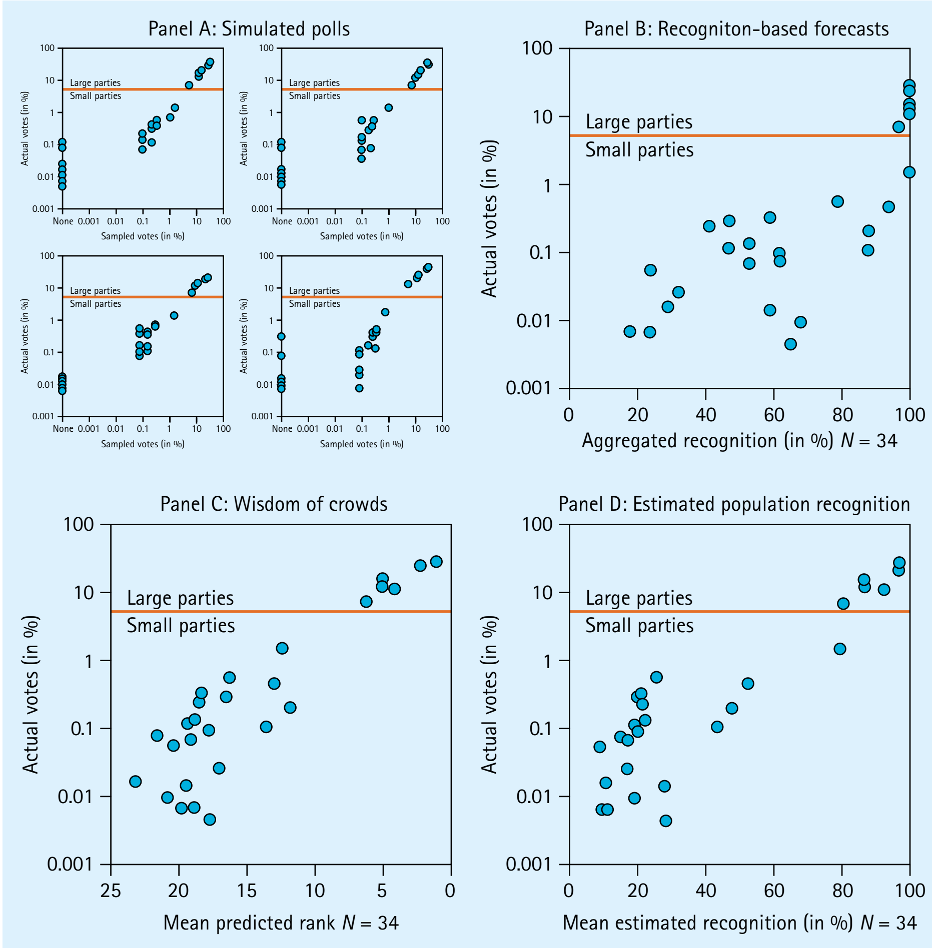


Figure 13. Comparison of four different models in their ability to forecast the success of the 27 parties in the German National Elections 2009 (Gaissmaier & Marewski, 2011). Predictors are on the x-axes and actual success on the y-axes. The orange line (large parties vs. small parties) indicates the threshold to enter parliament, which is 5 % in Germany. Panel A: Shown are four randomly drawn runs from simulated polls based on the actual election results with n = 1,000 each. These polls work well until the share of votes of a party is smaller than about 1 %, and there is a substantial risk of not at all observing voting intentions for very small parties. Panel B: Recognition-based forecasts work well for small parties, but do not discriminate among the major parties. Additionally, there are some very small parties that are nevertheless recognized by many, such as the German Communist Party (votes: 0.0044 %; recognition: 65 %). Panel C: Wisdom-of-crowds forecasts are generally better able to differentiate between parties than recognition-based forecasts as they draw on the benefits of recognition, but avoid its downsides. Panel D: Asking people about the proportion of the population that would recognize a party, rather than about their own recognition, also eliminates the downsides of recognition-based forecasts.

Theory Integration

Psychologists take pride in devising new theories, models, and frameworks that differ from those that preceded them. As Walter Mischel (2009) pointed out, psychologists have a tendency to treat theories like toothbrushes—no one wants to use anyone else's. This "toothbrush" mentality has hindered progress in psychology. But much can be gained when researchers venture out of their comfort zone, learn from theories developed in other areas, and discover how these theories relate to their own. Put simply, theory integration can lead to new, surprising discoveries and provide fresh impetus for understanding puzzling problems and unexplained phenomena. The interdisciplinary nature of the ABC Research Group means that we are well-poised to explore the benefits of theory integration and, in this section, we detail some examples.

Herbert Simon's Spell on Judgment and Decision Making

In order to assess the degree to which research in judgment and decision making attempts to integrate theories, Katsikopoulos and Lan (2011) analyzed all 377 articles published from 2006 to 2010 in *The Journal of Behavioral Decision Making* and *Judgment and Decision Making.* The first step was to identify the articles that focus on Herbert Simon's idea of bounded rationality. The authors found 91 such articles. For each article, they judged whether it was theoretically integrative or not. Articles on descriptive theory were judged to be integrative if they contributed to building a theory that *reconciled* different conceptualizations of cognition, such as neural networks and heuristics. That is, the goal was to find those articles that helped create a metamodel that incorporated concepts from various models. Articles on prescriptive theory were judged to be integrative if they contributed to building a theory that combined elements of other methods, such as heuristics and optimization models. The goal was to identify articles that helped to create an integrated view that fuses ideas from various sources.

The main results of this exercise were: (a) The number of descriptive articles was much higher than the number of prescriptive articles (71 vs. 27) and (b) the proportion of integrative articles was higher for prescriptive than for descriptive articles. In both cases, slightly more than half the articles were integrative (67 % and 52 %, respectively). Overall, it seems that a substantial number of articles focus on novel effects, but not on developing theories, which is consistent with complaints about a general lack of theory in social and cognitive psychology (Gigerenzer, 2010). The authors went on to provide more subtle examples of the lack of theoretical integration. For example, they pointed out that, in debates on the descriptive adequacy of cognitive theories, researchers were often divided into "advocates/proponents" and "critics" of different theories. In general, the authors concluded that too much time and ink have been spent on paying attention to who said what and when rather than trying to create a shared and improved understanding of the issues.

In the final part of their article, Katsikopoulos and Lan (2011) offer suggestions for fostering theory integration in research into judgment and decision making. They argue that researchers need to spend more effort on thinking about the primitive aspects of their theories (e. g., whether a model should include observable or latent variables). It was further suggested that precise conceptual thinking should be taught in classrooms, and examples should be given more exposure in textbooks.

Intuitive and Deliberate Judgments Are Based on Common Principles

Some of our judgments seem intuitive: They come to mind quickly and effortlessly without much of our awareness of their origins or of the manner of their formation. Others seem deliberate: They arise from a lengthy and painstaking thought process that is transparent and accessible to consciousness. Corresponding to this subjective experience, numerous models in social and cognitive psy-

Key References

Gigerenzer, G. (2010). Personal reflections on theory and psychology. *Theory and Psychology, 20,* 733–743.

Katsikopoulos, K. V., & Lan, C.-H. D. (2011). Herbert Simon's spell on judgment and decision-making. *Judgment and Decision Making, 6,* 722–732.

Mischel, W. (2009). The toothbrush problem. *Association for Psychological Science Observer, 21,* 11.

Key Reference

Kruglanski, A. W., & **Gigerenzer, G.** (2011a). Intuitive and deliberative judgments are based on common principles. *Psychological Review, 118,* 97–109. doi:10.1037/a0020762

chology have been premised on the assumption that judgments can be formed via two qualitatively distinct processes or systems. Such dual-system models typically characterize intuitive judgments as associative, quick, unconscious, effortless, heuristic, and error-prone, whereas deliberative judgments are described as rule-based, slow, conscious, effortful, analytic, and rational. This distinction, according to Kruglanski and Gigerenzer (2011), is superfluous. Instead, they present arguments and evidence for a unified theoretical approach to intuitive and deliberate judgments: Both types of judgment are rule-based and, in fact, the very same rules (e. g., tallying and take-the-best) can underlie both. Key to understanding the formation of judgments of any kind is rule selection: How do individuals select a rule from their adaptive toolbox for a given task? Kruglanski and Gigerenzer propose a two-step process in which: (a) characteristics of the task and an individual's memory constrain the set of applicable rules and (b) the individual's processing potential and the (perceived) ecological rationality of a rule—that is, a match between the rule and the informational structure of the task with regard to performance—guide the final selection from the rule set. The following points provide further insights on the rule-selection process.

(1) *There is no general relation between the type of rule and its difficulty of application.* Rules are based on core cognitive capacities, and individual differences in these capacities can influence the speed and the accuracy with which a rule is executed. Thus, rules typically characterized as intuitive may be easy or difficult to apply, depending on their degree of routinization and their momentary accessibility; and the same applies to rules considered deliberative.
(2) *The greater the difficulty of application, the more processing potential is needed from an individual.* Therefore, when processing potential is limited, only easy-to-apply rules will mediate judgments. In contrast, when processing potential is high, both easy and difficult rules may be considered and selected.
(3) *Rules' ecological rationality determines their accuracy.* Because of their better fit with the presented task, heuristics that require less effort to apply and ignore parts of the information can at times be more accurate than cognitive strategies that process more information and demand more computation.

In summary, Kruglanski and Gigerenzer (2011) suggest that the dichotomy between two separate systems of judgments is unwarranted. Though instances of judgment formation may differ in multiple ways, such as the content, effort invested, difficulty of formation, and so on, the underlying process is uniform across cases. It consists of rule application in conditions that require a given amount of cognitive resources, motivation, and core capacities.

A Signal-Detection Analysis of Fast-and-Frugal Trees

Models of decision making can be classified as the following two types: Those that aim for an optimal solution in a world that is precisely specified by a set of assumptions (a so-called "small world") and those that aim for a simple but satisfactory solution in an uncertain world where the assumptions of optimization models may not be met (a so-called "large world"). Despite the great advancement made in each model family, there have been few attempts to connect the two. Given the potential for theory integration to offer new insights, Luan, Schooler, and Gigerenzer (2011) attempted to draw connections between these two families of model. They showed how psychological concepts originating in a small-world approach to decision making, namely, the classic signal-detection theory (SDT), can be used to understand the workings of a class of large-world models known as the fast-and-frugal trees (FFTs). Their conclusions were:

(1) *The setting of a subjective decision criterion in SDT corresponds directly to the choice of the exit structure in an FFT.* This correspondence is illustrated in Figure 14. Specifically, the earlier an *s* exit, which points to a *signal* decision, and the more such exits in an FFT, the more "liberal" the FFT, which means a stronger tendency of the

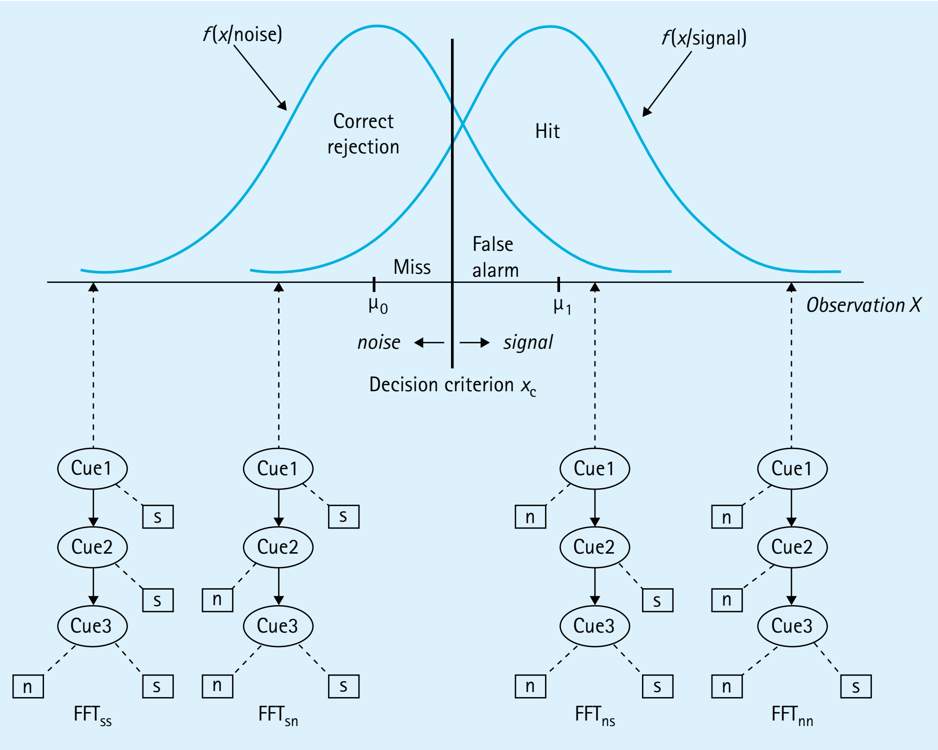


Figure 14. The correspondence between signal detection theory (SDT) and fast-and-frugal trees (FFTs) when understanding the decision criterion. The upper part illustrates the main assumptions and concepts of SDT in a binary decision task, and the lower part illustrates the four possible FFTs that can be constructed when three cues are searched in a set order. Based on the decisions pointed to by the first two exits, the trees are named from left to right FFT_{ss}, FFT_{sn}, FFT_{ns}, and FFT_{nn}. The arrows connecting the two figure parts indicate the rough locations of the four FFTs' decision criteria when they are used to make a binary s/n (for signal and noise, respectively) decision. Among the four, FFT_{ss} has the most liberal decision criterion and FFT_{nn} has the most conservative one. The decision criteria of FFT_{sn} and FFT_{ns} are less extreme than the other two, with FFT_{sn} being more liberal than FFT_{ns}.

Key Reference

Luan, S., Schooler, L. J., & **Gigerenzer, G.** (2011). A signal detection analysis of fast-and-frugal trees. *Psychological Review, 118,* 316–338. doi:10.1037/a0022684

tree to make more *signal* than *noise* decisions relative to their base rates. Setting a decision criterion that matches the payoff structure (e.g., the penalties for miss and false alarm) and base rates of a task is one crucial characteristic of an ideal observer in the world of SDT. The exit structure in an FFT can be adjusted to result in a proper decision criterion in this regard.

(2) *The sensitivity of an FFT is reflected by the order of cues searched and the properties of cues in an FFT.* In general, the more the cues are searched according to the orders of their *d*′s—a popular measure of sensitivity or accuracy in SDT—the higher the *d*′ of an FFT. The properties of the cues, including the mean and variance of the cues' individual *d*′s, the intercue correlation, and the number of cues, can affect an FFT's *d*′ as well.

(3) *FFTs perform well compared to the ideal and the optimal sequential sampling models in SDT.* Models in SDT are built to optimize. In a large world, where sample sizes are small, search is costly, and resources are limited, the performance of these models may fail to set the upper benchmarks as they are supposed to. FFTs can perform better or as well as these SDT models in the large world, with respect to frugality (i.e., the number of cues searched for a decision), accuracy, and expected payoffs.

These findings demonstrate the potential of theory integration to improve the understanding of common underlying psychological

Key References

Brighton, H., & **Gigerenzer, G.** (2012). Are rational actor models "rational" outside small worlds? In K. Binmore & S. Okasha (Eds.), *Evolution and rationality: Decisions, co-operation, and strategic behaviour* (pp. 84–109). Cambridge, UK: Cambridge University Press.

Savage, L. J. (1954). *The foundations of statistics.* New York: Wiley.

structures drawn from apparently disparate theories of cognition. They also demonstrate how discoveries can be made by examining models of one kind from the perspectives of another.

Statistical Foundations of Ecological Rationality

The distinction between small and large worlds mentioned above draws on the work of Leonard Savage (1954), the inventor of Bayesian decision theory. While Savage's theory, which he set out in *The Foundations of Statistics*, is accepted by many as providing a solid foundation for the study of rational decision making, Savage himself considered it "utterly ridiculous" to apply the theory outside what he termed small worlds, where all states, acts, and consequences are known. How does the work of the ABC Research Group, whose expressed purpose is to study decision making under uncertainty, relate to Savage's concerns? Investigating the connection, Brighton and Gigerenzer (2012) framed the study of ecological rationality as a response to what they called Savage's problem: the problem of assessing the potential dangers of using analytic methods geared for small worlds to theorize, and make statements about, large worlds.

From a statistical standpoint, the study of ecological rationality deviates from the common practice of assuming a probabilistic model of the environment. This is why our research rarely makes claims about, or assumes the existence of, optimal solutions. Instead, ecological rationality adopts what is sometimes termed the statistical culture of algorithmic modeling, where the "true" state of nature is treated as unknown, and the statistical objective changes to making accurate predictions relative to the observations. This is why much of our research stresses the ability of simple models to achieve high predictive accuracy relative to alternative models, rather than make optimal predictions relative to a model of nature. Put simply, in a large world, the concept of optimality will always rest on assumptions which are known to be incorrect. By focusing on the question of how to make accurate inferences in a "large," uncertain world, the ABC Research Group addresses Savage's problem by adopting alternative statistical foundations.

Risk Literacy in Health

In the 1930s, H. G. Wells predicted that, for an educated citizenship in a modern democracy, statistical thinking would be as indispensable as reading and writing. At the beginning of the 21st century, nearly everyone in industrial societies has been taught reading and writing, but not statistical thinking. However, in a world that is full of uncertainty and risk, statistical thinking is an indispensable skill. The general lack of training to deal with uncertainties and risks in today's technological society has become a huge problem, which has become apparent in various recent crises, from BSE (mad cow disease), to swine flu, to EHEC (Escherichia coli), to the Euro crisis.

HARDING CENTER FOR RISK LITERACY

"Our aim is to study how people behave in risk situations. We believe that our work can contribute toward the ideal of a society that knows how to calculate risks and live with them."
Gerd Gigerenzer

Should I have a flu vaccination or not? Is it safer to travel by car or by plane? Can early-detection screening tests for cancer prolong my life? Questions like these are the research focus of a team of scientists led by Gerd Gigerenzer, director of the Harding Center for Risk Literacy.

The goal of the Harding Center is to help people to understand and assess the risks facing them. The primary focus is on health and medicine as well as educating people from childhood onward to understand statistics. By conducting studies, experiments, and surveys, researchers investigate people's problems with understanding numbers, and then find solutions. Importantly, researchers of the Harding Center often leave the laboratory to study how real people make real decisions, including interviewing experts, such as physicians, and laypeople, such as patients. Their research is published in the top international journals in medicine (including *Annals of Internal Medicine, British Medical Journal, JAMA Internal Medicine, Vaccine*) as well as psychological journals. Gerd Gigerenzer writes a regular column on the art of risk communication for the *British Medical Journal.* The Harding Center is also involved in the university teaching of physicians as well as their continuing education, often in collaboration with leading universities, such as the Charité Universitätsmedizin Berlin and the Heidelberg University. Members of the Harding Center give about 50 keynotes, talks, and workshops per year to the medical community. Finally, the Harding Center aims to provide understandable health information to the public in collaboration with, for example, the Bertelsmann Foundation.

The Harding Center for Risk Literacy was established in 2009. It is named after David Harding, who provided a generous endowment for the Center. Harding—global investment manager and director of Winton Capital—became aware of Gerd Gigerenzer's work after reading *Reckoning with Risk,* which was shortlisted for the Royal Society Prize for Science Books.

Box 2. The Harding Center for Risk Literacy.

Key Reference

Arkes, H. R., & **Gaissmaier, W.** (2012). Psychological research and the prostate-cancer screening controversy. *Psychological Science, 23,* 547–553. doi:10.1177/0956797612437428

At the Harding Center for Risk Literacy (see Box 2), we investigate how people cope with risk and uncertainty, the major obstacles to understanding them clearly, and how citizens can be informed more effectively. It is therefore important to complement laboratory experiments by studying real-world problems and how people—such as physicians or patients—make real decisions, as opposed to studying hypothetical tasks using undergraduate students. One major focus of the Harding Center is risk literacy in health. Risk literacy in health means that patients and doctors understand the benefits and harms of different treatment options so that an informed decision based on the best available clinical evidence can take place. As we demonstrated in this section, difficulties in understanding health statistics are widespread and common among physicians and politicians. As a consequence, both societal and individual decisions about health are often not based on scientific evidence. Patients should not, therefore, blindly follow the advice of their doctors. Much can be done to remedy this situation, and we will illustrate new methods to assess risk literacy in a more effective way and new ways to better inform people of the risks they face. Educated citizens are the objective. These citizens will know which questions to ask and, as a consequence, acquire a more informed (and relaxed) attitude toward health risks as well as risks more generally.

Risk Illiteracy Has Severe Consequences for Societies and Individuals

Understanding the Prostate-Cancer Controversy

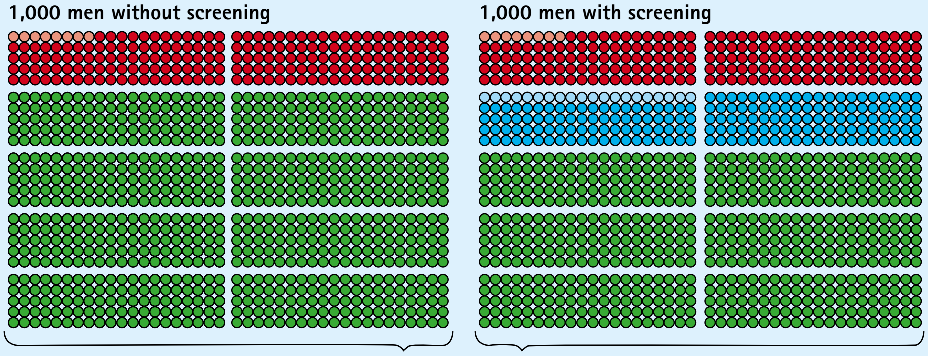
In early October 2011, the U.S. Preventive Services Task Force (USPSTF) released a draft report in which they recommended against using the prostate-specific antigen (PSA) test to screen for prostate cancer. Overall, their conclusion was that the test does more harm than good because it results in many unnecessary and sometimes dangerous treatments. This, too, was the conclusion in the final report released about half a year later. The resulting furor, fueled by presidential candidates, spokespersons for advocacy organizations, and prostate-cancer survivors, involved a number of serious misunderstandings. The PSA controversy engendered rancorous "discussion" punctuated by denigrating personal attacks on the panel members by politicians and other individuals. Even faced with overwhelming evidence, such as a meta-analysis that showed that the test did not save lives, many activists and medical professionals are clamoring for men to continue receiving their annual PSA test. How can the personal belief and also the personal experience of some people be so contrary to the scientific evidence that motivated the panel's recommendations?

Arkes and Gaissmaier (2012) discuss several factors documented by psychological research that may have contributed to the public's condemnation of the report. They summarize studies showing that an anecdote or two can have a more powerful effect on decision making than a compendium of more reliable statistical data. When a reader of the USPSTF report tries to digest the information about statistical lives, this information does not have the same impact as information about, for example, the reader's mail carrier's older brother who had a positive PSA test, a biopsy, and a radical prostatectomy, and is now still alive. The information given by the USPSTF that "no trial has shown a decrease in overall mortality with the use of PSA-based screening through 11 years of follow-up" will not have the same probative value as awareness of a putative identified beneficiary of the PSA test. The positive view of the PSA test is further exacerbated because many people do not understand that a control group is needed in order to evaluate the effectiveness of a medical intervention or test: Most men who receive PSA screening and are still alive do not realize that their outcome would have been the same had they not been screened.

Psychological research is not only instructive to understand the public reaction to the USPSTF report; it has also developed more effective means to represent statistical information about clinical evidence so that it can be easily understood even by laypeople. Two very helpful representations that have repeat-

Prostate cancer early detection
by PSA screening and digital-rectal examination. Numbers are for men aged 50 years or older, not participating versus participating in screening for 10 years.

HARDING CENTER FOR RISK LITERACY



Men dying from prostate cancer:	8	8
Men dying from any cause:	200	200
Men that were diagnosed and treated for prostate cancer unnecessarily:	–	20
Men without cancer that got a false alarm and a biopsy:	–	180
Men that are unharmed and alive:	800	600

Figure 15. An icon array illustrating the benefits (or lack thereof) and harms of prostate-specific antigen (PSA) screening and digital-rectal examination for men aged 50 years and older. Based on about 200,000 men in the screening groups and as many in the control groups in randomized trials (Djulbegovic et al., 2010). After 10 years, out of every 1,000 men in the control group (left side), 200 had died, including 8 from prostate cancer. These mortality rates did *not* differ among those in the screening group (right side), but about 200 men were harmed, such as being treated unnecessarily with incontinence and impotence for life (right panel, second group). These numbers are not meant to be the final verdict on PSA screening, but rather serve to illustrate the order of magnitude of the effects. Note that in light of the most favorable evidence reported, the number of men dying from prostate cancer could be reduced from 8 to 7 out of 1,000, but in light of the total evidence, there is no such reduction. In any case, overall mortality did not decrease as a result of screening in any of the existing trials.

Source. Arkes & Gaissmaier (2012).

edly been proven to be effective are facts boxes and icon arrays. Figure 15 illustrates the benefits (or lack thereof) and harms of the PSA test with such an icon array. The authors suggest that augmenting statistics with these representations might help committees communicate more effectively with the public and with the U.S. Congress and could more generally be used to educate the public and elevate the level of civic discussion.

Risk Literacy in Health as a Prerequisite to Shared Decision Making

Risk literacy in health is not only required to have civilized and informed debates on a societal level but also for each individual patient. Doctors have been increasingly encouraged to involve patients in decision making about their health, rather than pursuing the paternalistic model in which doctors make the decisions for their patients. However, it is not clear to what degree patients actually want to participate in medical decision making and whether their preferences are influenced by their abilities. An ability that is essential for the understanding and use of quantitative information about health, and which is therefore an essential aspect of risk literacy in health, is numeracy. Patients with low numeracy might prefer a passive role in their interactions with doctors because they have problems understanding the risks and benefits of different medical options. Extant studies cannot answer

Key Reference

Galesic, M., & **García-Retamero, R.** (2011b). Do low-numeracy people avoid shared decision making? *Health Psychology, 30,* 336–341. doi:10.1037/a0022723

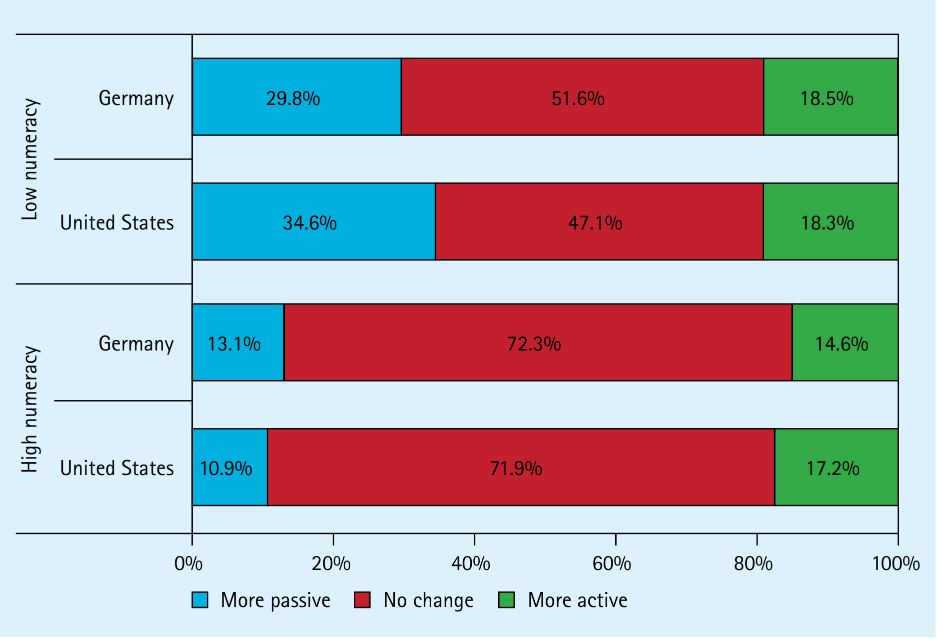


Figure 16. Divergence of usual and preferred role of patients in medical decision making by numeracy and country. Shown is the percentage of participants who would like to play a more passive role than they usually play, not to change the role they usually play, or to play a more active role than they usually play. People with low numeracy often wish to be more passive than they currently are.

these questions because most are based on nonprobabilistic, highly selective patient samples that prevent generalizations to a broader population.

In a survey on probabilistic national samples in the United States and Germany, Galesic and García-Retamero (2011) interviewed participants with low- and high-numeracy skills and asked them about their usual and preferred role in medical decision making. The roles could be more passive (doctor makes decisions), collaborative (doctor and patients decide together), or active (patient makes decisions). Figure 16 illustrates the difference between the participants' preferred and usual role. A significant number of people with low numeracy in both the United States and Germany preferred to be more passive than they currently were. High-numeracy people, in contrast, were mostly satisfied with their current role. These results suggest that education efforts to increase numeracy as well as using nonquantitative communication formats, such as analogies and visual displays, may foster involvement of low-numeracy patients in making decisions about their health.

Trust Your Doctor? Physicians Are Unlikely to Inform Their Patients Adequately

Some people argue that the general public will never be risk literate enough to make good decisions about their health. Rather, these decisions should mostly be delegated to the experts—physicians. There are, however, many reasons to assume that physicians will not always decide in the best interest of their patients. Besides conflicts of interest and defensive decision making, research at the Harding Center showed that physicians often do not inform their patients adequately and that many physicians themselves actually lack the skills to interpret health statistics correctly.

Patients Are Not Informed About Overdiagnosis and Overtreatment

Cancer screening looks for cancer in people without symptoms. It can produce benefits: Finding true cancer at an early stage can

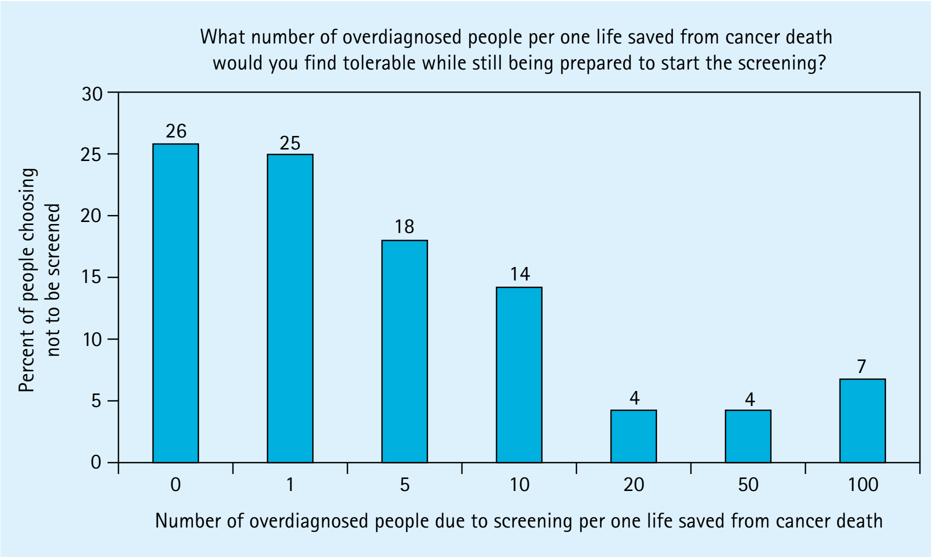


Figure 17. Faced with the decision to undergo cancer screening, how many overdiagnosed people per life saved are you willing to accept? This graph shows, as a function of overdiagnosed people per life saved, the proportion of people willing to undergo cancer screening.

Key Reference

Wegwarth, O., & **Gigerenzer, G.** (2013b). Overdiagnosis and overtreatment: Evaluation of what physicians tell their patients about screening harms. *JAMA Internal Medicine, 173,* 2086–2087. doi:10.1001/jamainternmed.2013.10363

reduce the likelihood of the person dying from it. But screening can also produce harms: The most important harm is overdiagnosis, which can eventually lead to overtreatment. Overdiagnosis is defined as the detection of an abnormality that would never progress to cause problems in a patient's lifetime, such as a nonprogressive prostate cancer. Treating a nonprogressive prostate cancer is obviously not beneficial, and it can even be harmful and cause impotence or incontinence as a side effect. What do people who are offered cancer screening by their physician learn about the potential harms of screening, and what extent of overdiagnosis would they tolerate?
Wegwarth and Gigerenzer (2013) surveyed 317 men and women from the United States, aged 50 to 69 years. Of those, 83 % had attended one or more cancer screenings in the past, but only 9 % (n = 30) had been informed about the possibility of overdiagnosis and overtreatment. In stark contrast, the great majority expressed a desire to be informed: 80 % of all participants said they would like to have been informed about screening harms before being screened. Of people who had not yet had any cancer screening, 34 % indicated that the possibility of overtreatment had been an argument against screening. Fifty-one percent of all participants were not prepared to enter a screening program that results in more than one overtreated person per one life saved from cancer death (see Figure 17). However, 59 % would continue their routine cancer screening even if they learned that it results in 10 overtreated persons per one life saved from cancer.
For counseling on screening, the results of the study indicate that physicians remain the most highly rated source of health information. However, the information they provide does not meet patients' standards.

Many Physicians Do Not Understand Cancer Statistics

While it seems natural to assume that survival is the same as "1–mortality," the term "survival" takes on a different meaning in the context of screening. Here, the calculation of survival is based only on those people diagnosed with cancer, while mortality is based on the whole study population. To illustrate, imagine a group of patients in whom cancer was diagnosed due to symptoms at 67 years of age, all of whom die at 70 years of age. Each patient survives only

Key Reference

Wegwarth, O., Schwartz, L. M., Woloshin, S., **Gaissmaier, W.,** & **Gigerenzer, G.** (2012). Do physicians understand cancer screening statistics? A national survey of primary care physicians in the United States. *Annals of Internal Medicine, 156,* 340–349, W-92-W-94.

3 years, so the 5-year survival for the group is 0 %. Now imagine that the same group undergoes screening. Screening tests by definition lead to earlier diagnosis. Suppose that with screening, cancer is diagnosed in all patients at 60 years of age, but they nevertheless die at 70 years of age. In this scenario, each patient survives 10 years, so the 5-year survival for the group is 100 %. Yet, despite this dramatic improvement in survival (from 0 % to 100 %), nothing has changed. The same people die at the same time.

Thus, only reduced mortality rates prove that cancer screening saves lives, whereas improved survival rates and increased early detection do not. Nevertheless, these two statistics are often used to promote screening in high-profile medical journals and patient leaflets alike. Do physicians who have to decide which screening tests to offer to their patient know what screening statistics to rely on?

To learn whether primary care physicians understand which statistics provide evidence about the benefits of screening, Wegwarth, Schwartz, Woloshin, Gaissmaier, and Gigerenzer (2012) presented 412 internal medicine physicians from the United States with two scenarios: In one scenario, the effect of a cancer screening X was described as improved 5-year survival and increased early detection; in the other scenario the effect of cancer screening Y was described as decreased cancer mortality and incidence. Physicians were further asked additional knowledge questions about screening statistics.

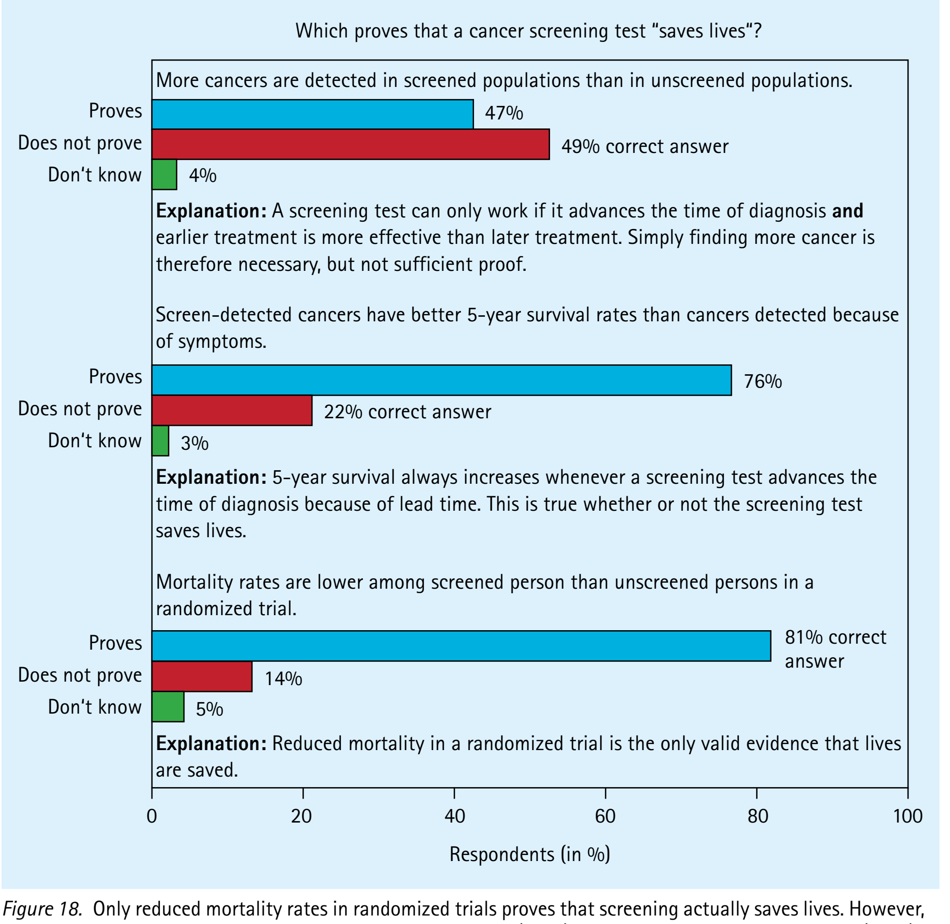


Figure 18. Only reduced mortality rates in randomized trials proves that screening actually saves lives. However, many physicians incorrectly believed that better survival rates (76 %) or even just higher detection rates (47 %) demonstrate that screening saves lives (Wegwarth et al., 2012).

Primary care physicians were more enthusiastic about the test when it was "supported" by misleading evidence (5-year survival increased from 68 % to 98 %); in this case, 69 % of physicians would definitely recommend the test. However, when actually the valid though less impressive sounding evidence about the test was provided (cancer mortality decreased from 2 to 1.6 in 1,000), the physicians were much less enthusiastic: Only 23 % of them would definitely recommend the test in this case. Furthermore, many physicians did not distinguish between misleading evidence (improved survival) and relevant evidence (reduced cancer mortality) when judging the benefit of screening: 76 % versus 81 %, respectively, stated that these data prove that screening saves lives. About half (47 %) of the physicians incorrectly believed that finding more cancers in screened as opposed to unscreened populations "proves that screening saves lives."

The majority of primary care physicians mistakenly interpreted improved survival and increased detection with screening as evidence that screening is beneficial. As shown in Figure 18, few correctly recognized that only reduced mortality constitutes evidence of benefit for screening.

Many Physicians Do Not Provide Complete and Transparent Information Even When They Have a Summary of All Relevant Clinical Evidence at Their Disposal

Because physicians are a primary source of information for patients during informed consent, it is important that physicians inform their patients both accurately and transparently. The last two examples have already shown this may often not be the case. Gaissmaier, Anderson, and Schulkin (in press) investigated in detail the statistical information physicians choose to provide their patients. To do so, they provided physicians with summary statistics describing the benefits and side effects of an antidepressant detailed in a Cochrane review summarized in Figure 19a. Cochrane reviews are considered to offer the most trustworthy summaries of clinical evidence. In one scenario, 142 physicians were asked to imagine a patient for whom they, in principle, believed the antidepressant to be safe and effective. Which pieces of information would they choose to provide to this (hypothetical) patient?

The authors assessed whether physicians chose statistical information that was complete, transparent, and interpretable, all of which is necessary to enable informed consent. *Completeness* means communicating both benefit and side effects. A *transparent* representation makes clear which proportion of people are affected by the antidepressant. An example of a transparent representation would be reporting the event rates for both the placebo and treatment groups (i. e., that the proportion increases from 5.5 % to 11.4 %). Alternatively, one could report the absolute risk change (i. e., that it increases by 5.9 percentage points). An example of a nontransparent representation is the use of relative risk. For example, stating that an antidepressant increases the risk of sexual problems by 107 % (100 % × (11.4–5.5) / 5.5)) details a relative risk. It is well documented that relative risks lead people—including physicians and health professionals—to overestimate the effects of drugs. Finally, *interpretability* means that the information is meaningful without additional information. This is not the case when only one event rate (either under treatment or placebo) is presented in isolation without providing comparative information about the other event rate or a measure of risk change. For instance, knowing that 45 % of patients who took the antidepressant got better is not interpretable without knowing that 26 % who took the placebo also got better.

The results showed that only about a quarter of physicians selected information that was complete and transparent (Figure 19b). Among the remaining three quarters of physicians, it is interesting to distinguish two ways in which the information could be presented in a nontransparent way. First, it could be represented in a way that makes it difficult to impossible for the patient to understand it. This was the case for about half of the physicians who selected information that was complete, but not transparent (Figure 19c), or that was not interpretable for the patient

Key Reference

Gaissmaier, W., Anderson, B. L., & Schulkin, J. (in press). How do physicians provide statistical information about antidepressants to hypothetical patients? *Medical Decision Making. Advance online publication.* doi:10.1177/0272989X13501720

(a) The complete information that was provided to physicians

	Under treatment (%)	Under placebo (%)	Absolute risk change in percent-age points	Relative risk change (%)
Benefit				
Condition improved	45.4	26.1	19.3	74
Side effects				
Dry mouth	22.4	12.1	10.3	85
Sexual problems	11.4	5.5	5.9	107

(c) 33 of 142 physicians (23.2 %) chose complete but nontransparent information (example)

	Under treatment (%)	Under placebo (%)	Absolute risk change in percent-age points	Relative risk change (%)
Benefit				
Condition improved				74
Side effects				
Dry mouth				85
Sexual problems				107

(b) 32 of 142 physicians (22.5 %) chose complete and transparent information (examples)

	Under treatment (%)	Under placebo (%)	Absolute risk change in percent-age points	Relative risk change (%)
Benefit				
Condition improved	45.4	26.1		
Side effects				
Dry mouth	22.4	12.1		
Sexual problems	11.4	5.5		

	Under treatment (%)	Under placebo (%)	Absolute risk change in percent-age points	Relative risk change (%)
Benefit				
Condition improved			19.3	
Side effects				
Dry mouth			10.3	
Sexual problems			5.9	

(d) 36 of 142 physicians (25.4 %) chose information that was not interpretable because comparative information was missing (example)

	Under treatment (%)	Under placebo (%)	Absolute risk change in percent-age points	Relative risk change (%)
Benefit				
Condition improved	45.4			
Side effects				
Dry mouth	22.4			
Sexual problems	11.4			

(e) 34 of 142 physicians (23.9 %) made the benefit appear to outweigh the harm (example, mismatched framing)

	Under treatment (%)	Under placebo (%)	Absolute risk change in percent-age points	Relative risk change (%)
Benefit				
Condition improved				74
Side effects				
Dry mouth			10.3	
Sexual problems			5.9	

Figure 19. Which information do physicians choose to provide to (hypothetical) patients when they have a summary of all relevant clinical evidence at their disposal? In this scenario, 142 physicians were asked to imagine a patient for whom they, in principle, believe an antidepressant to be safe and effective. They could select from complete information shown in (a). A similar proportion of physicians (roughly 25 % each) selected information that was (b) complete and transparent, (c) complete but not transparent, (d) not interpretable for the patient because necessary comparative information was missing, or (e) suited for nudging by making the benefit appear to outweigh the harm.

Measuring Risk Literacy: The Berlin Numeracy Test

We make sense of our complex and uncertain world with data about risks that are presented in terms of ratio concepts, such as probabilities, proportions, and percentages. Whether patients, consumers, and policymakers correctly understand these risks—that is, whether or not they are risk literate—depends in part on their statistical numeracy. To assess statistical numeracy, Cokely, Galesic, Schulz, Ghazal, and Garcia-Retamero (2012) introduced the Berlin Numeracy Test, a psychometrically sound instrument that quickly assesses statistical numeracy.
The Berlin Numeracy Test typically takes about 3 minutes to complete and is available in multiple languages and formats, including a paper and pencil version and an adaptive computer test that automatically scores and reports data to researchers (see www.riskliteracy.org for more information). Figure 20 illustrates the adaptive version of the test and the path and scoring depending on which questions are answered correctly (green arrows) or incorrectly (red arrows), respectively.

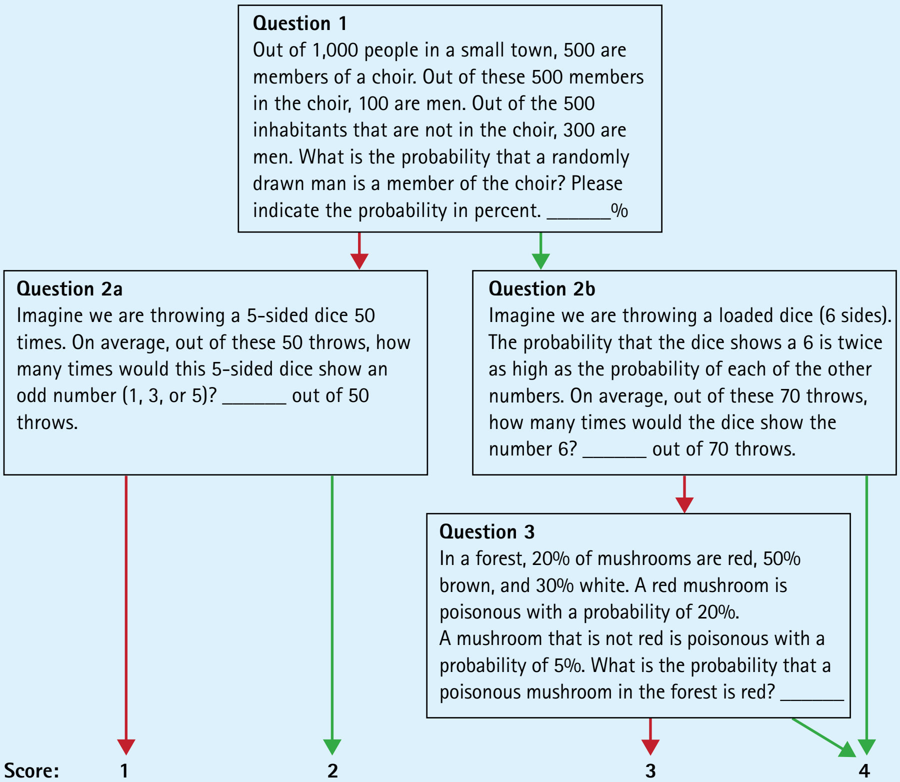


Figure 20. The Berlin Numeracy Test assesses risk literacy with two to three questions and takes only about 3 minutes to complete. The figure shows the adaptive version of the test and the path and scoring depending on which questions are answered correctly (green arrows) or incorrectly (red arrows), respectively. Correct answers are as follows: 1 = 25, 2a = 30, 2b = 20, 4 = 50.

A total of 21 studies (n = 5,336) showed robust psychometric discriminability across 15 countries (e. g., Germany, Pakistan, Japan, USA) and diverse samples (e. g., medical professionals, general populations, Mechanical Turk web panels). Analyses demonstrated desirable patterns of convergent validity (i. e., that it was correlated with related constructs such as numeracy or general cognitive abilities), discriminant validity (i. e., that it was not correlated with unrelated constructs such as personality or motivation), and criterion validity (it provided unique predictive validity for evaluating both numeric and nonnumeric information about risks). Additionally, the Berlin Numeracy Test was validated by being the strongest predictor of comprehension of everyday risks (e. g., evaluating claims about products and treatments; interpreting forecasts), doubling the predictive power of other numeracy instruments and accounting for unique variance beyond other cognitive tests (e. g., cognitive reflection, working memory, intelligence).

Box 3.

Key Reference

Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., & **García-Retamero, R.** (2012). Measuring risk literacy: The Berlin Numeracy Test. *Judgment and Decision Making, 7,* 25–47.

because necessary comparative information—primarily on the control group—was missing (Figure 19d). Second, the information could be represented in a way that makes the benefits appear to outweigh the side effects and is thereby suited to "nudge" the patient to take the antidepressant. This was the case for the final quarter of physicians (Figure 19e): They either used a technique called "mismatched framing" by presenting the benefit as relative risk change (big number), but the side effects as absolute risk change (smaller number); or they made the antidepressant look more favorable by completely omitting the side effects.

In sum, it cannot be assumed that physicians provide patients with complete, transparent, and interpretable information about a treatment, even if they have a summary of the relevant clinical evidence at their disposal. Only about a quarter of the physicians did so and thus would have enabled informed consent. The remaining three quarters of physicians failed to facilitate informed consent by either making it difficult to impossible for the patient to understand the information or by making the benefits appear to outweigh the side effects, thereby nudging patients toward taking the antidepressant.

Communicating Statistical Information About Health Risks More Effectively

What can be done to improve risk literacy in health? One promising way is to develop methods to communicate statistical information about health more effectively. Here, we discuss the use of graphical displays and analogies to help people make sense of health statistics.

Numbers Can Be Worth 1,000 Graphs: Some People Understand Numerical Representations of Risk Better Than Graphical Representations

Graphical displays are powerful tools that can facilitate the communication and comprehension of quantitative information. It is often assumed that visualizations are always preferable to numbers in risk communication, and many studies have demonstrated the benefits of graphical information. However, interpreting graphs requires additional skills beyond understanding numerical risks. Thus, it cannot automatically be assumed that graphs are intuitively understood by everyone.

In collaboration with the Zurich University of the Arts, Gaissmaier et al. (2012) developed graphical displays of the risks of smoking and the benefits and side effects of various painkillers. In an experiment involving 275 participants, they tested how well people understood graphical representations of health statistics in comparison to presentations of the same information using only numbers. Participants' comprehension of the health statistics was assessed when working with the materials (condition T1) as well as in recall after about half an hour (condition T2) and after about 2 weeks (condition T3). The authors also assessed graph literacy (i. e., the ability to understand graphically presented information) with a recently developed and validated instrument (Galesic & García-Retamero, 2011). As shown in Figure 21, people with high graph literacy were more accurate when working with graphs than when working with numbers. In contrast, people with low graph literacy were not only not better when receiving graphical instead of numerical information but their comprehension was even worse with graphs than with numbers. Similarly, people with high graph literacy subjectively perceived graphical information to be more accessible than numerical information, while the opposite was true for people with low graph literacy. However, when asked how much they liked the representations, most participants reported that they preferred graphical representations over numbers. This was true even for participants with low graph literacy.

Taken together, the results clearly show that it cannot be assumed that statistical information is better understood when communicated using graphs as opposed to numbers. Some people are obviously better off with numbers. However, since the majority of participants preferred graphs to numbers—including those who had difficulties understanding graphs—there is clearly a need to improve graphical presentations and make them more accessible, independent of levels of graph literacy.

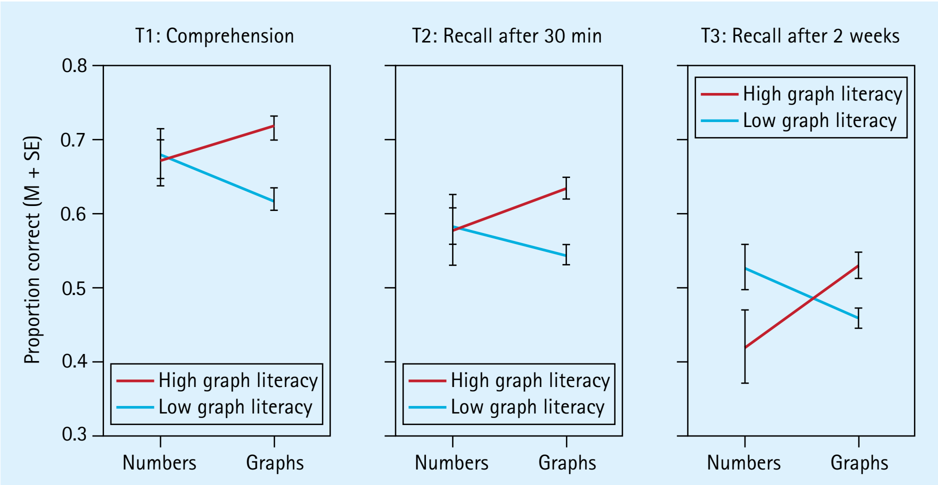


Figure 21. Gaissmaier et al. (2012) compared how well participants understood statistical information about health topics when these were represented with mere numbers or with graphs. Participants' comprehension of the health statistics was assessed when working with the materials (T1) as well as in recall after about half an hour (T2) and after about 2 weeks (T3). Graphical representations of health statistics were not better understood by everyone. Only participants with high graph literacy (i. e., high ability to understand graphical information) showed better comprehension with graphs than with numbers. Participants with low graph literacy, however, actually showed better comprehension and recall with mere numbers.

Key References

Gaissmaier, W., Wegwarth, O., Skopec, D., Müller, A.-S., Broschinski, S., & Politi, M. C. (2012). Numbers can be worth a thousand pictures: Individual differences in understanding graphical and numerical representations of health-related information. *Health Psychology, 31,* 286–296. doi:10.1037/a0024850

Galesic, M., & García-Retamero, R. (2011c). Graph literacy: A cross-cultural comparison. *Medical Decision Making, 31,* 444–457. doi:10.1177/0272989X10373805

Individual Differences in the Use of Spatial Information in Graph Comprehension

One key to the success of graphs is that they exploit the human ability to think about abstract concepts in spatial terms. Translations of spatial into conceptual information in graphs—spatial-to-conceptual mappings—are frequently rooted in our experience with the environment. For example, larger quantities of substances typically reach higher positions along the vertical dimension. This experience can be applied to infer that higher data points in graphs represent higher values. Hence, spatial features (e. g., bar heights) can convey meaning independent of the viewers' level of graph literacy. However, on some occasions, the meaning conveyed by spatial features can conflict with information in conventional features (e. g., titles, axes labels, or numerical values on scales; see Figure 22).

Okan, García-Retamero, Galesic, and Cokely (2012) investigated the impact of such conflicts on interpretations and decisions made on the basis of bar graphs depicting medical data. Results showed that people frequently misinterpreted the data, neglecting information in conventional features. Such errors were more common among individuals with low graph literacy, indicating that such individuals more often relied on spatial features to interpret graphs. In sum, these findings indicate that caution is required to ensure that individuals with low graph literacy infer the correct meaning from graphs. Designing graphs in which spatial and conventional features convey the same meaning is an essential step toward this aim.

Using Analogies to Communicate Information About Health Risks

Doctors often use analogies to explain medical concepts to patients, but it is unclear whether analogies actually improve understanding of health information. Building on existing theories of analogies, Galesic and García-Retamero (2013) designed several analogies to explain the usefulness of medical screenings. An example is "Cancer screening is to cancer as a car alarm is to car theft." The analogy relates the domain that requires explanation (the relationship between cancer screening and cancer or the *target* of the analogy) to the domain that is better grounded in everyday experience (the relationship between a car alarm and car theft or the *base* of the analogy). Here, the

Key Reference

Okan, Y., **García-Retamero, R., Galesic, M.,** & **Cokely, E. T.** (2012). When higher bars are not larger quantities: On individual differences in the use of spatial information in graph comprehension. *Spatial Cognition & Computation, 12,* 195–218. doi: 10.1080/13875868.2012.659302

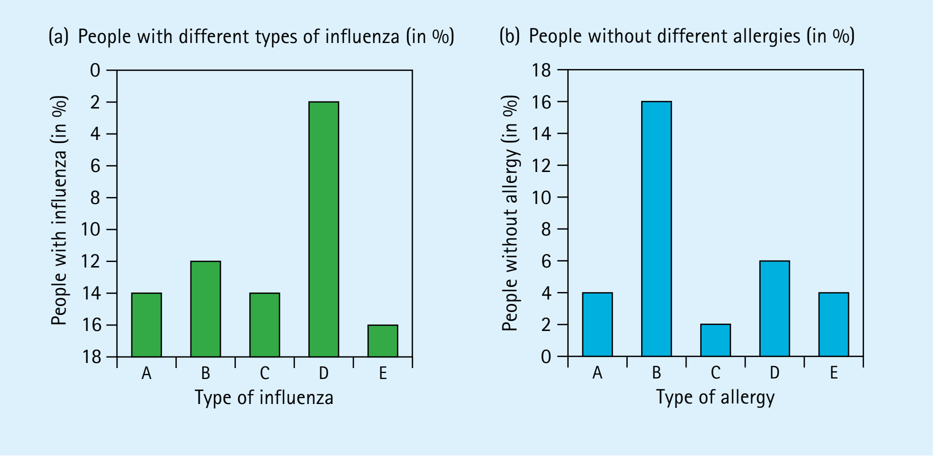


Figure 22. Examples of graphs containing conflicts between spatial and conventional features that were frequently misinterpreted in the study by Okan et al. (2012), particularly by those with low graph literacy. Such a conflict can occur when spatial features (i. e., bar heights) convey different meaning than (1) numerical values on scales (scale-spatial conflicts; left panel) or (2) textual information in the title and axes labels (textual-spatial conflicts; right panel). In both cases, a correct interpretation requires considering information in conventional features and overriding direct spatial-to-conceptual mappings (e. g., recognizing that the usual correspondence between height and quantity is reversed, implying that higher bars do not necessarily represent higher values). For instance, the graph in the left panel includes a numerical scale where values increase from top to bottom. Identifying the type of influenza affecting the largest percentage of people requires attending to the scale. The graph in the right panel presents data about percentages of people without different types of allergy. Identifying the most prevalent allergy requires attending to the title and/or the axis label.

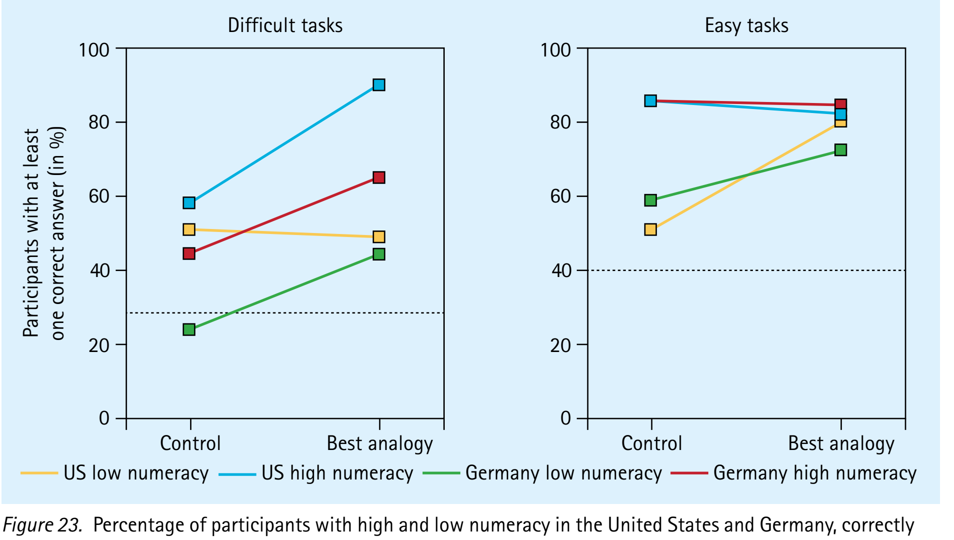


Figure 23. Percentage of participants with high and low numeracy in the United States and Germany, correctly answering at least one of the problems without analogies and with the analogy that most improved accuracy of that group. Difficulty was determined in a pretest with 400 participants in each country. The dotted line indicates chance level of performance.

relationship that holds in the car domain (the fact that a car alarm sometimes signals theft, but sometimes gives false alarms or does not activate when it should) is also applicable to the cancer screening domain.

In a study on probabilistic national samples in two countries, Galesic and García-Retamero (2013f) investigated whether such analogies help people with low and high numeracy skills to understand easy and difficult problems involving medical screenings. They also investigated whether the helpfulness of analogies depended on the similarity of the target and the base of the analogies, familiarity of patients with the base of the analogies, and the ease of visualization of the base of the analogies. As shown in Figure 23, they found that, for difficult medical problems, analogies helped high-numeracy people more than low-numeracy people. For easy medical problems, analogies did not further improve an already high level of understanding among people with high numeracy, but they enhanced understanding among people with low numeracy. The most helpful analogies were those with high similarity of the relationships between objects in their target and base and those with highly familiar bases. These results suggest that properly designed analogies can be useful to help patients understand complex medical information.

Key Reference

Galesic, M., & **García-Retamero, R.** (2013f). Using analogies to communicate information about health risks. *Applied Cognitive Psychology, 27*, 33–42. doi:10.1002/acp.2866

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, beginning with behavioral reactions to terrorism and moving on to financial regulation, sports, and slot machines.

9/11, Act II: Regional Variations in Traffic Fatalities in the Aftermath of the Terrorist Attacks

Terrorists can strike twice: first, by directly killing people and, second, through dangerous behaviors induced by fear in our minds. In the 12 months subsequent to the 9/11 terrorist attacks, there were about 1,600 more traffic fatalities in the United States than expected, presumably because fear of dread risks led people to drive rather than fly (Gigerenzer, 2006). But why would such an increase in traffic and, correspondingly, in traffic deaths be observed in some states, but not in others? And why was no increase in driving and in traffic accidents seen following the similarly devastating train bombings in Madrid in 2004 (López-Rousseau, 2005)? To answer these questions, Gaissmaier and Gigerenzer (2012) conducted new analyses.

What they found is that car traffic increased particularly in the New York vicinity, close to where the main attacks on the World Trade Center occurred. Images of these attacks, and thus the accompanying fear, appear to be particularly present for people who lived in the surrounding area; other studies also support this assumption. However, the authors further identify an even stronger factor that could explain why the traffic volume increased sharply even in some states far away from New York, especially in the Midwest: There, the infrastructure was simply very favorable to driving instead of flying, with a large number of car-friendly streets and a large number of registered vehicles in relation to the number of inhabitants (see Figure 24).

The study findings support the assumption that the fear created by terrorist attacks can cause potentially risky behavior. But they also make it clear that fear alone is not enough to explain risky behavior. To predict where the indirect damage of terrorist attacks can have particularly fatal consequences and to possibly curb similar psychological attacks in the future, one must pay close attention to the general conditions—such as the respective infrastructure—that are conducive to risky, fear-induced behaviors. This could also explain why there were fewer Spanish train travelers following the train bombings in Madrid on 11 March 2004, but without any corresponding increase in car travel. Spain has a less pronounced car-driving culture, which Gaissmaier and Gigerenzer (2012) express in numbers: In the United States in 2001, there were around 800 cars registered per 1,000 inhabitants while, in Spain in 2004, this figure was around 600.

Dread Risk

Which aspect of our brain's psychology do terrorists exploit in their second strike? Low-probability events in which many people are suddenly killed, so-called dread risks, trigger an unconscious rule of thumb: *If many people die at one point in time, react with fear and avoid that situation.*

Note that the fear is not about dying per se. It is about dying together *at one point in time,* or in a short interval. Where does this tendency to fear dread risks come from? One hypothesis is that, in human history, it was likely a rational response. For most of our evolution, humans lived in small hunter–gatherer bands that may have comprised around 100 individuals. In small bands, the sudden loss of many lives could increase the risk of predation and starvation, and thus threaten survival of the entire group.

It is difficult to test such historical explanations directly. Galesic and García-Retamero (2012) derived and tested an ingenious implication of this explanation. Although there

Key References

Gaissmaier, W., & **Gigerenzer, G.** (2012). 9/11, Act II: A fine-grained analysis of regional variations in traffic fatalities in the aftermath of the terrorist attacks. *Psychological Science, 23,* 1449–1454. doi:10.1177/0956797612447804

Gigerenzer, G. (2006). Out of the frying pan into the fire: Behavioral reactions to terrorist attacks. *Risk Analysis, 26,* 347–351.

López-Rousseau, A. (2005). Avoiding the death risk of avoiding a dread risk. *Psychological Science, 16,* 426–428.

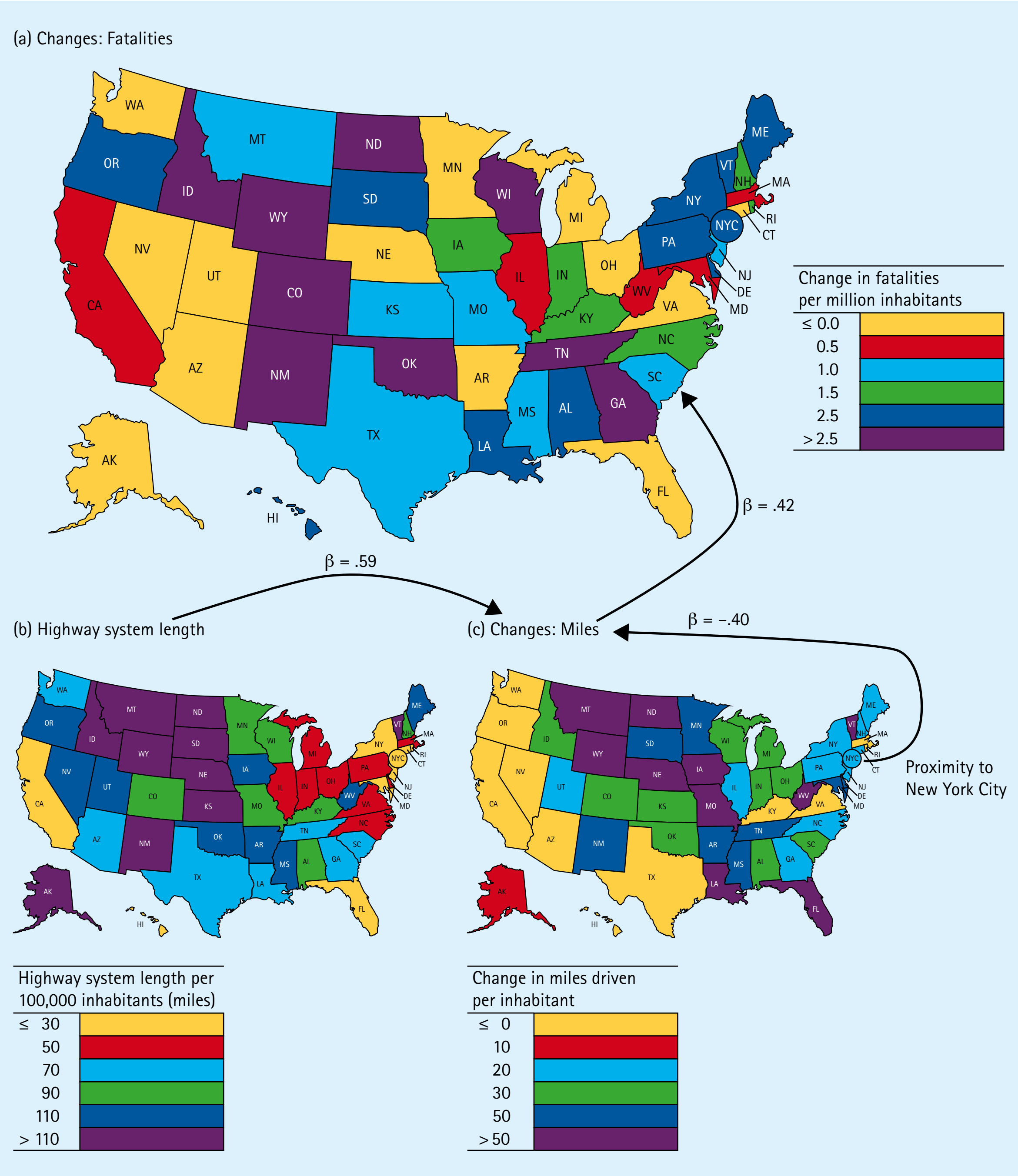


Figure 24. Maps of the United States showing by state (a) the change in driving fatalities in the 3 months subsequent to the 11 September 2001 terrorist attacks, (b) highway system length, and (c) the changes in the number of miles driven in the 3 months subsequent to the attacks. Also shown are results of regression analyses in which highway system length and proximity to New York City were predictors of changes in miles driven, which, in turn, predicted changes in driving fatalities.

Key References

Bodemer, N., Ruggeri, A., & Galesic, M. (2013a). When dread risks are more dreadful than continuous risks: Comparing cumulative population losses over time. *PLoS One*, *8*(6): e66544. doi:10.1371/journal.pone.0066544

Galesic, M., & García-Retamero, R. (2012). The risks we dread: A social circle account. *PLoS One*, *7*(4): e32837. doi:10.1371/journal.pone.0032837

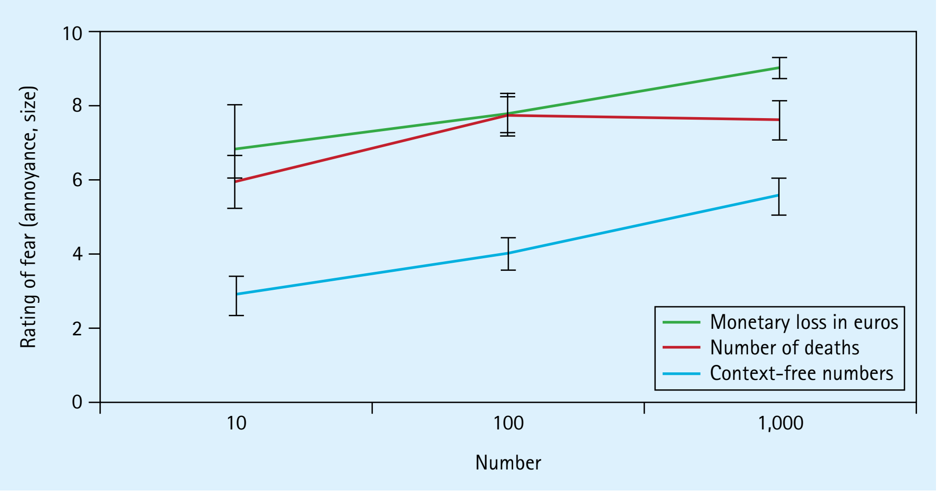


Figure 25. Ratings of fear of risks that kill 10, 100, and 1,000 people (red line), annoyance with losses of 10, 100, and 1,000 euros (green line), and size of numbers 10, 100, and 1,000 (blue line). The ratings of loss of 1,000 euros and size of number 1,000 were larger than the ratings of loss of 100 euros and size of number 100. However, fear of risks killing 1,000 people was not larger than fear of risks killing 100 people. Error bars represent ±1 standard error.

is some variability in the estimated sizes of human groups, past and present, these are in the order of 100 people (estimated sizes are strikingly similar for both Pleistocene groups and modern social circles, such as on Facebook). If (a) dread risk fear originates from a response to the danger that a human group will be wiped out and (b) traces of this fear still exist, then risks that kill 100 people (and thus wipe out the entire social group) should be dreaded more than those that kill 10 people, while risks that kill 1,000 people should not be feared more than those that kill 100 people. This prediction was supported in nine experiments dealing with various dangers, most of which were conducted outside the laboratory with nonstudent participants. As Figure 25 shows, the effect is specific to lives lost and is not observed for money lost, that is, when 10, 100, or 1,000 euros are lost or when no context is specified for the numbers. These results indicate that dread risk fear may indeed have an ecological origin and also stress the importance of considering social environments when studying people's reactions to dangers.

In a study on the adaptive nature of dread risks, Bodemer, Ruggeri, and Galesic (2013) tested the hypothesis that a dread risk may have a stronger negative impact on the cumulative population size over time in comparison with a continuous risk causing the same number of fatalities. This difference should be particularly strong when the risky event affects children and young adults who would have produced future offspring if they had survived longer. The authors conducted a series of simulations with varying assumptions about population size, population growth, age group affected by risky event, and the underlying demographic model. Results confirmed their hypothesis, suggesting that fearing a dread risk more than a continuous risk is an ecologically rational strategy.

Taken together, the three studies on dread risk provide a consistent picture, indicating that (1) dread risks shape our fears and avoidance behavior, which is why an estimated 1,600 people lost their lives on the road by driving rather than flying after 9/11; (2) for dread risk fear to be elicited, the number of fatalities apparently needs to coincide with the typical size of human groups in history; and (3) dread risk appears to have been rational in environments with isolated small groups because the sudden death of a large number of its members is much more detrimental to the survival of the entire group than if the same number of deaths occur over time. These results also highlight the domain-specificity of this emotion and the importance of risk literacy as a general skill in dealing with modern threats such as terrorism. If 9/11 ever repeats itself, terrorists should ideally face a public that does not allow them to exploit this fear.

Simple Heuristics for a Safer World of Finance

The Bank of England Project

The financial system has grown in complexity over recent years. Both the private sector and public authorities have met this complexity with complexity, whether through increasingly elaborate modeling and risk management strategies or ever-lengthening regulatory rulebooks. (The Basel Accords mushroomed from 30 pages in 1998 to 347 pages in Basel II to 616 pages in Basel III.) But this helped neither to predict nor to prevent the current financial crisis. Worse, financial models appeared to show that such a crisis was virtually impossible. In August 2007, when Goldman Sachs' flagship hedge fund lost 27 % of its value from the start of the year, its Chief Financial Officer explained that "we were seeing things that were 25-standard deviation moves, several days in a row." This seems extraordinarily unlucky, considering that many models predict even a 7-standard deviation move happening only once between the Big Bang and now.

In early 2012, Andrew G. Haldane, Bank of England's Executive Director of Financial Stability, and Gerd Gigerenzer met in a meeting arranged by Mervyn King, then-governor of the Bank. The goal was to combine the economic competences of the Bank with the research on simple heuristics at the Institute. This meeting was the first of several, and a research group of four (later five) economists from the Bank regularly visited the Institute in Berlin in 2012, 2013, and 2014 as part of a project titled *Simple Heuristics for a Safer World of Finance*.

What inspired the project was the realization that an alternative is needed to traditional finance theory. Financial models may work well in a world where risks can be reliably measured, but have consistently failed in the increasingly uncertain world since the 1980s. Research on simple heuristics has shown that, with increasing uncertainty, highly parameterized models suffer correspondingly from overfitting and prediction failure, whereas simple heuristics can be more robust and better equipped to deal with it. The key questions addressed are:

(1) Given the failure of complex models (such as value-at-risk) to predict bank failure, can simple heuristics make better predictions? And if so, under what conditions (such as bank size)?
(2) Given the failure of regulatory measures, what set of simple heuristics could help to create a safer world of finance?

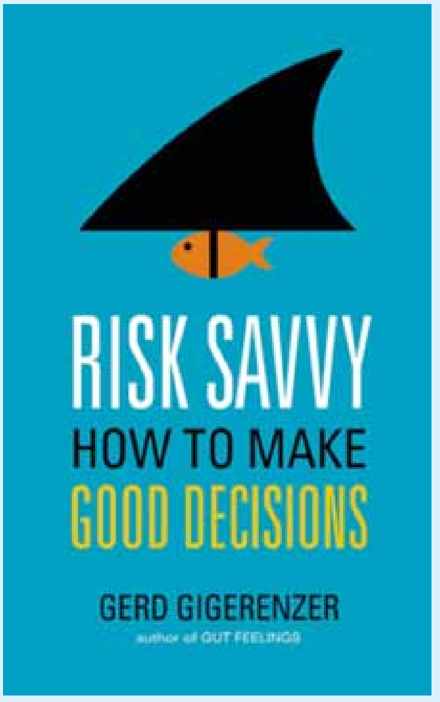
One of the heuristics investigated was a simple, unweighted leverage ratio (the ratio between debt and capital). After the first results of our joint investigation were in, Haldane decided to change the topic of his 2012 Jackson Hole lecture at the annual meeting of the central banks in the United States. In his talk *The Dog and the Frisbee*, he argued that the way complex problems are solved by simple heuristics (e. g., the gaze heuristic used by dogs to catch Frisbees and by outfielders to catch baseballs) could serve as a model of a new approach to bank regulation. He noted that the general conditions for the ecological rationality of heuristics relative to complex models include (a) a large number of parameters to estimate, (b) relatively small samples of data, and (c) an instable or unpredictable world. Consistent with these principles, an analysis of simple leverage ratios for the major global banks in 2006 was better than an analysis of risk-based capital ratios at distinguishing between distressed and nondistressed banks. Across the banking book, a large bank may have to estimate some 1,000 default probabilities and other parameters, and the number of parameters set for the trading book can be even larger. Estimating the covariance matrix for each of these risk factors entails estimating millions of individual risk parameters. It follows that in small, simply structured banks—for instance, FDIC-insured (Federal Deposit Insurance

Key Reference

Haldane, A. G. (2012). *The dog and the Frisbee.* Speech, Jackson Hole, August 31, 2012. http://www.bankofengland.co.uk/publications/Pages/speeches/2012/596.aspx

Key Reference

Aikman, D., **Galesic, M., Gigerenzer, G.,** Kapadia, S., **Katsikopoulos, K. V., Kothiyal, A.,** Murphy, E., & Neumann T. (2013). Taking uncertainty seriously: Simplicity versus complexity in financial regulation. *Financial Stability Papers,* Bank of England.



Remember the volcanic ash cloud? The subprime disaster? How about mad cow disease? Each new crisis makes us worry until we forget and start worrying about the next one. When something goes wrong, we are told that the way to prevent further crises is better technology, more laws, and more bureaucracy. How can we protect ourselves from the threat of terrorism? Homeland security, full body scanners, further sacrifice of individual freedom. How can we counteract exploding costs in health care? Tax increases, rationalization, better genetic markers.

One idea is absent from these lists: risk-savvy citizens. And there is a reason. Behavioral economists as well as many psychologists argue that people are predictably irrational and may never learn to deal with risks due to their cognitive illusions. The political consequence proposed is paternalism, soft or hard. Based on the experimental evidence accumulated by the ABC Research Group and colleagues around the world, this book takes a different perspective: First, *everyone can learn to deal with risk and uncertainty.* This book explains principles that are easily understood by everyone who dares to know. Second, *experts are part of the problem rather than the solution.* Many experts themselves struggle with understanding risks, lack skills in communicating them, and pursue interests not aligned with yours. Giant banks go bust for exactly these reasons. Little is gained when risk-illiterate authorities are placed in charge of guiding the public. Third, *less-is-more.* When we face a complex problem, we look for a complex solution. And when it doesn't work, we seek an even more complex one. In an uncertain world, this is mistake. Complex problems do not always require complex solutions. Overly complicated systems, from financial derivatives to tax systems, are difficult to comprehend, easy to exploit, and possibly dangerous. And they do not increase the trust of the people. Simple rules, in contrast, can make us smart and create a safer world.

Box 4.

Corporation) banks in the United States—the complex models may pay (which the second result of our project confirmed). Haldane's talk was named *Speech of the Year* by *The Wall Street Journal.*

Since then, a number of further studies have been conducted on both questions, and the results were jointly published in the Bank of England Financial Regulation Series. Financial systems are much better characterized by uncertainty than by risk. As such, conventional methods for modeling and regulating financial systems may be flawed when the complexity is high. In these situations, simple approaches can dominate more complex ones—"less can be more." This is borne out by both simulations of capital requirements against potential losses and the empirical evidence on individual bank failures during the most recent financial crisis.

The specific results are important, but equally important is to increase awareness of an alternative to traditional finance theory, in the form of studying the ecological rationality of simple heuristics. To the many who consider heuristics to be approximations to optimal solutions, it is not yet clear that in an uncertain world, where optimization is unfeasible, heuristics may be the best strategy. As a sign of an emerging change in thinking, the term simplicity has now entered the language of bank regulation. On 8 July 2013, for instance, the Basel Committee on Banking Supervision released a press release in which "balancing risk sensitivity, simplicity and comparability" were referred to in the title. There is also a Task Force on Simplicity and Comparability, whose goal is to eliminate undue complexity from the regulatory framework.

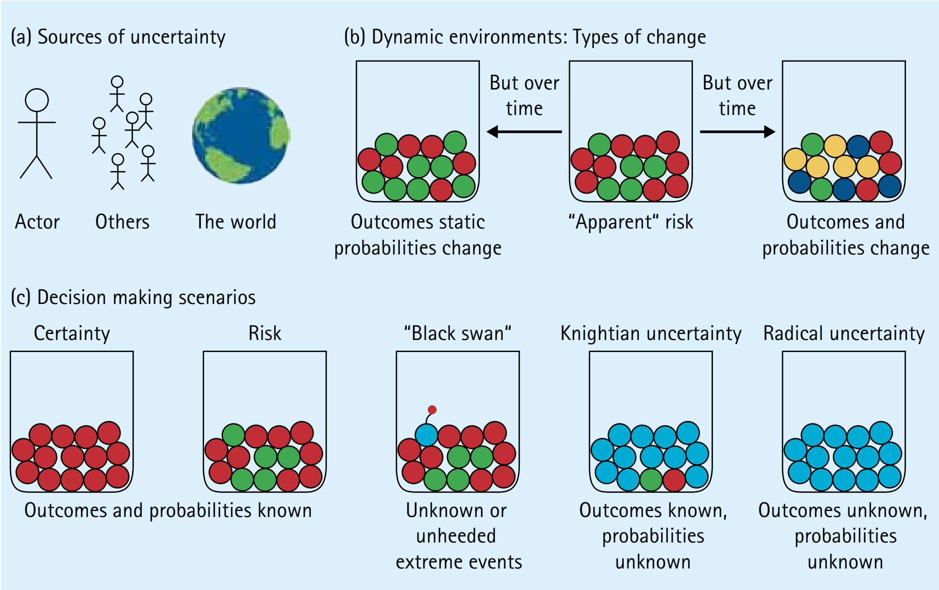


Figure 26. Uncertainty in its various guises. Illustrating sources of uncertainty and situations of decision making under uncertainty using an urn model. (a) Uncertainty can reside in the mind of the boundedly rational agent. Uncertainty can also result from the decisions and influences from other agents and from genuine randomness in the external environment (i.e., the data-generating process). (b) Examples of dynamic environments that involve changes in the decision-making situation over time. Left: The proportion of balls changes in unpredictable (or unknown) ways over time, therefore probability estimates at t1 are of little use at t2. Right: The outcomes themselves change over time, requiring a reformulation of the decision situation. (c) Examples of decision-making scenarios. From left to right: In situations of certainty and risk the outcomes and their probabilities are known. In a "black swan" situation, the urn contains a rare but highly consequential event ("bomb" or, in the case of a positive event, a "diamond"), which is either unknown to the decision maker or ignored in the representation of the decision situation. In a situation of "Knightian uncertainty," only the outcomes are known, but their probabilities. The right-most situation example is of radical uncertainty, in which both outcomes and their probabilities are unknown.

Key Reference

Meder, B., Le Lec, F., & Osman, M. (2013). Decision making in uncertain times: What can cognitive and decision sciences say about or learn from economic crises? *Trends in Cognitive Sciences, 17,* 257–260. doi:10.1016/j.tics.2013.04.008

Understanding the Shades of Uncertainty

In order to develop tools that lead to a safer world of finance, understanding the distinction between measurable risk and uncertainty is essential. Uncertainty refers to situations in which risks cannot be reliably measured or where the full range of alternatives and consequences is not known in the first place. Probability theory is the proper tool for known risks, and heuristics are tools for uncertainty.

Yet some economists attribute blame to people rather than to models. A popular assumption is that economic models need to be remolded to factor in people's apparent irrationality, their "animal spirits" or "cognitive biases." Yet the problem is that these models are not fit to accommodate uncertainty in the first place. Meder, Le Lec, and Osman (2013) argue that a critical analysis of existing models remains incomplete without a better characterization of the many forms of uncertainty with which people have to cope. For instance, high-stake decisions, such as whether to bail out banks, highlight the ubiquity of situations in which decisions need to be made in the absence of an objective basis for calculating probabilities of success.

The conceptual difference between situations in which probabilities and outcome values are known (or estimated from data) and those in which they are not was already emphasized in the seminal work of Frank Knight, who first referred to them as situations of risk versus uncertainty. Since then, however, little progress has been made in developing a more fine-grained taxonomy of uncertainty. Meder and colleagues propose such a categorization (Figure 26) and argue that, if the goal is to explain how decisions should be made,

Key References

Bennis, W. M., **Katsikopoulos, K. V.,** Goldstein, D. G., Dieckmann, A., & Berg, N. (2012). Designed to fit minds: Institutions and ecological rationality. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality* (pp. 409–427). New York: Oxford University Press.

Gilovich, T., Vallone, R., & Tversky, A. (1985). The hot hand in basketball: On the misperception of random sequences. *Cognitive Psychology, 17,* 295–314.

Raab, M., Gula, B., & **Gigerenzer, G.** (2012). The hot hand exists in volleyball and is used for allocation decisions. *Journal of Experimental Psychology, 18,* 81–94. doi:10.1037/a0025951

what is needed is a better understanding of uncertainty in its various (dis)guises. At the Cognitive Science Conference 2013 in Sapporo, they organized a workshop on the role of uncertainty in financial crises, which drew much attention.

Does the Hot Hand Exist?

The "hot hand" belief in sports refers to the conviction that a player has a higher chance of making a shot after two or three successful shots than after two or three misses (resulting in "streaks"). Beginning with a landmark article by Gilovich, Vallone, and Tversky (1985) on basketball, this belief has been usually considered a cognitive fallacy because the actual statistics do not show the effect. A key contention is that in basketball the defense will attack a "hot" player and thus prevent streaks from occurring. To address this argument, Raab, Gula, and Gigerenzer (2012) conducted the first study on the hot hand in volleyball, where the net limits direct defensive counterstrategies, meaning that streaks are more likely to emerge if a player is hot. The study addressed three questions. First, do athletes and coaches believe in a hot hand in volleyball? The answer was strongly affirmative: 91 % of 115 athletes and 92 % of 16 coaches believed in the hot hand. Second, and most critically, does the hot hand exist in volleyball? The answer was again yes: Depending on the criterion used, 53 % of the top 26 German first-division players showed significant streaks and 46 % showed significant autocorrelations. Finally, is the hot hand belief used to inform allocation decisions? Once more, the answer was yes. The experiments and systematic observations indicated an adaptive use of the hot hand belief: Playmakers allocate the ball more often to players with streaks, which leads to better performance than when allocating the ball to the player with the higher average base rate. Moreover, the study showed that coaches are able to detect players' performance variability and use it to make strategic decisions. In volleyball, the hot hand exists, coaches and playmakers are able to detect it, and playmakers tend to use it "adaptively," resulting in more hits for a team.

Las Vegas and Slot Machines: The Illusion of Winning Is Not All in the Players' Heads

In 2007, Americans spent $ 34 billion gambling in commercial casinos, considerably more than the $ 600 million spent on going to the movies. To make a profit, gambling institutions are designed so that the average gambler loses money. Because gamblers can expect to lose, the fact that so many people, who are otherwise risk averse, nonetheless gamble is perplexing. A number of psychologists and economists have proposed a variety of internal causes as an explanation, from people's failure to understand probabilities to motivational illusions such as overconfidence. Yet there is another way to explain this behavior, an ecological one. False beliefs may in fact be caused by the intentional design of the external environment, not simply by internal shortcomings.

To explore this hypothesis, Bennis, Katsikopoulos, Goldstein, Dieckmann, and Berg (2012) analyzed the design of Las Vegas resort casinos. They show in detail how the casino environment is carefully designed to encourage gamblers' falsely optimistic beliefs about the probability of winning. These casino resorts have one or more floors of hundreds, sometimes thousands, of slot machines that are arranged back to back. The first type of illusory information is acoustic, delivered for instance by machines that greatly amplify the clanking of coins that drop several inches onto a metal tray in order to signal wins. When winners do not immediately collect their tokens, wins are accompanied by music at an escalating volume; the amplified sound of growing credits often accrues at a faster pace than the credits themselves, adding to the perception that players have won more than they actually have. Second, visual cues such as siren lights on top of the slot machines spin and flash whenever a major jackpot has been hit. Larger jackpots are paid by hand, and attendants are instructed to walk slowly toward the winner to extend the waiting time so that on busy nights many sirens can be simultaneously seen and heard.

A third and most deceptive trick has become possible with the advent of the electronic slot machine. Whereas the symbols (e.g., a red seven) on the interior reels of the old mechanical machines reflected what gamblers saw on the outside window, such a one-to-one correspondence no longer exists. If, for instance, the largest jackpot requires three red sevens, the gambler may see two red sevens and the foot of the third seven just one slot above the window, suggesting a near miss, even though there may not have actually been one. By inflating the number of near misses, the outside representation creates a false perception of their actual frequency. Given that these tricks are unknown to most gamblers, no cognitive illusions are needed to explain why players overestimate the probabilities of winning. The environment provides an explanation for gambling behavior that is often overlooked in theories that search for causes inside the mind. In the casino, the illusion of winning is real; it is part of the design of the environment.

Publications 2011–2013

(last update: January 2014)

Aikman, D., **Galesic, M., Gigerenzer, G.,** Kapadia, S., **Katsikopoulos, K. V., Kothiyal, A.,** Murphy, E., & Neumann T. (2013). Taking uncertainty seriously: Simplicity versus complexity in financial regulation. *Financial Stability Papers,* Bank of England.

Anderson, B. L., **Gigerenzer, G.,** Parker, S., & Schulkin, J. (in press). Statistical literacy in obstetricians and gynecologists. *Journal of Healthcare Quality.* Advance online publication. doi:10.1111/j.1945-1474.2011.00194.x

Arkes, H. R., & **Gaissmaier, W.** (2012). Psychological research and the prostate-cancer screening controversy. *Psychological Science, 23,* 547–553. doi:10.1177/0956797612437428

Artinger, F., Fleischhut, N., Levati, V., & **Stevens, J. R.** (2012). Cooperation in risky environments: Decisions from experience in a stochastic social dilemma. In N. Miyake, D. Peebles, & R. P. Cooper (Eds.), *Building bridges across cognitive sciences around the world: Proceedings of the 34th Annual Conference of the Cognitive Science Society* (pp. 84–89). Austin, TX: Cognitive Science Society.

Avugos, S., Köppen, J., **Czienskowski, U.,** Raab, M., & Bar-Eli, M. (2013). The "hot hand" reconsidered: A meta-analytic approach. *Psychology of Sport and Exercise, 14,* 21–27. doi:10.1016/j.psychsport.2012.07.005

Balatel, A., Boero, R., Jonaityte, I., **Monti, M.,** Novarese, M., & Pacelli, V. (2013). *Beyond the MiFID: Envisioning cognitively suitable and representationally supportive approaches to assessing investment preferences for more informed financial decisions* (CAREFIN Working Paper, 2013-07-29). Milan: Università Commerciale Luigi Bocconi.

Barkoczi, D., & **Galesic, M.** (2013). Social learning in complex networks: The role of building blocks and environmental change. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 1821–1826). Austin, TX: Cognitive Science Society.

Baucells, M., & **Katsikopoulos, K. V.** (2011). Descriptive models of decision making. In J. J. Cochran (Ed.), *Wiley encyclopedia of operations research and management science* (Vol. 2, pp. 1286–1301). Hoboken, NJ: Wiley.

Beier, H. M., Van den Daele, W., Diedrich, K., Dudenhausen, J. W., Felberbaum, R., **Gigerenzer, G.,** ... Te Velde, E. (2012). Medizinische und biologische Aspekte der Fertilität. In G. Stock, H. Bertram, A. Fürnkranz-Prskawetz, W. Holzgreve, M. Kohli, & U. M. Staudinger (Eds.), *Zukunft mit Kindern: Fertilität und gesellschaftliche Entwicklung in Deutschland, Österreich und der Schweiz* (pp. 294–390). Frankfurt a. M.: Campus.

Bennis, W. M., **Katsikopoulos, K. V.,** Goldstein, D. G., Dieckmann, A., & Berg, N. (2012). Designed to fit minds: Institutions and ecological rationality. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 409–427). New York: Oxford University Press.

Betsch, C., Brewer, N. T., Brocard, P., Davies, P., **Gaissmaier, W.,** Haase, N., ... Stryk, M. (2012). Opportunities and challenges of Web 2.0 for vaccination decisions. *Vaccine, 30,* 3727–3733. doi:10.1016/j.vaccine.2012.02.025

Biele, G., Rieskamp, J., Krugel, L. K., & **Heekeren, H. R.** (2011). The neural basis of following advice. *PLoS Biology, 9*(6): e1001089. doi:10.1371/journal.pbio.1001089

Bleichrodt, H., **Kothiyal, A.,** Prelec, D., & Wakker, P. P. (2013). Compound invariance implies prospect theory for simple prospects. *Journal of Mathematical Psychology, 57,* 68–77. doi:10.1016/j.jmp.2013.04.002

Bodemer, N., & **Gaissmaier, W.** (2012). Risk communication in health. In S. Roeser, R. Hillerbrand, P. Sandin, & M. Peterson (Eds.), *Handbook of risk theory: Epistemology, decision theory, ethics, and social implications of risk* (Vol. 2, pp. 621–660). Dordrecht: Springer. doi:10.1007/978-94-007-1433-5_24

Bodemer, N., Müller, S. M., Okan, Y., **García-Retamero, R.,** & Neumeyer-Gromen, A. (2012). Do the media provide transparent health information? A cross-cultural comparison of public information about the HPV vaccine. *Vaccine, 30,* 3747–3756. doi:10.1016/j.vaccine.2012.03.005

Bodemer, N., & **Ruggeri, A.** (2012). Finding a good research question, in theory. *Science, 335*(6075), 1439.

Bodemer, N., Ruggeri, A., & **Galesic, M.** (2013a). When dread risks are more dreadful than continuous risks: Comparing cumulative population losses over time. *PLoS ONE, 8*(6): e66544. doi:10.1371/journal.pone.0066544

Bodemer, N., Ruggeri, A., & **Galesic, M.** (2013b). Why 100 once is worse than 10 times 10: Dread risks versus "continuous" risks. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 1923–1927). Austin, TX: Cognitive Science Society.

Bosnjak, M., Haas, I., **Galesic, M.,** Kaczmirek, L., Bandilla, W., & Couper, M. P. (2013). Sample composition discrepancies in different stages of a probability-based online panel. *Field Methods, 25,* 339–360. doi:10.1177/1525822X12472951

Brighton, H. (2013). Die Zukunft der Diagnostik: Von Optimierung zu "Satisficing." In G. Gigerenzer & J. A. Muir Gray (Eds.), *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen* (Strüngmann Forum Reports) (pp. 289–302). Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft.

Brighton, H. (2011). The future of diagnostics: From optimizing to satisficing. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning health care 2020* (pp. 281–293). Cambridge, MA: MIT Press.

Brighton, H., & **Gigerenzer, G.** (2012a). Are rational actor models "rational" outside small worlds? In K. Binmore & S. Okasha (Eds.), *Evolution and rationality: Decisions, co-operation and strategic behaviour* (pp. 84–109). Cambridge, UK: Cambridge University Press.

Brighton, H., & **Gigerenzer, G.** (2012b). Homo heuristicus and the bias-variance dilemma. In J. Schulkin (Ed.), *Action, perception and the brain: Adaptation and cephalic expression* (pp. 68–91). Basingstoke: Palgrave Macmillan.

Brighton, H., & **Gigerenzer, G.** (2012c). Homo heuristicus: Less-is-more effects in adaptive cognition. *Malaysian Journal of Medical Sciences, 19,* 6–17.

Brighton, H., & **Gigerenzer, G.** (2012d). How heuristics handle uncertainty. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 33–60). New York: Oxford University Press.

Brighton, H., & Selina, H. (2012). *Introducing artificial* *intelligence: A graphic guide.* Cambridge, UK: Icon Books.

Brighton, H., & **Gigerenzer, G.** (2011). Towards competitive instead of biased testing of heuristics: A reply to Hilbig & Richter (2011). *Topics in Cognitive Science, 3,* 197–205. doi:10.1111/j.1756-8765.2010.01124.x

Brugman, D., **Keller, M.,** & Sokol, B. (2013). Meaning, measurement, and correlates of moral development: Introduction. *European Journal of Developmental Psychology, 10,* 99–105. doi:10.1080/17405629.2013.769368

Chater, N., Fiedler, K., **Gigerenzer, G.,** Klauer, K. C., Oaksford, M., & Stenning, K. (2013). New frameworks of rationality. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 59–60). Austin, TX: Cognitive Science Society.

Cokely, E. T., & **Feltz, A.** (in press). Expert intuition. In L. M. Osbeck & B. S. Held (Eds.), *Rational intuition: Philosophical roots, scientific investigations.* Cambridge, UK: Cambridge University Press.

Cokely, E. T., & **Feltz, A.** (2011). Virtue in business: Morally better, praiseworthy, trustworthy, and more satisfying. *Journal of Organizational Moral Psychology, 2,* 13–26.

Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., & **García-Retamero, R.** (2012). Measuring risk literacy: The Berlin Numeracy Test. *Judgment and Decision Making, 7,* 25–47.

Cokely, E. T., Ghazal, S., **Galesic, M., García-Retamero, R.,** & Schulz, E. (2013). How to measure risk comprehension in educated samples. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 29–52). New York: Springer.

Cokely, E. T., Ghazal, S., & **García-Retamero, R.** (in press). Measuring numeracy. In B. L. Anderson & J. Schulkin (Eds.), *Numerical reasoning in judgments and decision making about health.* Cambridge, UK: Cambridge University Press.

Degond, P., Appert-Rolland, C., **Moussaïd, M.,** Pettré, J., & Theraulaz, G. (2013). A hierarchy of heuristic-based models of crowd dynamics. *Journal of Statistical Physics, 152,* 1033-1068. doi:10.1007/s10955-013-0805-x

Dimov, C. M., **Marewski, J. N.,** & **Schooler, L. J.** (2013). Constraining ACT-R models of decision strategies: An experimental paradigm. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 2201–2206). Austin, TX: Cognitive Science Society.

Drechsler, M., **Katsikopoulos, K. V.,** & **Gigerenzer, G.** (in press). Axiomatizing bounded rationality: The priority heuristic. *Theory and Decision.* Advance online publication. doi:10.1007/s11238-013-9393-0

Durand, M.-A., **Wegwarth, O.,** Boivin, J., & Elwyn, G. (2012). Design and usability of heuristic-based deliberation tools for women facing amniocentesis. *Health Expectations, 15,* 32–48. doi:10.1111/j.1369-7625.2010.00651.x

Edele, A., Dziobek, I., & **Keller, M.** (2013). Explaining altruistic sharing in the dictator game: The role of affective empathy, cognitive empathy, and justice sensitivity. *Learning and Individual Differences, 24,* 96–102. doi:10.1016/j.lindif.2012.12.020

Feest, U. (in press-a). The enduring relevance of 19th-century philosophy of psychology: Brentano and the autonomy of psychology. In T. Uebel (Ed.), *Proceedings of Conference Philosophy of Science in a European Perspective.* Dordrecht: Springer.

Feest, U. (in press-b). Phenomenal experiences, first-person methods, and the artificiality of experimental data. *Philosophy of Science.*

Feest, U. (in press-c). Quantifying gestalt qualities: Modernism and the measurement of experience. In M. Epple & F. Müller (Eds.), *Modernism in the sciences.* Berlin: Akademie-Verlag.

Feltz, A., & **Cokely, E. T.** (2013a). Predicting philosophical disagreement. *Philosophy Compass, 8,* 978–989. doi:10.1111/phc3.12076

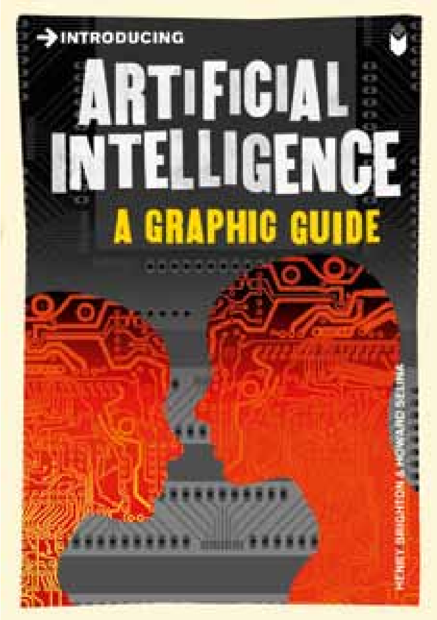
Feltz, A., & **Cokely, E. T.** (2013b). Virtue or consequences: The folk against pure evaluational internalism. *Philosophical Psychology, 26,* 702–717. doi:10.1080/09515089.2012.692903

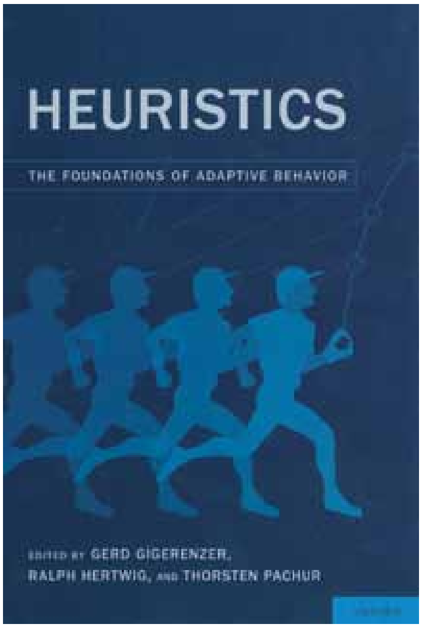
Feltz, A., & **Cokely, E. T.** (2013c). The virtues of ignorance. *The Review of Philosophy and Psychology, 3,* 335–350. doi:10.1007/s13164-012-0107-2

Feltz, A., & **Cokely, E. T.** (2012). The philosophical personality argument. *Philosophical Studies, 161,* 227–246. doi:10.1007/s11098-011-9731-4

Feltz, A., & **Cokely, E. T.** (2011). Individual differences in theory-of-mind judgements: Order effects and side effects. *Philosophical Psychology, 24,* 343–355. doi:10.1080/09515089.2011.556611

Feufel, M. A. (2013). Ein kurzer "Knigge" über den Umgang mit Risiken und Unsicherheit.





Gynäkologische Praxis, 37, 519–529.

Feufel, M. A., Antes, G., Steurer, J., **Gigerenzer, G.,** Muir Gray, J. A., Mäkelä, M., ... Wild, C. (2013). Wie verbessern wir die Gesundheitsversorgung: Durch bessere Systeme, bessere Patienten oder beides? In G. Gigerenzer & J. A. Muir Gray (Eds.), *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen* (Strüngmann Forum Reports) (pp. 117–134). Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft.

Feufel, M. A., Antes, G., Steurer, J., **Gigerenzer, G.,** Muir Gray, J. A., Mäkelä, M., ... Wild, C. (2011). What is needed for better health care: Better systems, better patients or both? In G. Gigerenzer & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning health care 2020* (pp. 117–134). Cambridge, MA: MIT Press.

Feufel, M. A., Robinson, F. E., & Shalin, V. L. (2011). The impact of medical record technologies on collaboration in emergency medicine. *International Journal of Medical Informatics, 80,* e85–e95. doi:10.1016/j.ijmedinf.2010.09.008

Feufel, M. A., & Stahl, S. F. (2012). What do web-use skill differences imply for online health information searches? *Journal of Medical Internet Research, 14,* 321–331. doi:10.2196/jmir.2051

Feufel, M. A., Stahl, S. F., & Lee, S.-Y. (2012). Was Hänschen nicht googelt, findet Hans nimmermehr? Online-Suche im Vergleich der Generationen (Age of Access? Grundfragen der Informationsgesellschaft No. 2). In K. Marx & M. Schwarz-Friesel (Eds.), *Sprache und Kommunikation im technischen Zeitalter: Wieviel Internet (v)erträgt unsere Gesellschaft?* (pp. 166–185). Berlin: de Gruyter.

Fific, M., & Buckmann, M. (2013). Stopping Rule Selection (SRS) theory applied to deferred decision making. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 2273–2278). Austin, TX: Cognitive Science Society.

Fific, M., & **Gigerenzer, G.** (in press). Are two interviewers better than one? *Journal of Business Research.*

Filimon, F., Philiastides, M. G., **Nelson, J. D.,** Kloosterman, N. A., & Heekeren, H. R. (2013). How embodied is perceptual decision making? Evidence for separate processing of perceptual and motor decisions. *The Journal of Neuroscience, 33,* 2121–2136. doi:10.1523/JNEUROSCI.2334-12.2013

Fleischhut, N., & **Gigerenzer, G.** (2013a). Can simple heuristics explain moral inconsistencies? In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 459–485). New York: Oxford University Press.

Fleischhut, N., & **Gigerenzer, G.** (2013b). Psychologie der Erkenntnis und Rationalität. In T. Bonk (Ed.), *Lexikon der Erkenntnistheorie* (pp. 203–209). Darmstadt: WBG.

Gaissmaier, W. (2012). Warum Patienten ein Recht auf verständliche Informationen haben. *Bauchredner, 108,* 85–89.

Gaissmaier, W. (2011a). Die Evidenz transparent machen. *Das Österreichische Gesundheitswesen, 52,* 13–15.

Gaissmaier, W. (2011b). Risk communication: Why we need understandable information. *Way Ahead, 15,* 10–12.

Gaissmaier, W., Anderson, B. L., & Schulkin, J. (in press). How do physicians provide statistical information about antidepressants to hypothetical patients? *Medical Decision Making.* Advance online publication. doi:10.1177/0272989X13501720

Gaissmaier, W., Fific, M., & Rieskamp, J. (2011). Analyzing response times to understand decision processes. In M. Schulte-Mecklenbeck, A. Kühberger, & R. Ranyard (Eds.), *A handbook of process tracing methods for decision research: A critical review and user's guide* (pp. 141–162). New York: Psychology Press.

Gaissmaier, W., & **Gigerenzer, G.** (2013). Wenn fehlinformierte Patienten versuchen, informierte Gesundheitsentscheidungen zu treffen. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen* (Strüngmann Forum Reports) (pp. 29–44). Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft.

Gaissmaier, W., & **Gigerenzer, G.** (2012). 9/11, Act II: A fine-grained analysis of regional variations in traffic fatalities in the aftermath of the terrorist attacks. *Psychological Science, 23,* 1449–1454. doi:10.1177/0956797612447804

Gaissmaier, W., & **Gigerenzer, G.** (2011). When misinformed patients try to make informed health decisions. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning healthcare 2020* (pp. 29–43). Cambridge, MA: MIT Press.

Gaissmaier, W., & **Marewski, J. N.** (2011). Forecasting elections with mere recognition from small, lousy samples: A comparison of collective recognition, wisdom of crowds, and representative polls. *Judgment and Decision Making, 6,* 73–88.

Gaissmaier, W., Wegwarth, O., Skopec, D., Müller, A.-S., Broschinski, S., & Politi, M. C. (2012). Numbers can be worth a thousand pictures: Individual differences in understanding graphical and numerical representations of health-related information. *Health Psychology, 31,* 286–296. doi:10.1037/a0024850

Galesic, M., & **García-Retamero, R.** (2013a). Communicating information about preventive medical treatments and screenings. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 99–118). New York: Springer.

Galesic, M., & **García-Retamero, R.** (2013b). Graph literacy for health. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 53–65). New York: Springer.

Galesic, M., & **García-Retamero, R.** (2013c). Helping people memorize consequences of risky behaviors. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 119–129). New York: Springer.

Galesic, M., & **García-Retamero, R.** (2013d). Introduction: Transparent communication in a globalized world. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 1–12). New York: Springer.

Galesic, M., & **García-Retamero, R.** (2013e). On the effect of individual differences on shared decision making. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 215–225). New York: Springer.

Galesic, M., & **García-Retamero, R.** (2013f). Using analogies to communicate information about health risks. *Applied Cognitive Psychology, 27,* 33–42. doi:10.1002/acp.2866

Galesic, M., & **García-Retamero, R.** (2012). The risks we dread: A social circle account. *PLoS ONE, 7*(4): e32837. doi:10.1371/journal.pone.0032837

Galesic, M., & **García-Retamero, R.** (2011a). Communicating consequences of risky behaviors: Life expectancy versus risk of disease. *Patient Education and Counseling,* *82*, 30–35. doi:10.1016/j.pec.2010.02.008

Galesic, M., & **García-Retamero, R.** (2011b). Do low-numeracy people avoid shared decision making? *Health Psychology, 30,* 336–341. doi:10.1037/a0022723

Galesic, M., & **García-Retamero, R.** (2011c). Graph literacy: A cross-cultural comparison. *Medical Decision Making, 31*, 444–457. doi:10.1177/0272989X10373805

Galesic, M., Olsson, H., & Rieskamp, J. (2013). False consensus about false consensus. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 472–476). Austin, TX: Cognitive Science Society.

Galesic, M., Olsson, H., & Rieskamp, J. (2012). Social sampling explains apparent biases in judgments of social environments. *Psychological Science, 23,* 1515–1523. doi:10.1177/0956797612445313

Galesic, M., & Yan, T. (2011). Use of eye tracking for studying survey response processes. In M. Das, P. Ester, & L. Kaczmirek (Eds.), *Social and behavioral research and the internet: Advances in applied methods and research strategies* (pp. 349–370). New York: Routledge.

García-Retamero, R., & **Cokely, E. T.** (in press-a). The influence of skills, message frame, and visual aids on prevention of sexually transmitted diseases. *Journal of Behavioral Decision Making.* Advance online publication. doi:10.1002/bdm.1797

García-Retamero, R., & **Cokely, E. T.** (in press-b). Simple but powerful health messages for increasing condom use in young adults. *Journal of Sex Research.* Advance online publication. doi:10.1080/00224499.2013.806647

García-Retamero, R., & **Cokely, E. T.** (in press-c). Using visual aids to help people with low numeracy make better decisions. In B. L. Anderson & J. Schulkin (Eds.), *Numerical reasoning in judgments and decision making about health.* Cambridge, UK: Cambridge University Press.

García-Retamero, R., & **Cokely, E. T.** (2013). Communicating health risks with visual aids. *Current Directions in Psychological Science, 22*, 392–399. doi:10.1177/0963721413491570

García-Retamero, R., & **Cokely, E. T.** (2012). Advances in efficient health communication: Promoting prevention and detection of STDs. *Current HIV Research, 10,* 262–270.

García-Retamero, R., & **Cokely, E. T.** (2011). Effective communication of risks to young adults: Using message framing and visual aids to increase condom use and STD screening. *Journal of Experimental Psychology: Applied, 17,* 270–287. doi:10.1037/a0023677

García-Retamero, R., Cokely, E. T., & **Galesic, M.** (2013). Reducing the effect of framed messages about health. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 165–191). New York: Springer.

García-Retamero, R., & Dhami, M. K. (2013). On avoiding framing effects in experienced decision makers. *The Quarterly Journal of Experimental Psychology, 66, 829–842.* doi:10.1080/17470218.2012.727836

García-Retamero, R., & Dhami, M. K. (2011). Pictures speak louder than numbers: On communicating medical risks to immigrants with limited non-native language proficiency. *Health Expectations, 14* (Suppl.1), 46–57. doi:10.1111/j.1369-7625.2011.00670.x

García-Retamero, R., & **Galesic, M.** (in press). On defensive decision making: How doctors make decisions for their patients. *Health Expectations.* Advance online publication. doi:10.1111/j.1369-7625.2012.00791.x

García-Retamero, R., & **Galesic, M.** (2013a). Appendix: Numeracy and graph literacy scales. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 239–264). New York: Springer.

García-Retamero, R., & **Galesic, M.** (2013b). Does young adults' preferred role in decision making about health, money, and career depend on their advisors' leadership skills? *International Journal of Psychology, 48*, 492–501. doi:10.1080/00207594.2012.688135

García-Retamero, R., & **Galesic, M.** (2013c). Guidelines for transparent communication in a globalized world. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 229–238). New York: Springer.

García-Retamero, R., & **Galesic, M.** (2013d). Improving the understanding of treatment risk reduction. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 131–144). New York: Springer.

García-Retamero, R., & **Galesic, M.** (Eds.). (2013e). *Transparent communication of health risks: Overcoming cultural differences.* New York: Springer.

García-Retamero, R., & **Galesic, M.** (2012). Doc, what would you do if you were me? On self-other discrepancies in medical decision making. *Journal of Experimental Psychology: Applied, 18*, 38–51. doi:10.1037/a0026018

García-Retamero, R., & **Galesic, M.** (2011). Using plausible group sizes to communicate information about medical risks. *Patient Education and Counseling, 84,* 245-250. doi:10.1016/j.pec.2010.07.027

García-Retamero, R., Galesic, M., & Dhami, M. K. (2013). Reducing denominator neglect. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 145–164). New York: Springer.

García-Retamero, R., Galesic, M., & **Gigerenzer, G.** (2011a). Cómo favorecer la comprensión y la comunicación de los riesgos sobre la salud [Improving comprehension and communication of risks about health]. *Psicothema, 23*, 599–605.

García-Retamero, R., Galesic, M., & **Gigerenzer, G.** (2011b). Enhancing understanding and recall of quantitative information about medical risks: A cross-cultural comparison between Germany and Spain. *The Spanish Journal of Psychology, 14,* 218–226. doi:10.5209/rev_SJOP.2011.v14.n1.19

García-Retamero, R., Müller, S. M., & López-Zafra, E. (2011). The malleability of gender stereotypes: Influence of population size on perceptions of men and women in the past, present, and future. *The Journal of Social Psychology, 151,* 635–656. doi:10.1080/00224545.2010.522616

García-Retamero, R., Okan, Y., & **Cokely, E. T.** (2012). Using visual aids to improve communication of risks about health: A review. *The Scientific World Journal, 2012:* 562637. doi:10.1100/2012/562637

García-Retamero, R., Takezawa, M., Woike, J. K., & **Gigerenzer, G.** (2013). Social learning: A route to good cue orders. In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 343–353). New York: Oxford University Press.

García-Retamero, R., Wicki, B., **Cokely, E. T.,** & Hanson, B. (in press). Factors predicting surgeons' preferred and actual roles in interactions with their patients. *Health Psychology.*

Ghazal, S., **Cokely, E. T.,** & **García-Retamero, R.** (in press). Predicting biases in very highly educated samples: Numeracy and metacognition. *Judgment and Decision Making.*

Gigerenzer, G. (in press-a). How I got started teaching physicians and judges risk literacy. *Applied Cognitive Psychology.* Advance online publication. doi:10.1002/acp.2980

Gigerenzer, G. (in press-b). *Risk savvy: How to make good decisions.* New York: Viking.

Gigerenzer, G. (2013a). Entscheiden unter Unsicherheit. In M. A. Wirtz & J. Strohmer (Eds.), *Dorsch Lexikon der Psychologie* (16th compl. rev. ed., pp. 457–458). Bern: Huber.

Gigerenzer, G. (2013b). HIV screening: Helping clinicians make sense of test results to patients. Natural frequencies foster insight and should become part of the training of every medical student and HIV counsellor. *British Medical Journal, 347:* f5151. doi:10.1136/bmj.f5151

Gigerenzer, G. (2013c). Kognition. In M. A. Wirtz & J. Strohmer (Eds.), *Dorsch Lexikon der Psychologie* (16th compl. rev. ed., pp. 837–838). Bern: Huber.

Gigerenzer, G. (2013d). Ökologische Rationalität. In M. A. Wirtz & J. Strohmer (Eds.), *Dorsch Lexikon der Psychologie* (16th compl. rev. ed., p. 1120). Bern: Huber.

Gigerenzer, G. (2013e). Rationalität. In M. A. Wirtz & J. Strohmer (Eds.), *Dorsch Lexikon der Psychologie* (16th compl. rev. ed., pp. 1290–1291). Bern: Huber.

Gigerenzer, G. (2013f). *Risiko: Wie man die richtigen Entscheidungen trifft.* München: Bertelsmann.

Gigerenzer, G. (2013g). Risikokommunikation, kognitionspsychologische. In M. A. Wirtz & J. Strohmer (Eds.), *Dorsch Lexikon der Psychologie* (16th compl. rev. ed., p. 1335). Bern: Huber.

Gigerenzer, G. (2013h). Risikokompetenz. In M. A. Wirtz & J. Strohmer (Eds.), *Dorsch Lexikon der Psychologie* (16th compl. rev. ed., pp. 1335–1336). Bern: Huber.

Gigerenzer, G. (2013i). Smart heuristics. In J. Brockman (Ed.), *Thinking: The new science of decision-making, problem-solving, and prediction* (pp. 39–54). New York: Harper Collins.

Gigerenzer, G. (2013j). Über Wahl. In Deutscher Hochschulverband (Ed.), *Glanzlichter der Wissenschaft: Ein Almanach* (pp. 47–52). Saarwellingen: Saarländische Druckerei und Verlag.

Gigerenzer, G. (2013k). Warum gute Intuitionen nicht logisch sein müssen. In J. Küpper, M. Rautzenberg, M. Schaub, & R. Strätling (Eds), *The Beauty of Theory: Zur Ästhetik und Affektökonomie von Theorien* (pp. 167–175). Paderborn: Fink.

Gigerenzer, G. (2012a). Das andere Ich. In C. Markschies & E. Osterkamp (Eds.), *Vademekum der Inspirationsmittel* (pp. 40–41). Göttingen: Wallstein.

Gigerenzer, G. (2012b). Risk literacy. In J. Brockman (Ed.), *This will make you smarter: New scientific concepts to improve your thinking* (pp. 259–261). New York: Harper Perennial.

Gigerenzer, G. (2011a). Foreword. In H. M. Enzensberger, *Fatal numbers: Why count on chance* (Subway Line No. 3) (pp. 7–9). New York: Upper Westside Philosophers.

Gigerenzer, G. (2011b). Outsourcing the mind. In J. Brockman (Ed.), *Is the Internet changing the way you think? The net's impact on our minds and future* (pp. 147–149). New York: Harper Perennial.

Gigerenzer, G. (2011c). Rationalität, Heuristiken und Evolution. In V. Gerhardt, K. Lucas, & G. Stock (Eds.), *Evolution: Theorie, Formen und Konsequenzen eines Paradigmas in Natur, Technik und Kultur* (pp. 195–206). Berlin: Akademie-Verlag.

Gigerenzer, G. (2011d). The science of heuristics: Decision-making in an uncertain world. In X. T. Wang & Y.-J. Su (Eds.), *Thus spake evolutionary psychologists* (pp. 181–183). Beijing: Peking University Press.

Gigerenzer, G. (2011e). Die Verlagerung des Geistes nach außen. In J. Brockman (Ed.), *Wie hat das Internet Ihr Denken verändert? Die führenden Köpfe unserer Zeit über das digitale Dasein* (pp. 213–215). Frankfurt a. M.: Fischer-Taschenbuch-Verlag.

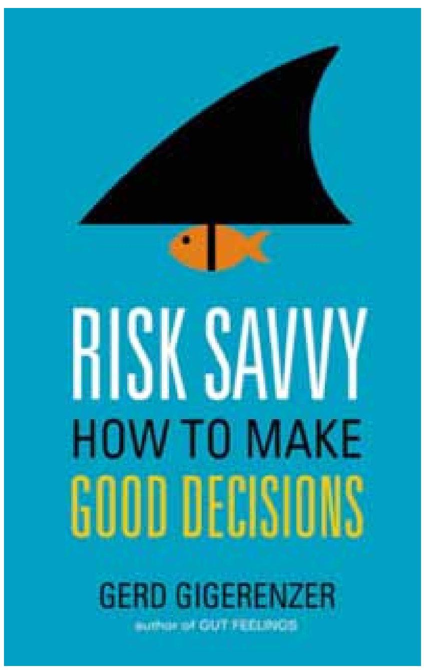
Gigerenzer, G. (2011f). What are natural frequencies? Doctors need to find better ways to communicate risk to patients. *British Medical Journal, 343:* d6386. doi:10.1136/bmj.d6386

Gigerenzer, G., Dieckmann, A., & **Gaissmaier, W.** (2012). Efficient cognition through limited research. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 241–273). New York: Oxford University Press.

Gigerenzer, G., Fiedler, K., & **Olsson, H.** (2012). Rethinking cognitive biases as environmental consequences. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 80–110). New York: Oxford University Press.

Gigerenzer, G., & **Gaissmaier, W.** (2012). *Intuition und Führung: Wie gute Entscheidungen entstehen.* Gütersloh: Bertelsmann-Stiftung.

Gigerenzer, G., & **Gaissmaier, W.** (2011). Heuristic deci-



sion making. *Annual Review of Psychology, 62,* 451–482. doi:10.1146/annurev-psych-120709-145346

Gigerenzer, G., & **Galesic, M.** (2012). Why do single event probabilities confuse patients? Statements of frequency are better for communicating risk. *British Medical Journal, 344:* e245. doi:10.1136/bmj.e245

Gigerenzer, G., Galesic, M., & **García-Retamero, R.** (2014). Stereotypes about men's and women's intuitions: A study of two nations. *Journal of Cross-Cultural Psychology, 45,* 62–81. doi:10.1177/0022022113487074

Gigerenzer, G., & Goldstein, D. G. (2011). The recognition heuristic: A decade of research. *Judgment and Decision Making, 6,* 100–121.

Gigerenzer, G., Hertwig, R., & **Pachur, T.** (Eds.). (2011). *Heuristics: The foundations of adaptive behavior.* Oxford: Oxford University Press.

Gigerenzer, G., Hertwig, R., & **Pachur, T.** (2011). Introduction. In G. Gigerenzer, R. Hertwig, & T. Pachur (Eds.), *Heuristics: The foundations of adaptive behavior* (pp. XVII–XXIII). Oxford: Oxford University Press.

Gigerenzer, G., & Muir Gray, J. A. (2013). Aufbruch in das Jahrhundert des Patienten. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen* (Strüngmann Forum Reports) (pp. 3–28). Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft.

Gigerenzer, G., & Muir Gray, J. A. (Eds.). (2011a). *Better doctors, better patients, better decisions: Envisioning health care 2020.* Cambridge, MA: MIT Press. (German translation: *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen.* Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft, 2013) (Chapter 1 in part reprinted in *Gesundheit & Gesellschaft, 3,* 2013, 34–39)

Gigerenzer, G., & Muir Gray, J. A. (2011b). Launching the century of the patient. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning health care 2020* (pp. 3–28). Cambridge, MA: MIT Press.

Gigerenzer, G., & Sturm, T. (2012). How (far) can rationality be naturalized? *Synthese, 187,* 243–268. doi:10.1007/s11229-011-0030-6

Gigerenzer, G., & Sturm, T. (2011). ¿Herramientas=teorías =datos? Sobre cierta dinámica circular en la ciencia cognitiva [Tools=Theories=Data? On some circular dynamics in cognitive science]. *Quaderns de Psicologia, 13,* 35–61.

Gigerenzer, G., & **Todd, P. M.** (2012). Ecological rationality: The normative study of heuristics. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 487–497). New York: Oxford University Press.

Gigerenzer, G., & **Wegwarth, O.** (2013). Five year survival rates can mislead. *British Medical Journal, 346:* f548. doi:10.1136/bmj.f548

Gluck, K. A., McNamara, J. M., **Brighton, H.,** Dayan, P., ... **Stevens, J. R.,** Voelkl, B., & Wimsatt, W. C. (2012). Robustness in a variable environment. In P. Hammerstein & J. R. Stevens (Eds.), *Evolution and the mechanisms of decision making* (Strüngmann Forum Reports No. 11) (pp. 195–214). Cambridge, MA: MIT Press.

Goldstein, D. G., & **Gigerenzer, G.** (2011). The beauty of simple models: Themes in recognition heuristic research. *Judgment and Decision Making, 6,* 392–395.

Gummerum, M., & **Keller, M.** (2012). East German children's and adolescents' friendship and moral reasoning before and after German reunification. *Journal of Genetic Psychology, 173,* 440–462. doi:10.1080/00221325.2011.630435

Hagmayer, Y., & **Meder, B.** (2013). Repeated causal decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 39,* 33–50. doi:10.1037/a0028643

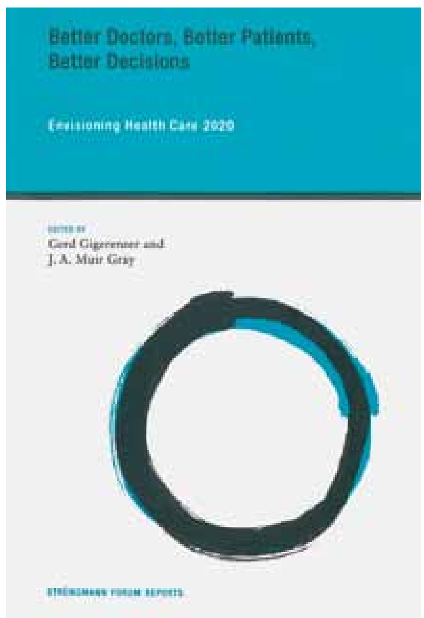
Hagmayer, Y., **Meder, B.,** Sydow, M. von, & Waldmann, M. R. (2011). Category transfer in sequential causal learning: The unbroken mechanism hypothesis. *Cognitive Science, 35,* 842–873. doi:10.1111/j.1551-6709.2011.01179.x

Hammerstein, P., & **Stevens, J. R.** (Eds.). (2012a). *Evolution and the mechanisms of decision making* (Strüngmann Forum Reports No. 11). Cambridge, MA: MIT Press.

Hammerstein, P., & **Stevens, J. R.** (2012b). Six reasons for invoking evolution in decision theory. In P. Hammerstein & J. R. Stevens (Eds.), *Evolution and the mechanisms of decision making* (Strüngmann Forum Reports No. 11) (pp. 1–17). Cambridge, MA: MIT Press.

Heesen, C., **Gaissmaier, W.,** Nguyen, F., Stellmann, J.-P., Kasper, J., Köpke, S., ... Daumer, M. (2013). Prognostic risk estimates of patients with Multiple Sclerosis and their physicians: Comparison to an online analytical risk counseling tool. *PLoS ONE, 8*(5): e59042. doi:10.1371/journal.pone.0059042

Helversen, B. von, Karlsson, L., **Mata, R.,** & Wilke, A. (2013). Why does cue polarity information provide benefits in inference problems? The role of strategy selection and knowledge of cue importance. *Acta Psychologica,*



144, 73–82. doi:10.1016/j.actpsy.2013.05.007

Helversen, B. von, & **Mata, R.** (2012). Losing a dime with a satisfied mind: Positive affect predicts less search in sequential decision making. *Psychology and Aging, 27*, 825–839. doi:10.1037/a0027845

Helversen, B. von, **Schooler, L. J.,** & **Czienskowski, U.** (2013). Are stripes beneficial? Dazzle camouflage influences perceived speed and hit rates. *PLoS ONE, 8*(4): e61173. doi:10.1371/journal.pone.0061173

Helversen, B. von, Wilke, A., Johnson, T., Schmid, G., & Klapp, B. (2011). Performance benefits of depression: Sequential decision making in a healthy sample and a clinically depressed sample. *Journal of Abnormal Psychology, 120*, 962–968. doi:10.1037/a0023238

Hertwig, R., Buchan, H., Davis, D. A., **Gaissmaier, W.,** Härter, M., Kolpatzik, K., ... Wormer, H. (2013). Wie werden Gesundheitsfachkräfte und Patienten im Jahr 2020 zusammenarbeiten? Ein Manifest für den Wandel. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen* (Strüngmann Forum Reports) (pp. 325–347). Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft.

Hertwig, R., Buchan, H., Davis, D. A., **Gaissmaier, W.,** Härter, M., Kolpatzik, K., ... Wormer, H. (2011). How will health care professionals and patients work together in 2020? A manifesto for change. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning health care 2020* (pp. 317–337). Cambridge, MA: MIT Press.

Hertwig, R., & **Gigerenzer, G.** (2011). Behavioral inconsistencies do not imply inconsistent strategies. *Frontiers in Cognition, 2*, 292. doi:10.3389/fpsyg.2011.00292

Hicks, J. S., Burgman, M. A., **Marewski, J. N.,** Fidler, F., & **Gigerenzer, G.** (2012). Decision making in a human population living sustainably. *Conservation Biology, 26*, 760–768. doi:10.1111/j.1523-1739.2012.01911.x

Hutchinson, J. M. C., Fanselow, C., & **Todd, P. M.** (2012). Car parking as a game between simple heuristics. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 454–484). New York: Oxford University Press.

Jarecki, J., Meder, B., & **Nelson, J. D.** (2013). The assumption of class-conditional independence in category learning. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 2650–2655). Austin, TX: Cognitive Science Society.

Kaighobadi, F., & **Stevens, J. R.** (2013). Does fertility status influence impulsivity and risk taking in human females? Adaptive influences on intertemporal choice and risky decision making. *Evolutionary Psychology, 11*, 700–717.

Kämmer, J. E., Gaissmaier, W., & **Czienskowski, U.** (2013). The environment matters: Comparing individuals and dyads in their adaptive use of decision strategies. *Judgment and Decision Making, 8*, 299–329.

Kämmer, J. E., Gaissmaier, W., Reimer, T., & Schermuly, C. C. (in press). The adaptive use of recognition in group decision making. *Cognitive Science.*

Katsikopoulos, K. V. (2013). Why do simple heuristics perform well in choices with binary attributes? *Decision Analysis, 10*, 327–340. doi:10.1287/deca.2013.0281

Katsikopoulos, K. V. (2012). Decision methods for design: Insights from psychology. *Journal of Mechanical Design, Transactions of the ASME, 134*(8): 084504. doi:10.1115/1.4007001

Katsikopoulos, K. V. (2011a). Advanced guide signs and behavioral decision theory. In D. L. Fisher, J. D. Lee, J. Card, & M. Rizzo (Eds.), *Handbook of driving simulation for engineering, medicine and psychology* (pp. 489–495). Boca Raton, FL: CRC Press.

Katsikopoulos, K. V. (2011b). "How to model it?" [Review of the book Cognitive Modeling by J. R. Busemeyer & A. Diederich]. *Journal of Mathematical Psychology, 55*, 198–201. doi:10.1016/j.jmp.2010.07.002

Katsikopoulos, K. V. (2011c). Lernen über Risiken beim Wetten. *Stochastik in der Schule, 31*, 25–28.

Katsikopoulos, K. V. (2011d). Psychological heuristics for making inferences: Definition, performance, and the emerging theory and practice. *Decision Analysis, 8*, 10–29. doi:10.1287/deca.1100.0191

Katsikopoulos, K. V., & **Gigerenzer, G.** (2013a). Behavioral operations management: A blind spot and a research program. *Journal of Supply Chain Management, 49*, 3–7. doi:10.1111/j.1745-493x.2012.03285.x

Katsikopoulos, K. V., & **Gigerenzer, G.** (2013b). Modeling decision heuristics. In J. D. Lee & A. Kirlik (Eds.), *The Oxford handbook of cognitive engineering* (pp. 490–500). New York: Oxford University Press.

Katsikopoulos, K. V., & Lan, C.-H. D. (2011). Herbert Simon's spell on judgment and decision making. *Judgment and Decision Making, 6*, 722–732.

Katsikopoulos, K. V., & Reimer, T. (2012). How groups use partial ignorance to make good decisions. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 167–183). New York: Oxford University Press.

Keller, M. (2013a). Die Entwicklung und Förderung moralischen Denkens und moralischer Gefühle in der Kindheit. In P. Wagner (Ed.), *Handbuch Inklusion: Grundlagen vorurteilsbewusster Bildung und Erziehung* (pp. 66–86). Freiburg: Herder.

Keller, M. (2013b). Ich oder wir: Was ist fair? Und was ist unfair? In Technische Universität Dresden (Ed.), *Mehr Glück und weniger Pech—kann man das mathematisch errechnen? Ein Buch der Kinder-Universität Dresden* (pp. 186–195). Dresden: Technische Universität Dresden.

Keller, M. (2012). Moral developmental science between changing paradigms. *International Journal of Developmental Science, 6*, 65–69. doi:10.3233/DEV-2012-11090

Keller, M. (2011). Moralische Entwicklung: Kognition, Gefühl und moralisches Selbst. In S. Benzler (Ed.), *Vor allzu langer Zeit? Die Praxis historisch-politischer Bildung zum Nationalsozialismus heute* (Loccumer Protokolle No. 21/09) (pp. 89–108). Rehburg-Loccum: Evangelische Akademie Loccum.

Keller, M., Gummerum, M., Canz, T., **Gigerenzer, G.,** & Takezawa, M. (2013). The Is and Ought of sharing: The equality heuristic across the lifespan. In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 171–195). New York: Oxford University Press.

Kothiyal, A., Spinu, V., & Wakker, P. P. (in press-a). Average utility: A preference foundation. *Operations Research.*

Kothiyal, A., Spinu, V., & Wakker, P. P. (in press-b). An experimental test of prospect theory for predicting choice under ambiguity. *Journal of Risk and Uncertainty.*

Kruglanski, A. W., & **Gigerenzer, G.** (2011a). Intuitive and deliberate judgments are based on common principles. *Psychological Review, 118*, 97–109. doi:10.1037/a0020762

Kruglanski, A. W., & **Gigerenzer, G.** (2011b). "Intuitive and deliberate judgments are based on common principles": Correction to Kruglanski and Gigerenzer (2011). *Psychological Review, 118*, 522. doi:10.1037/a0023709

Kurz-Milcke, E., **Gigerenzer, G.,** & **Martignon, L.** (2011). Risiken durchschauen: Grafische und analoge Werkzeuge. *Stochastik in der Schule, 31*, 8–16.

Latten, S., **Martignon, L.,** Monti, M., & **Multmeier, J.** (2011). Die Förderung erster Kompetenzen für den Umgang mit Risiken bereits in der Grundschule: Ein Projekt von RIKO-STAT und dem Harding Center. *Stochastik in der Schule, 31*, 17–25.

Lenzner, T., Kaczmirek, L., & **Galesic, M.** (2011). Seeing through the eyes of the respondent: An eye-tracking study on survey question comprehension. *International Journal of Public Opinion Research, 23*, 361–373. doi:10.1093/ijpor/edq053

Lopéz-Zafra, E., & **García-Retamero, R.** (2011). The impact of nontraditionalism on the malleability of gender stereotypes in Spain and Germany. *International Journal of Psychology, 46*, 249–258. doi:10.1080/00207594.2010.551123

Lopéz-Zafra, E., **García-Retamero, R.,** & Berrios Martos, M. P. (2012). The relationship between transformational leadership and emotional intelligence from a gendered approach. *The Psychological Record, 62*, 97–114.

Luan, S., Katsikopoulos, K. V., & Reimer, T. (2013). The "Less-Is-More" effect in group decision making. In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 293–317). New York: Oxford University Press.

Luan, S., Katsikopoulos, K. V., & Reimer, T. (2012). When does diversity trump ability (and vice versa) in group decision making? A simulation study. *PLoS ONE, 7*(2): e31043. doi:10.1371/journal.pone.0031043

Luan, S., Schooler, L. J., & **Gigerenzer, G.** (2011). A signal-detection analysis of fast-and-frugal trees. *Psychological Review, 118*, 316–338. doi:10.1037/a0022684

Malti, T., Gummerum, M., **Keller, M.,** Chaparro, M. P., & Buchmann, M. (2012). Early sympathy and social acceptance predict the development of sharing in children. *PLoS ONE, 7*(12): e52017. doi:10.1371/journal.pone.0052017

Malti, T., **Keller, M.,** & Buchmann, M. (2013). Do moral choices make us feel good? The development of adolescents' emotions following moral decision making. *Journal of Research on Adolescence, 23*, 389–397. doi:10.1111/jora.12005

Marewski, J. N. (2011). Vom Vorteil des Nichtwissens bei (Konsum)entscheidungen (AID-Infodienst: Tagungsband zum 13. aid-Forum). In AID-Infodienst, Ernährung, Landwirtschaft, Verbraucherschutz (Ed.), *Mehr als wir verdauen können! Strategien zum Umgang mit der Informationsflut* (pp. 55–68). Bonn: AID.

Marewski, J. N., & **Gigerenzer, G.** (2013). Entscheiden. In W. Sages (Ed.), *Management-Diagnostik* (4th, rev. and ext. ed., pp. 228–241). Göttingen: Hogrefe.

Marewski, J. N., & **Gigerenzer, G.** (2012). Heuristic decision making in medicine. *Dialogues in Clinical Neuroscience, 14*, 77–89.

Marewski, J. N., & Hoffrage, U. (2013). Processes models, environmental analyses, and cognitive architectures: Quo vadis quantum probability theory? [Commentary on Pothos and Busemeyer]. *Behavioral and Brain Sciences, 36*, 297–298. doi:10.1017/S0140525X12003032

Marewski, J. N., & Krol, K. (in press). Fast, frugal, & moral: Uncovering the heuristics of morality. *Journal of Organizational Moral Psychology.*

Marewski, J. N., & Link, D. (in press). Strategy selection: An introduction to the modeling challenge. *Wiley Interdisciplinary Reviews: Cognitive Science.*

Marewski, J. N., & Mehlhorn, K. (2011). Using the ACT-R architecture to specify 39 quantitative process models of decision making. *Judgment and Decision Making, 6*, 439–519.

Marewski, J. N., Pohl, R. F., & Vitouch, O. (2011a). Recognition-based judgments and decisions: Introduction to the special issue (II). *Judgment and Decision Making, 6*, 1–6.

Marewski, J. N., Pohl, R. F., & Vitouch, O. (2011b). Recognition-based judgments and decisions: What we have learned (so far). *Judgment and Decision Making, 6*, 359–380.

Marewski, J. N., & **Schooler, L. J.** (2011). Cognitive niches: An ecological model of strategy selection. *Psychological Review, 118*, 393–437. doi:10.1037/a0024143

Martignon, L., **Katsikopoulos, K. V.,** & Woike, J. K. (2012). Naive, fast, and frugal trees for classification. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 360–378). New York: Oxford University Press.

Mata, J., Frank, R., & **Gigerenzer, G.** (in press). Symptom recognition of heart attack and stroke in nine European countries: A representative study. *Health Expectations. Advance online publication.* doi:10.1111/j.1369-7625.2011.00764.x
(Reprinted in *Transparent communication of health risks: Overcoming cultural differences,* pp. 79–96, by R. García-Retamero & M. Galesic, Eds., 2013, New York: Springer)

Mata, J., Lippke, S., Dieckmann, A., & **Todd, P. M.** (2011). Meat label information: Effects of separate versus conjoint presentation on product evaluation. *Journal of Applied Social Psychology, 41*, 1947–1957. doi:10.1111/j.1559-1816.2011.00788.x

Mata, R., Helversen, B. von, Karlsson, L., & Cüpper, L. (2012). Adult age differences in categorization and multiple-cue judgment. *Developmental Psychology, 48*, 1188–1201. doi:10.1037/a0026084

Mata, R., Helversen, B. von, & Rieskamp, J. (2011). When easy comes hard: The development of adaptive strategy selection. *Child Development, 82*, 687–700. doi:10.1111/j.1467-8624.2010.01535.x

Mata, R., Pachur, T., Helversen, B. von, **Hertwig, R.,** Rieskamp, J., & **Schooler, L. J.** (2012). Ecological rationality: A framework for understanding and aiding the aging decision maker. *Frontiers in Neuroscience, 6*, 19. doi:10.3389/fnins.2012.00019

Mata, R., Wilke, A., & **Czienskowski, U.** (2013). Foraging across the life span: Is there a reduction in exploration with aging? *Frontiers in Neuroscience, 7*, 53. doi:10.3389/fnins.2013.00053

Meder, B., & **Gigerenzer, G.** (2014). Statistical thinking: No one left behind. In E. J. Chernoff & B. Sriraman (Eds.), *Probabilistic thinking: Presenting plural perspectives* (Advances in Mathematics Education) (pp. 127–148). Dordrecht: Springer.

Meder, B., Le Lec, F., & Osman, M. (2013). Decision making in uncertain times: What can cognitive and decision sciences say about or learn from economic crises? *Trends in Cognitive Sciences, 17*, 257–260. doi:10.1016/j.tics.2013.04.008

Meder, B., & Mayrhofer, R. (2013). Sequential diagnostic reasoning with verbal information. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 1014–1019). Austin, TX: Cognitive Science Society.

Meder, B., Mayrhofer, R., & Waldmann, M. (in press). Structure induction in diagnostic causal reasoning. *Psychological Review.*

Meder, B., & **Nelson, J. D.** (2012). Information search with situation-specific reward functions. *Judgment and Decision Making, 7,* 119–148.

Mehlhorn, K., & **Marewski, J. N.** (2011). Using a cognitive architecture to specify and test process models of decision making. In J. Özyurt, A. Anschütz, S. Bernholt, & J. Lenk (Eds.), *Interdisciplinary perspectives on cognition, education and the brain* (Hanse-Studien No. 7) (pp. 77–85). Oldenburg: BIS-Verlag der Carl-von-Ossietzky-Universität.

Miron-Shatz, T., Mühlhauser, I., Bower, B., Diefenbach, M., Goldacre, B., Smith, R. S. W., Spiegelhalter, D., & **Wegwarth, O.** (2013). Warum medizinische Information oft nicht genutzt wird und was man dagegen tun kann. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen* (Strüngmann Forum Reports) (pp. 193–213). Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft.

Miron-Shatz, T., Mühlhauser, I., Bower, B., Diefenbach, M., Goldacre, B., Smith, R. S. W., Spiegelhalter, D., & **Wegwarth, O.** (2011). Barriers to health information and building solutions. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning health care 2020* (pp. 191–212). Cambridge, MA: MIT Press.

Monti, M., Boero, R., Berg, N., **Gigerenzer, G.,** & **Martignon, L.** (2012). How do common investors behave? Information search and portfolio choice among bank customers and university students. *Mind & Society, 11,* 203–233. doi:10.1007/s11299-012-0109-x

Monti, M., **Gigerenzer, G.,** & **Martignon, L.** (2012). Le scelte di investimento: Strategie semplici e frugali per decisioni complesse [Investment choices: Simple and fast strategies for complex decisions]. *Sistemi Intelligenti, 24,* 201–226. doi:10.1422/37898

Monti, M., **Martignon, L.,** Pelligra, V., & Berg, N. (in press). Retail investors and financial advisors: New evidence on trust and advice taking heuristics. *Journal of Business Research.*

Monti, M., **Martignon, L.,** Pelligra, V., & Guglielmetti, C. (2011). *The insurance by my side: Better risk assessment for smarter insurance decisions* (CAREFIN Working Paper No. 3/2011). Milan: Università Commerciale Luigi Bocconi.

Morais, A. S., Neth, H., & Hills, T. T. (2013). How healthy aging and dementia impact memory search. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 3104–3109). Austin, TX: Cognitive Science Society.

Morais, A. S., Olsson, H., & **Schooler, L. J.** (2013). Mapping the structure of semantic memory. *Cognitive Science, 37,* 125–145. doi:10.1111/cogs.12013

Morais, A. S., Olsson, H., & **Schooler, L. J.** (2011). Does the structure of causal models predict information search? In B. Kokinov, A. Karmiloff-Smith, & N. J. Nersessian (Eds.), *European perspectives on cognitive science.* Sofia: New Bulgarian University Press.

Mousavi, S., & **Gigerenzer, G.** (in press). Risk, uncertainty and heuristics. *Journal of Business Research.*

Mousavi, S., & **Gigerenzer, G.** (2011). Revisiting the "error" in studies of cognitive errors. In D. A. Hofmann & M. Frese (Eds.), *Errors in organizations* (pp. 97–112). New York: Taylor & Francis.

Moussaïd, M., Guillot, E. G., Moreau, M., Fehrenbach, J., Cahbiron, O., Lemercier, S., … Theraulaz, G. (2012). Traffic instabilities in self-organized pedestrian crowds. *PLoS Computational Biology, 8*(3): e1002442. doi:10.1371/journal.pcbi.1002442

Moussaïd, M., Kämmer, J. E., Pipergias Analytis, P., & **Neth, H.** (2013). Social influence and the collective dynamics of opinion formation. *PLoS ONE, 8*(11): e78433. doi:10.1371/journal.pone.0078433

Moussaïd, M., & **Nelson, J. D.** (in press). Simple heuristics and the modelling of crowd behaviour. *Pedestrian and Evacuation Dynamics.*

Mühlhoff, N., **Stevens, J. R.,** & Reader, S. R. (2011). Spatial discounting of food and social rewards in guppies (Poecilia reticulata). *Frontiers in Psychology, 2,* 68. doi:10.3389/fpsyg.2011.00068

Müller, S. M., **Bodemer, N.,** Okan, Y., **García-Retamero, R.,** & Neumeyer-Gromen, A. (2013). Transparent health information in the media. In R. García-Retamero & M. Galesic (Eds.), *Transparent communication of health risks: Overcoming cultural differences* (pp. 195–213). New York: Springer.

Müller, S. M., **García-Retamero, R., Cokely, E. T.,** & Maldonado, A. (2011). Causal beliefs and empirical evidence: Decision-making processes in two-alternative forced-choice tasks. *Experimental Psychology, 58,* 324–332. doi:10.1027/1618-3169/a000099

Müller, S. M., **García-Retamero, R., Galesic, M.,** & Maldonado, A. (2013). The impact of domain-specific beliefs on decisions and causal judgments. *Acta Psychologica, 144,* 472–480. doi:10.1016/j.actpsy.2013.08.004

Multmeier, J., Gaissmaier, W., & **Wegwarth, O.** (in press). Collective statistical illiteracy in health. In B. L. Anderson & J. Schulkin (Eds.), *Numerical reasoning in judgments and decision making about health.* Cambridge, UK: Cambridge University Press.

Nelson, J. D., Divjak, B., Gudmundsdottir, G., **Martignon, L.,** & **Meder, B.** (2014). Children's sequential information search is sensitive to environmental probabilities. *Cognition, 130,* 74–80. doi:10.1016/j.cognition.2013.09.007

Neth, H., Czienskowski, U., Schooler, L. J., & **Gluck, K. A.** (2013). Making robust classification decisions: Constructing and evaluating Fast and Frugal Trees (FFTs). In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Cooperative minds: Social interaction and group dynamics. Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 43–44). Austin, TX: Cognitive Science Society.

Neth, H., Meder, B., Kothiyal, A., & **Gigerenzer, G.** (in press). Homo Heuristicus in the financial world: From risk management to managing uncertainty. *Journal of Risk Management in Financial Institutions.*

Neumeyer-Gromen, A., **Bodemer, N.,** Müller, S. M., & **Gigerenzer, G.** (2011). Ermöglichen Medienberichte und Broschüren informierte Entscheidungen zur Gebärmutterhalskrebsprävention? *Bundesgesundheitsblatt—Gesundheitsforschung—Gesundheitsschutz, 54,* 1197–1210. doi:10.1007/s00103-011-1347-5

Neumeyer-Gromen, A., **Bodemer, N.,** Müller, S. M., & **Gigerenzer, G.** (2011). Erratum zu: Ermöglichen Medienberichte und Broschüren informierte Entscheidungen zur Gebärmutterhalskrebsprävention? [Bundesgesundheitsblatt—Gesundheitsforschung—Gesundheitsschutz, 54, 2011, 1197–1210, doi:10.1007/s00103-011-1347-5]. *Bundesgesundheitsblatt—Gesundheitsforschung—Gesundheitsschutz, 54,* 1350. doi:10.1007/s00103-011-1384-0

Neuner-Jehle, S., Senn, O., **Wegwarth, O.,** Rosemann, T., & Steurer, J. (2011). How do family physicians communicate about cardiovascular risk? Frequencies and determinants of different communication formats. *BMC Family Practice, 12*, 15. doi:10.1186/1471-2296-12-15

Norman, G. R., Sherbino, J., Dore, K. L., Wood, T. J., Young, M. E., **Gaissmaier, W.,** Monteiro, S., & Krueger, S. (in press). The etiology of diagnostic errors: A controlled trial of system 1 vs. system 2 reasoning. *Academic Medicine.*

Nosofsky, R. M., Little, D. R., Donkin, C., & **Fific, M.** (2011). Short-term memory scanning viewed as exemplar-based categorization. *Psychological Review, 118*, 280–315. doi:10.1037/a0022494

Okan, Y., **García-Retamero, R., Cokely, E. T.,** & Maldonado, A. (2012). Individual differences in graph literacy: Overcoming denominator neglect in risk comprehension. *Journal of Behavioral Decision Making, 25,* 390–401. doi:10.1002/bdm.751

Okan, Y., **García-Retamero, R., Galesic, M.,** & **Cokely, E. T.** (2012). When higher bars are not larger quantities: On individual differences in the use of spatial information in graph comprehension. *Spatial Cognition & Computation, 12*, 195–218. doi:10.1080/13875868.2012.659302

Olsson, H., & **Galesic, M.** (2011). History and logic of significance tests. In M. Lovric (Ed.), *International encyclopedia of statistical science* (Vol. 3, pp. 1321–1323). New York: Springer. doi:10.1007/978-3-642-04898-2_70

Ortner, T. M., Müller, S. M., & **García-Retamero, R.** (2011). Estimations of parental and self intelligence as a function of parents' status: A cross-cultural study in Germany and Spain. *Social Science Research, 40,* 1067–1077. doi:10.1016/j.ssresearch.2011.03.006

Pachur, T., & **Galesic, M.** (2013). Strategy selection in risky choice: The impact of numeracy, affect, and cross-cultural differences. *Journal of Behavioral Decision Making, 26,* 260–271. doi:10.1002/bdm.1757

Pachur, T., Hertwig, R., Gigerenzer, G., & Brandstätter, E. (2013). Testing process predictions of models of risky choice: A quantitative model comparison approach. *Frontiers in Psychology, 4,* 646. doi:10.3389/fpsyg.2013.00646

Pachur, T., & **Olsson, H.** (2012). Type of learning task impacts performance and strategy selection in decision making. *Cognitive Psychology, 65,* 207–240. doi:10.1016/j.cogpsych.2012.03.003

Pachur, T., Schooler, L. J., & **Stevens, J. R.** (2014). We'll meet again: Revealing distributional and temporal patterns of social contact. *PLoS ONE, 9* (1): e86081. doi:10.1371/journal.pone.0086081

Pachur, T., Schooler, L. J., & **Stevens, J. R.** (2013). When will we meet again? Regularities of social connectivity and their reflections in memory and decision making. In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 199–224). New York: Oxford University Press.

Pachur, T., Todd, P. M., Gigerenzer, G., Schooler, L. J., & Goldstein, D. G. (2012). When is the recognition heuristic an adaptive tool? In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 113–143). New York: Oxford University Press.

Pachur, T., Todd, P. M., Gigerenzer, G., Schooler, L. J., & Goldstein, D. G. (2011). The recognition heuristic: A review of theory and tests. *Frontiers in Cognitive Science, 2,* 147. doi:10.3389/fpsyg.2011.00147

Park, S. Q., Kahnt, T., **Rieskamp, J.,** & **Heekeren, H. R.** (2011). Neurobiology of value integration: When value impacts valuation. *The Journal of Neuroscience, 31,* 9307–9314. doi:10.1523/JNEUROSCI.4973-10.2011

Pipergias Analytis, P., Moussaïd, M., Artinger, F., Kämmer, J. E., & **Gigerenzer, G.** (in press). "Big data" needs an analysis of decision processes. *Behavioral and Brain Sciences.*

Raab, M., Gula, B., & **Gigerenzer, G.** (2012). The hot hand exists in volleyball and is used for allocation decisions. *Journal of Experimental Psychology: Applied, 18,* 81–94. doi:10.1037/a0025951

Riva, S., **Monti, M.,** & Antonietti, A. (2011). Simple heuristics in over-the-counter drug choices: A new hint for medical education and practice. *Advances in Medical Education and Practice, 2,* 59–70. doi:10.2147/AMEP.S13004

Riva, S., **Monti, M.,** Iannello, P., & Antonietti, A. (2012). The representation of risk in routine medical experience: What actions for contemporary health policy? *PLoS ONE, 7*(11): e48297. doi:10.1371/journal.pone.0048297

Riva, S., **Monti, M.,** Iannello, P., Schulz, P., & Antonietti, A. (in press). A preliminary mixed-method investigation of trust and hidden signals in medical consultation. *PLoS ONE.*

Ruggeri, A., & **Katsikopoulos, K. V.** (2013). Make your own kinds of cues: When children make more accurate inferences than adults. *Journal of Experimental Child Psychology, 115,* 517–535. doi:10.1016/j.jecp.2012.11.007

Scheibehenne, B., **Mata, J.,** & **Todd, P. M.** (2011). Older but not wiser: Predicting a partner's preferences gets worse with age. *Journal of Consumer Psychology, 21*, 184–191. doi:10.1016/j.jcps.2010.08.001

Schneider, T. R., **Feufel, M. A.,** & Berkel, H. J. (2011). Promoting colorectal cancer screening in public health outreach campaigns. *Human Factors, 53,* 637–646. doi:10.1177/0018720811427134

Schooler, L. J., Burgess, C., Goldstone, R. L., Fu, W.-T., Gavrilets, S., Lazer, D., Marshall, J. A. R., Neumann, F., & Wiener, J. M. (2012). Search environments, representation, and encoding. In P. M. Todd, T. T. Hills, & T. W. Robinns (Eds.), *Cognitive search: Evolution, algorithms, and the brain* (Strüngmann Forum Reports No. 9) (pp. 317–333). Cambridge, MA: MIT Press.

Schooler, L. J., Hertwig, R., & **Herzog, S. M.** (2012). How smart forgetting helps heuristic inference. In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 144–166). New York: Oxford University Press.

Schulz, E., **Cokely, E. T.,** & **Feltz, A.** (2011). Persistent bias in expert judgments about free will and moral responsibility: A test of the expertise defense. *Consciousness and Cognition, 20,* 1722–1731. doi:10.1016/j.concog.2011.04.007

Seed, A., Clayton, N., Carruthers, P., Dickinson, A., Glimcher, P. W., … **Stevens, J. R.,** & Tebbich, S. (2011). Planning, memory, and decision making. In R. Menzel & J. Fischer (Eds.), *Animal thinking: Contemporary issues in comparative cognition* (pp. 121–147). Cambridge, MA: MIT Press.

Sherbino, J., Dore, K. L., Wood, T. J., Young, M. E., **Gaissmaier, W.,** Kreuger, S., & Norman, G. R. (2012). The relationship between response time and diagnostic accuracy. *Academic Medicine, 87,* 785–791. doi:10.1097/ACM.0b013e318253acbd

Sherbino, J., Norman, G. R., & **Gaissmaier, W.** (2013). In reply to Croskerry and Tait. *Academic Medicine, 88,* 150–151. doi:10.1097/ACM.0b013e31827b2941

Sims, C. R., **Neth, H.,** Jacobs, R. A., & **Gray, W. D.** (2013). Melioration as rational choice: Sequential decision making in uncertain environments. *Psychological Review, 120,* 139–154. doi:10.1037/a0030850

Şimşek, Ö. (in press). Linear decision rule as aspiration for simple decision heuristics. In *Advances in neural information processing systems: Vol. 26. Proceedings of the 27th An-*

nual Conference on Neural Information Processing Systems, December 5–8, 2013, Lake Tahoe, Nevada, USA. Red Hook, NY: Curran Associates.

Stevens, A. N. P., & **Stevens, J. R.** (2012). Animal cognition. *Nature Education Knowledge, 3*(11), 1.

Stevens, J. R. (2011). Mechanisms for decisions about the future. In R. Menzel & J. Fischer (Eds.), *Animal thinking: Contemporary issues in comparative cognition* (pp. 93–104). Cambridge, MA: MIT Press.

Stevens, J. R., & King, A. J. (2013). The lives of others: Social rationality in animals. In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 409–431). New York: Oxford University Press.

Stevens, J. R., & Mühlhoff, N. (2012). Intertemporal choice in lemurs. *Behavioural Processes, 89*, 121–127. doi:10.1016/j.beproc.2011.10.002

Stevens, J. R., Pachur, T., & **Schooler, L. J.** (2013). Rational analysis of the adaptive and predictive nature of memory. *Journal of Applied Research in Memory and Cognition, 2,* 251–253. doi:10.1016/j.jarmac.2013.10.006

Stevens, J. R., Rosati, A. G., Heilbronner, S. R., & Mühlhoff, N. (2011). Waiting for grapes: Expectancy and delayed gratification in bonobos. *International Journal of Comparative Psychology, 24,* 99–111.

Stevens, J. R., Volstorf, J., **Schooler, L. J.,** & Rieskamp, J. (2011). Forgetting constrains the emergence of cooperative decision strategies. *Frontiers in Psychology, 1,* 235. doi:10.3389/fpsyg.2010.00235

Todd, P. M., Gigerenzer, G., & the ABC Research Group (2012a). *Ecological rationality: Intelligence in the world.* New York: Oxford University Press.

Todd, P. M., & **Gigerenzer, G.** (2012b). What is ecological rationality? In P. M. Todd, G. Gigerenzer, & the ABC Research Group, *Ecological rationality: Intelligence in the world* (pp. 3–30). New York: Oxford University Press.

Tomlinson, T., **Marewski, J. N.,** & Dougherty, M. (2011). Four challenges for cognitive research on the recognition heuristic and a call for a research strategy shift. *Judgment and Decision Making, 6,* 89–99.

Treverna, L. J., Zikmund-Fisher, B. J., Edwards, A., **Gaissmaier, W., Galesic, M.,** Han, P. K. J., ... Woloshin, S. (2013). Presenting quantitative information about decision outcomes: A risk communication primer for patient decision aid developers. *BMC Medical Informatics and Decision Making, 13*(Suppl. 2), S7. doi:10.1186/1472-6947-13-S2-S7

Trevena, L., Zikmund-Fisher, B., Edwards, A., **Gaissmaier, W., Galesic, M.,** Han, P., ... Woloshin, S. (2012). Presenting probabilities. In R. Volk & H. Llewellyn-Thomas (Eds.), *2012 Update of the International Patient Decision Aids Standards (IPDAS) collaboration's background document* (chap. C). Cardiff, UK: IPDAS Collaboration.

Verweij, M., **Luan, S.,** & Nowacki, M. (2011). How to test cultural theory: Suggestions for future research. *PS: Political Science & Politics, 44,* 745–748. doi:10.1017/S1049096511001399

Volstorf, J., Rieskamp, J., & **Stevens, J. R.** (2011). The good, the bad, and the rare: Memory for partners in social interactions. *PLoS ONE, 6*(4): e18945. doi:10.1371/journal.pone.0018945

Volz, K. G., & **Gigerenzer, G.** (in press). The brain is not "as-if": Taking stock of the neuroscientific approach on decision making. In *Functional magnetic resonance imaging* (Vol. 1). Rijeka: IntechOpen.

Volz, K. G., & **Gigerenzer, G.** (2012). Cognitive processes in decisions under risk are not the same as in decisions under uncertainty. *Frontiers in Neuroscience, 6,* 105. doi:10.3389/fnins.2012.00105

Wegwarth, O. (2013a). Krebsfrüherkennung und Risikokommunikation. *Therapeutische Umschau, 70,* 245–250. doi:10.1024/0040-5930/a000396

Wegwarth, O. (2013b). Statistical illiteracy in residents: What they do not learn today will hurt their patients tomorrow. *Journal of Graduate Medical Education, 5,* 340–341. doi:10.4300/JGME-D-13-00084.1

Wegwarth, O. (2012). Wie steht es um Ihr Statistik-Know-how? Fünfjahres-Überlebensrate. *UroForum, 4*, 30–31.

Wegwarth, O., Day, R. W., & **Gigerenzer, G.** (2011). Decisions on pharmacogenomic tests in the USA and Germany. *Journal of Evaluation in Clinical Practice, 17,* 228–235. doi:10.1111/j.1365-2753.2010.01426.x

Wegwarth, O., Gaissmaier, W., & **Gigerenzer, G.** (2011). Deceiving numbers: Survival rates and their impact on doctors' risk communication. *Medical Decision Making, 31*, 386–394. doi:10.1177/0272989X10391469

Wegwarth, O., & **Gigerenzer, G.** (2013a). Mangelnde Statistikkompetenz bei Ärzten. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Bessere Ärzte, bessere Patienten, bessere Medizin: Aufbruch in ein transparentes Gesundheitswesen* (Strüngmann Forum Reports) (pp. 137–151). Berlin: Medizinisch Wissenschaftliche Verlagsgesellschaft.

Wegwarth, O., & **Gigerenzer, G.** (2013b). Overdiagnosis and overtreatment: Evaluation of what physicians tell patients about screening harms. *JAMA Internal Medicine, 173,* 2086–2087. doi:10.1001/jamainternmed.2013.10363

Wegwarth, O., & **Gigerenzer, G.** (2013c). Trust-your-doctor: A simple heuristic in need of a proper social environment. In R. Hertwig, U. Hoffrage, & the ABC Research Group, *Simple heuristics in a social world* (pp. 67–102). New York: Oxford University Press.

Wegwarth, O., & **Gigerenzer, G.** (2011a). Nutzen und Risiken richtig verstehen. *Deutsches Ärzteblatt, 108,* A568–A570.

Wegwarth, O., & **Gigerenzer, G.** (2011b). Risiken und Unsicherheiten richtig verstehen lernen. *Deutsches Ärzteblatt, 108,* A448–A451.

Wegwarth, O., & **Gigerenzer, G.** (2011c). Statistical illiteracy in doctors. In G. Gigerenzer & J. A. Muir Gray (Eds.), *Better doctors, better patients, better decisions: Envisioning health care 2020* (pp. 137–151). Cambridge, MA: MIT Press.

Wegwarth, O., & **Gigerenzer, G.** (2011d). Sterblichkeitsstatistik als valides Maß. *Deutsches Ärzteblatt, 108,* A760–A762.

Wegwarth, O., & **Gigerenzer, G.** (2011e). "There is nothing to worry about": Gynecologists' counseling on mammography. *Patient Education and Counseling, 84,* 251–256. doi:10.1016/j.pec.2010.07.025

Wegwarth, O., & **Gigerenzer, G.** (2011f). Unnötige Ängste vermeiden. *Deutsches Ärzteblatt, 108,* A943–A944.

Wegwarth, O., Kurzenhäuser-Carstens, S., & **Gigerenzer, G.** (in press). Overcoming the knowledge-behavior gap: The effect of evidence-based HPV vaccination leaflets on understanding, intention, and actual vaccination decision. *Vaccine.*

Wegwarth, O., Schwartz, L. M., Woloshin, S., **Gaissmaier, W.,** & **Gigerenzer, G.** (2012). Do physicians understand cancer screening statistics? A national survey of primary care physicians in the United States. *Annals of Internal Medicine, 156,* 340–349, W-92-W-94.

Wheeler, G. (2011). Explaining the limits of Olsson's impossibility result. *Southern Journal of Philosophy, 50,* 136–150. doi:10.1111/j.2041-6962.2011.00083.x

Wolf, M., Van Doorn, G. S., & Weissing, F. J. (2011). On the coevolution of social responsiveness and behavioural consistency. *Proceedings of the Royal Society of London: B, Biological Sciences, 278*(1704), 440–448. doi:10.1098/rspb.2010.1051

Woller-Carter, M. M., Okan, Y., **Cokely, E. T.,** & **García-Retamero, R.** (2012). Communicating and distorting risks with graphs: An eye-tracking study. *Proceedings of the Human Factors and Ergonomics Society 56th Annual Meeting, 56,* 1723–1727. doi:10.1177/1071181312561345

Zhu, L., **Gigerenzer, G.,** & Huangfu, G. (2013). Psychological traces of China's socio-economic reforms in the ultimatum and dictator games. *PLoS ONE, 8*(8): e70769. doi:10.1371/journal.pone.0070769

Zhu, W., & Timmermans, H. (2011). Modeling pedestrian shopping behavior using principles of bounded rationality: Model comparison and validation. *Journal of Geographical Systems, 13,* 101–126. doi:10.1007/s10109-010-0122-8