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Recognition-based judgments and decisions: What we have learned (so far)

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Abstract

This special issue on recognition processes in inferential decision making represents an adversarial collaboration among the three guest editors. This introductory article to the special issue's third and final part comes in three sections. In Section 1, we summarize the six papers that appear in this part. In Section 2, we give a wrap-up of the lessons learned. Specifically, we discuss (i) why studying the recognition heuristic has led to so much controversy, making it difficult to settle on mutually accepted empirically grounded assumptions, (ii) whether the development of the recognition heuristic and its theoretical descriptions could explain some of the past controversies and misconceptions, (iii) how additional cue knowledge about unrecognized objects could enter the decision process, (iv) why recognition heuristic theory should be complemented by a probabilistic model of strategy selection, and (v) how recognition information might be related to other information, especially when considering real-world applications. In Section 3, we present an outlook on the thorny but fruitful road to cumulative theory integration. Future research on recognition-based inferences should (i) converge on overcoming past controversies, taking an integrative approach to theory building, and considering theories and findings from neighboring fields (such as marketing science and artificial intelligence), (ii) build detailed computational process models of decision strategies, grounded in cognitive architectures, (iii) test existing models of such strategies competitively, (iv) design computational models of the mechanisms of strategy selection, and (v) effectively extend its scope to decision making in the wild, outside controlled laboratory situations.

Keywords: adversarial collaboration, recognition heuristic, special issue.

So much the worse for the facts!
- Georg Wilhelm Friedrich Hegel (attrib.), when confronted with the central theory of his PhD thesis *De orbitis planetarum* (1801) being not in line with the facts

Mind, not space, is science's final frontier.
- John Horgan (1996, p. 159)

[Vicky:] I'm not going to Oviedo. First off, I never heard of Oviedo. I don't find him winning. Third, even if I wasn't engaged and was free to have some kind of dalliance with a Spaniard, I wouldn't pick this one.
- Woody Allen & Letty Aronson (2008)

The compilation of this special issue on recognition-based decisions represents an adversarial collaboration among the three guest editors. At the beginning of this editorial to Part III of the special issue, a comment is warranted. The editorial consists of three sections, with Rüdiger Pohl serving as the lead author for Section 1, Oliver Vitouch for Section 2, and Julian Marewski for Section 3. While we have commented on each other's sections and, where needed, striven to formulate a text that represents a compromise between our positions, in some cases, we have not succeeded to achieve compromises, and therefore have agreed to disagree. As a result, the three sections are still firstly and foremostly written from the perspective of the respective lead author, who

In closing, the three of us want to express our gratitude to all the contributing authors of this triple special issue, and especially to *Judgment and Decision Making*'s editor-in-chief, Jonathan Baron, for his wise, patient, and fair guidance from start to finish. Without Jon's efforts it would not have been possible to compile this special issue. We also want to thank the following colleagues for providing manuscript reviews, greatly contributing to the project's overall success: C. Athena Aktipis, Jonathan Baron, William H. Batchelder, Manel Baucells, Arndt Bröder, Colin F. Camerer, Jason Dana, Clintin P. Davis-Stober, Michael R. P. Dougherty, Edgar Erdfelder, Ido Erev, Wolfgang Gaissmaier, Andreas Glöckner, Daniel G. Goldstein, Hauke Heekeren, Ralph Hertwig, Benjamin E. Hilbig, Ulrich Hoffrage, Robin M. Hogarth, Natalia Karelaia, Konstantinos V. Katsikopoulos, Damian Läge, Rui Mata, Ben R. Newell, Robert M. Nosofsky, Christopher Olivola, Henrik Olsson, Thorsten Pachur, Timothy J. Pleskac, Markus Raab, Sascha Serwe, Thomas S. Wallsten, Warren Waren, Anders Winman, Gal Zauberman, and six more reviewers who remain anonymous to the guest editors. All reviewers are acknowledged in the journal's annual reports.

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takes full responsibility for the section's text. We have decided to spare the readers from working their way through a myriad of footnotes, signalling our points of discord; rather we challenge the so inclined to scent out the paragraphs still smoldering.

1 Introduction *[Rüdiger F. Pohl]*

When we released our call for papers, we did not anticipate such an overwhelming response. What was initially planned as one special issue turned into a three-part issue with eight articles in Vol. 5 (4), seven in Vol. 6 (1), and six in Vol. 6 (5) of *Judgment and Decision Making*. Several more submitted manuscripts were rejected or withdrawn. Table 1 provides an overview of the published papers, not in the order in which they appeared, but in a topical order trying to sort them according to their main focus. Sorting papers into that order was easy for some, but more difficult for others that actually relate to more than one topic. We nevertheless put all papers into one category each, in order to keep the overview simple.

Those articles from Table 1 that appeared in Parts I and II of the special issue were already introduced there (Marewski, Pohl, & Vitouch, 2010, 2011). In the remainder of this section, we describe the six new papers in Part III.

Ayton et al. (2011) apply the recognition heuristic to the study of forecasts (see also, e.g., Herzog & Hertwig, 2011; Pachur & Biele, 2007), specifically to the forecasting of soccer match results. Their first experiment (which is a classic one, as it is already cited as an unpublished manuscript in Goldstein & Gigerenzer, 1999, 2002) compares the forecasting behavior of British and Turkish students on the results of British soccer matches. The results showed that both samples predicted the outcomes almost equally well, suggesting that the Turkish students who were less familiar with the British soccer teams could exploit their valid recognition knowledge to improve their predictions. After making their predictions, the Turkish students received the half-time scores and were asked to make new predictions. This manipulation leads to a situation that deviates from what Goldstein and Gigerenzer (e.g., 1999, 2002) considered the proper domain of the recognition heuristic. Cue values are given—and not retrieved from memory—and the half-time scores also provide information about unrecognized teams. Ayton et al. report that knowing the half-time score affected a substantial number of participants' predictions, even in cases where only one of the teams was recognized.

In their second experiment, Ayton et al. (2011) asked British students to predict results of foreign soccer matches. Before making their predictions, participants could get the half-time score, separately for each match.

Table 1: Topical categories of the special issue's articles.

Tests of the recognition heuristic and tests of theory extensions

Ayton, Önkal, & McReynolds (2011) — Influence of conflicting information
Erdfelder, Küpper-Tetzel, & Mattern (2011) — Recognition memory states
Gaissmaier & Marewski (2011) — Use of recognition in forecasting
Gigerenzer & Goldstein (2011) — Clarification and extension of the recognition heuristic
Glöckner & Bröder (2011) — Strategy classification method
Herzog & Hertwig (2011) — Recognition of crowds in forecasting
Hilbig, Scholl, & Pohl (2010) — Effort-reduction feature of using the recognition heuristic
Hochman, Ayal, & Glöckner (2010) — Arousal in information integration
Hoffrage (2011) — Discovery and first test of the recognition heuristic
Oeusoonthornwattana & Shanks (2010) — Recognition in preference judgments

The less-is-more effect

Beaman, Smith, Frosch, & McCloy (2010) — Extension of the less-is-more effect to knowledge-driven inferences
Davis-Stober, Dana, & Budescu (2010) — Mathematical foundation of optimal one-reason decision strategies
Katsikopoulos (2010) — Conditions and methodological problems of finding the less-is-more effect
Smithson (2010) — Generalization of the less-is-more effect to new conditions

Methodological challenges

Hilbig (2010a) — Measures of using the recognition heuristic
Tomlinson, Marewski, & Dougherty (2011) — Methodological challenges

Comments and discussions

Goldstein & Gigerenzer (2011) — Fruitful avenues and misunderstandings
Hauser (2011) — Marketing science perspective
B. R. Newell (2011) — Status of the recognition heuristic
Pachur (2011) — Measures and recognition processes
Pohl (2011) — Summary of the debate surrounding the recognition heuristic

The authors found that participants sought the half-time information in about two thirds of all cases where only one team was recognized. This, however, did not influence the subsequent overall percentages of choosing the recognized team in cases with and without knowledge of half-time scores. But the direction of the half-time score largely determined whether the recognized or the unrecognized team was predicted to finally win (as in Exp. 1). The authors argue that their results show that conflicting information may compensate for the recognition cue, thus contradicting the assumed noncompensatory property of the recognition heuristic. As already mentioned, it may be countered that this situation is not a proper test of the recognition heuristic, as additional information could be sought for unrecognized teams (see also Glöckner & Bröder, 2011).

Goldstein and Gigerenzer's (2011) comment on the special issue focusses on four topics. In the first, they highlight the use of optimization models that allow for a better understanding under which conditions heuristics such as the recognition heuristic would be most effective. Davis-Stober et al. (2010) followed this approach and incorporated the recognition heuristic into a general framework of linear models. Second, Goldstein and Gigerenzer point to an important extension of the recognition heuristic that incorporates a new *memory state heuristic* (Erdfelder et al., 2011). In this extension, Erdfelder et al. propose that utilizing knowledge about the certainty of recognition (or non-recognition) would help to understand several contradictory findings. In their third topic, Goldstein and Gigerenzer note that several new papers have extended the conditions under which a less-is-more effect may be found (Beaman et al., 2010; Katsikopoulos, 2010; Smithson, 2010). This effect is said to occur whenever recognizing less objects leads to a better decision performance. Finally, Goldstein and Gigerenzer turn to an ongoing discussion about the boundary conditions of the recognition heuristic and to which study may thus be called a proper test of the heuristic (see also Gigerenzer & Goldstein, 2011, and Pohl, 2011). Specifically, they stress that the recognition heuristic has been devised as a tool for memory-based inferences, where no other information is known than what can be retrieved from memory about recognized objects.

Hauser (2011) provides an applied view on decision strategies and the recognition heuristic in the wild. In an overview of marketing science, he discusses which role recognition-based heuristics may play in models of consumer decisions (see also Oeusoonthornwattana & Shanks, 2010). The focus of these models is much more in the field than in the lab. For example, models that forecast the purchase of new products use product awareness as one of their parameters. *Unaided awarenes* (similar to free recall) determines choice in the absence of product lists, while *aided awareness* (similar to recognition) influences choice in the field. Hauser also discusses the concept of ecological rationality as related to which cues provide valid information for consumer choice (e.g., advertisement) and which decision rules (e.g., noncompensatory heuristics) are thus applied in which context. Hauser's article may be seen as a wake-up call to recognition heuristic researchers: As he illustrates, marketing science and experimental psychology have developed theories and methods for similar phenomena—regrettably largely independently, without nearly as much exchange among the disciplines as the parallels between the studied subjects would suggest. We hope that Hauser's article can be taken as a starting point for more joint research and theory development in the future.

B. R. Newell (2011) primarily reacts to Gigerenzer and Goldstein's (2011) summary of a decade of research on the recognition heuristic. He sees the addition of an evaluation stage—prior to the application of the recognition heuristic—as an advancement of the framework, but also as a loss to its assumed simplicity (see also Pohl, 2011). The further fate of the recognition heuristic framework, according to B. R. Newell, now depends on how these assumptions can be turned into a complete process model of decision making (see also Pachur, 2011, and Section 2.4 of this introduction). In addition, B. R. Newell critically discusses the role and types of additional knowledge (beyond mere recognition) that may or may not enter the decision process. Especially the finding that the recognized object (in pairs of one recognized and one unrecognized object) is chosen more often when participants have further knowledge about it than when they do not (e.g., Marewski, Gaissmaier, Schooler, Goldstein, & Gigerenzer, 2010; B. R. Newell & Fernandez, 2006; Pohl, 2006) appears difficult to reconcile with the assumption that only recognition is considered in such inferences (but see Marewski & Schooler, 2011, for a computational model of heuristic selection aiming to explain this result). Finally, B. R. Newell contrasts ecological rationality and learning to adapt to specific environments as two different constructs to explain heuristic selection.

Pachur (2011) responds to a methodological challenge and discusses routes for future developments of the recognition heuristic as a process model. The methodological challenge was raised by some researchers who questioned the validity of previous measures of using the recognition heuristic, such as *adherence rates* which represent the percentage that a recognized object was chosen in pairs of one recognized and one unrecognized object (e.g., Hilbig, 2010a, 2010b; Hilbig, Erdfelder, & Pohl, 2010; Hilbig & Pohl, 2008; Pohl, 2011). These authors argued that adherence rates could be confounded and therefore suggested alternative, presumably more precise measures of using the recognition heuristic (see also Pachur & Hertwig, 2006; Pleskac, 2007). These measures still showed substantial use of the recognition heuristic, though much less than implied by adherence rates. Pachur, in turn, questions the usefulness of these approaches (see also Tomlinson et al., 2011) as long as they do not specify alternative models that explain the data better than the recognition heuristic does. In addition, Pachur questions previous attempts to derive and test decision-time predictions from the recognition heuristic (e.g., Hilbig & Pohl, 2009). The main reason for the Pachur's critique of these attempts is that the recognition heuristic itself does not provide a cognitive process model that allows such quantitative predictions (see also B. R. Newell, 2011; Pohl, 2011; but see Marewski & Mehlhorn, in press, for quantitative decision time predictions that are grounded in a cognitive process model of the recognition heuristic). In a further section of his paper, Pachur calls for an extension of the recognition heuristic to include memory-retrieval processes (see also, e.g., Dougherty, Franco-Watkins, & Thomas, 2008; Erdfelder et al., 2011; Marewski & Mehlhorn, in press; Marewski & Schooler, 2011; Pachur & Hertwig, 2006; Pachur, Mata, & Schooler, 2009; Pleskac, 2007; Schooler & Hertwig, 2005) and also discusses different types and uses of recognition information that help to specify the theory underlying the recognition heuristic.

Pohl (2011) gives an overview about several controversial topics surrounding the recognition heuristic. He first sketches the development of the underlying theory and then summarizes arguments and empirical evidence that shed light on the conceptual adequacy of the recognition heuristic but that are—naturally—evaluated differently by different researchers. One such point concerns the so far largely neglected impact of memory-retrieval processes on subsequent decisions (which Pachur, 2011, also calls to consider). Based on such processes, it should be possible to translate the recognition heuristic into a cognitive process model. Another area of debate that Pohl addresses concerns the proper conditions of testing the recognition heuristic. Some critical evidence has been refuted because it would not conform to those conditions. Thus, it appears helpful to clarify the boundary conditions under which the recognition heuristic is assumed to work. Building on their earlier publications, Gigerenzer and Goldstein (2011) provided such a list (featuring recognition validity, memory-based inferences, and natural recognition) in their latest description of the recognition heuristic. Additionally, Pohl critically discusses the assumed evaluation stage that checks whether the recognition heuristic should be applied, the empirical plausibility of a noncompensatory recognition heuristic, and the empirical evidence for the less-is-more effect. Finally, he speculates whether the toolbox approach with its multiple heuristics (and evaluation stages) is a plausible model for repeated decision making, which is the typical procedure in experiments on inferential decision making. The assumption that the decision maker decides in each trial anew which tool to take appears highly questionable in Pohl's view, because such a behavior would not be very frugal.

2 What we have learned (so far) *[Oliver Vitouch]*

This special issue project was launched with a double mission. First, after more than 10 years of research on the recognition heuristic, the intention was to answer some core questions about this heuristic on empirical grounds, to report on the most recent research, and to give an up-to-date evaluation of the state of the heuristic. Second, there was a goal of adversarial collaboration, bringing authors with different views together in the same (triple) issue to see if their substantial controversies can be scientifically resolved. This section tries to discuss what we have learned, so far.

Rhetorically borrowing from Randow (1992, p. 9), one might ask three questions about the debate on the recognition heuristic:

1. Why has the heuristic triggered so much controversy?
2. Why has it been so difficult to settle who's right?
3. Why is everyone so angry?

2.1 Questions from the adversarial collaboration

2.1.1 Why has the recognition heuristic triggered so much controversy?

The recognition heuristic forms part of the *simple heuristics* or *fast and frugal heuristics* framework (Gigerenzer, Todd, & the ABC Research Group, 1999; see Marewski, Gaissmaier, & Gigerenzer, 2010a, 2010b for a recent overview); indeed, it has sometimes been framed as "the simplest of all heuristics" in this program (e.g., Goldstein & Gigerenzer, 2002, p. 75). Both the program in general and the recognition heuristic as such make a number of what one might see as bold assumptions about the structure of cognitive processes and the success of simple decision rules. Among the most prominent examples for such a strong assumption is the strict *stopping rule* of several heuristics from the program: If a single cue (e.g., recognition) discriminates between two objects, choose the object with the positive predictor (e.g., recognized), and ignore all other information. This leads to the so-called *noncompensatory property* of the recognition heuristic (and of other heuristics, such as *take-the-best* or *minimalist*, see Gigerenzer et al., 1999) and to *one-reason decision making*. These assumptions are at odds with the idea that people usually integrate (at least some) information, for instance in the form of simply added unit weights (*Dawes's rule*), to make robust decisions under uncertainty. It is these assumptions that have raised considerable controversy.

Gerd Gigerenzer has repeatedly advocated boldness in the behavioral and cognitive sciences. The most articulate passage documenting this in print may be the opening from Gigerenzer (1998, p. 195):

> I like conference dinners. At such a dinner several years ago, I was crammed in with four graduate students and four professors around a table laden with Chinese food. The graduate students were eager to learn first-hand how to complete a dissertation and begin a research career, and the professors were keen to give advice. With authority, one colleague advised them: "Don't think big. Just do four or five experiments, clip them together, and hand them in." The graduate students nodded gratefully. They continued to nod when I added: "Don't follow this advice unless you are mediocre or unimaginative. Try to think in a deep, bold, and precise way. Take risks and be courageous." What a dilemma. How could these students apply these contradictory pieces of advice?
>
> Based on an analysis of articles in two major social psychology journals, the *Journal of Personality and Social Psychology* and the *Journal of Experimental Social Psychology,* Wallach and Wallach (1994, 1998) concluded that the theoretical argument in almost half of the studies reported borders on tautology. If an argument is a "near-tautology", there is no point in spending time and money to try to experimentally confirm it. "Don't think big" seems to be a prescription followed by many professional researchers, not merely conservative advice for graduate students.

Of course, what is *bold & correct* vs. *bold & wrong*, and if sufficient corroboration has been presented for a new theory, often lies in the eye of the beholder (for early reactions to the fast and frugal heuristics program, see, for instance, the Open Peer Commentaries on Todd & Gigerenzer, 2000). Many chapters in the seminal book by Gigerenzer et al. (1999) did not *primarily* aim to demonstrate that people actually use the proposed heuristics (e.g., via classic behavioral experiments), but rather that these heuristics work well on an algorithmic level (e.g., via simulations or mathematical proof), showing that they can match or even surpass the success of established and more complex decision rules under some conditions.[1] So especially when it comes to the methodologically challenging question which decision routines are actually implemented in people's heads, there was plenty of such stuff as scientific controversies are made on.

2.1.2 Why has it been so difficult to settle who's right?

Why is it not possible to just remain sober and matter-of-fact, until it has been empirically decided if (or under which conditions) the recognition heuristic is really out there in the vast and unexplored space of the human mind? Why not patiently wait and design the *experimentum crucis* that properly settles the case, once and for all?

There seem to be two elements here. On the one hand, as most judgment and decision making researchers know from their own experience, it is painstakingly difficult to nail down mental processes. Even if one demonstrates that the conjecture that one's subjects follow a certain decision routine nicely fits the data, this is of course no causal proof, and does not rule out an equally good or even better fit of other, untested, routines. This is demonstrated by Hilbig (2010a), who shows that adherence rates[2] can, as any measure of association, be misleading under some conditions, and proposes alternative approaches (but see Pachur, 2011, and Tomlinson et al., 2011). An even more general problem of identifiability is the *uniformity assumption*, namely the fact that some models, in order to be computable, assume that participants are applying one and the same decision rule (if applicable) in each and every trial of a decision task (see Section 2.4 for a more detailed discussion).

The other element is that the recognition heuristic may be perceived as a moving target. There were several instances where empirical findings were published that seemed to falsify the pervasive existence of the recognition heuristic (at least under some conditions), with the promotors of the heuristic responding "but we did not mean it that way." A good example for this is the critical work of Daniel Oppenheimer (e.g., Oppenheimer, 2003), and the section about misconceptions and misunderstandings in Gigerenzer and Goldstein (2011, p. 107 ff.). It seems that some critics had the

[1] A notable exception, already visible from the chapter's title, is Rieskamp and Hoffrage (1999). Goldstein and Gigerenzer (1999) used a broad mix of methodologies. In the following decade, descriptive work on when people use simple heuristics and how we can tell has strongly expanded.

[2] The *adherence rate* (or *accordance rate*) is the proportion of cases in which the participant's decision matches the prediction of the recognition heuristic, relative to the total number of cases where the heuristic is applicable.

impression to encounter a paradigmatic case of theory immunization, in the Lakatosian (e.g., Lakatos, 1970) and Duhem/Quineian sense: The attempted falsifications were not turned against the core theory, but instead the conflicts were transferred to the side show of auxiliary assumptions, demonstrating the conceptual pitfalls of naïve falsificationism (we might call this *Popper's despair*).[3] Section 2.2 tries to disentangle how the recognition heuristic was originally defined, and which auxiliary assumptions are essential to the theory.

2.1.3 Why is everyone so angry?

Well, you should know by now: Because the fast and frugal heuristics program has made bold assumptions, several researchers did not buy these assumptions, and it turned out quite difficult to decide who and what is right. Mutual misunderstandings and an appetite for spirited debates have played their roles, too. Section 2.2 should be helpful in shedding a bit more light on these.

2.2 The original recognition heuristic ®

The recognition heuristic has been generally defined as follows, in the universe of inferences (not preferences) and in the framework of paired comparison (two-alternative forced choice) tasks:

> Recognition heuristic: If one of two objects is recognized and the other is not, then infer that the recognized object has the higher value with respect to the criterion. (Goldstein & Gigerenzer, 2002, p. 76; see also Gigerenzer & Goldstein, 2011, p. 101)

The heuristic has also been formally generalized to a model for inferences about *N* alternatives:

> If there are *N* alternatives, then rank all *n* recognized alternatives higher on the criterion than the *N–n* unrecognized ones. (Marewski, Gaissmaier, Schooler, et al., 2010, p. 288; see also Frosch, Beaman, & McCloy, 2007; McCloy, Beaman, & Smith, 2008)

These rules sound like *allsatz* formulations (or *universal statements*). "If there are two objects, and you recognize just one of them, choose the recognized one, period." They are deterministic and seem to imply a high level of generality. In my [OV] perception, it was this kind of supposed *allsatz* that was perceived as provocative by some researchers, and fueled their fervor to demonstrate that it does not hold under a number of conditions. However, the *allsatz* has not, *or not always,* been meant as such. It has been developed in a certain setting, within a specific mindset (see Gigerenzer & Goldstein, 2011, p. 101). First, consider that the application of the recognition heuristic was considered useful only if it is empirically valid:

> The recognition heuristic is useful when there is a strong correlation—in either direction—between recognition and criterion. For simplicity, we assume that the correlation is positive. (Goldstein & Gigerenzer, 2002, p. 76)

The question of strategy selection from an adaptive toolbox, which is a theoretical cornerstone of the simple heuristics program, has itself led to numerous debates. It has been a considerable problem up to now to answer how humans and other mammals decide if they should apply the recognition heuristic in a certain environment or not (see Hilbig & Richter, 2011, and response by Brighton & Gigerenzer, 2011; see Marewski, 2010, and response by Glöckner & Betsch, 2010). For instance, as has been pointed out by many (e.g., B. R. Newell, 2011), if the recognition heuristic aims to be a process model, it would also have to model exactly that, namely under which conditions it is fetched from the adaptive toolbox (see also Sections 2.4 and 3.4). Without a formal model for how to adaptively choose the heuristic in charge, the basic argument that a heuristic is applied if it matches the structure of the environment, that is, if it is successful, is circular. It has been argued that the triggers for applying the recognition heuristic can be both inherited and learned; for the recent development of a quantitative ecological model of strategy selection, the *cognitive niche framework*, see Marewski and Schooler (2011) and Section 3.4.

Beyond this point of adaptive application, there is another, much simpler point of contextual constraints. Originally there were three major articles defining the basic properties of the recognition heuristic. Two of them, Goldstein and Gigerenzer (1999, 2002), have the recognition heuristic in their title and exclusively focus on it. But there was an earlier *Psychological Review* paper, Gigerenzer and Goldstein (1996), which contains some important additional information and shows plainly in which context the recognition heuristic was created (or discovered). Gigerenzer and Goldstein (1996, p. 653) still speak of a *recognition principle,* which is a constitutive first building block of the take-the-best algorithm.[4]

[3]This is a tricky issue in the philosophy and sociology of science. Self-consciously fighting for bold new ideas that break with previous conceptual traditions, and at the same time being your own hypotheses' most critical foe in the Popperian sense, is obviously not easy to reconcile. Carl Djerassi, the biochemist and "father of the pill", recently stated that the worst intellectual disease were the "falling in love with one's own hypothesis, which makes one ignore all other scientific facts" (Djerassi, 2011; transl. OV). But this is again just one side of a fickle coin.

[4]Gigerenzer and Goldstein (1996) is actually Gerd Gigerenzer's most-cited paper (Harzing, 2011, based on citations covered in *Google*

The authors state here:

> We study two-alternative-choice tasks in situations where a person has to make an inference based solely on knowledge retrieved from memory. We refer to this as *inference from memory as* opposed to *inference from givens.* Inference from memory involves search in declarative knowledge .... Studies of inference from givens, on the other hand, involve making inferences from information presented by an experimenter .... (Gigerenzer & Goldstein, 1996, p. 651 ff.)

Now this is an important point. This is the logical context in which the recognition heuristic, which received its name in journal print only three years later (Goldstein & Gigerenzer, 1999), was devised. Gigerenzer and Goldstein (1996) make this point explicit, while the later papers (Goldstein & Gigerenzer, 1999, 2002) are less clear on this. For instance, the word "givens" does not appear at all in the entire 2002 paper. While this inital restriction to *inference from memory* might seem trivial at first, it indeed has some eminent implications, especially concerning the plausibility of noncompensatory decision making.

Think about a person comparing two cities (the meanwhile classic task), one recognized by name, the other unrecognized. This person may well have further knowledge on the recognized city. However, if inference is *entirely memory-based,* it is implausible (if not logically impossible) that this person could have additional information about the city that she does not even recognize. So for the unrecognized city, this means that no further information whatsoever is available (see Section 2.3 for exceptions, and Section 3.1). Following Gigerenzer and Goldstein (1996), there cannot be any additional information about the unrecognized object, so there can also be *no compensatory effects of positive information* linked to the unrecognized object and favorably overruling the fact that it is unrecognized. "Thus, in inferences from memory, recognition is *not* like other cues. Rather, recognition can be seen as a prior condition for being able to recall further cue values from memory." (Gigerenzer & Goldstein, 2011, p. 107) Still, there can be additional cues available (from memory) for the recognized city, which may imply that it is rather small than large. This is why Goldstein and Gigerenzer (2002, p. 82 ff.) experimentally tested what happens if *recognized + negatively predictive information* meets *unrecognized*, showing that recognition typically still wins in their data, in line with the predicted noncompensatory property (resulting in "one-reason decision making"). While Oppenheimer (2003) experimentally demonstrated that knowledge about cities being small can well overrule recognition effects,[5] Gigerenzer and Goldstein (2011, p. 107) counter, in line with their earlier probabilistic mental model theory of inference (Gigerenzer, Hoffrage, & Kleinbölting, 1991), that this is not *inference* about the city size anymore, but plain *knowledge*—their "Misunderstanding # 2". See Section 2.5 for further debate on this.

So *that's* why, as it seems. The supposed *allsatz* was not an exuberant product of German idealism in the Hegelian tradition, but indeed a specifically limited "non-allsatz under constraints". What Gigerenzer and Goldstein originally had in mind was a very precisely (and narrowly, see below) defined set of cases. This is why B. R. Newell and Fernandez (2006, Experiment 1) and Glöckner and Bröder (2011), both introducing additional knowledge for the unrecognized object, are not accepted as evidence against the recognition heuristic by Gigerenzer and Goldstein (2011)—their "Misunderstanding # 3". The same refutation would hold for Zdrahal-Urbanek & Vitouch (2006, Exp. 1). See also Pohl (2011) for facets of this *givens* debate, and Pachur, Bröder, and Marewski (2008) for an overview of published work.

Tightly sticking to the original contextual definition of the recognition heuristic has an advantage and a flipside. The advantage is that the predictive accuracy of the recognition heuristic is high, then: It often seems to very accurately describe what people actually do. The flipside, however, playing the devil's advocate here, is that there may not be too many scenarios indeed apart from quiz shows and (badly prepared) school exams where people have to make merely recognition-based inferential decisions in the original sense (see the real-world considerations in Hauser, 2011). So, strictly limiting the recognition heuristic to cases without any givens makes the story more accurate, maybe even water-tight, but also less bold in scope. What shall people possibly do if they have to decide between a recognized and an unrecognized object, and they cannot get any (more) information about the unrecognized option? They can essentially *(a)* guess, *(b)* choose the recognized one, or *(c)* gamble by choosing the unrecognized one in case the recognized one is supposed or known to have negatively predictive cue values. All the work on the recognition heuristic then "only"

Scholar; data retrieved April 30, 2011). With 1222 hits, it easily beats the more recent Goldstein and Gigerenzer (2002) at the time being, with the latter still counting 459 hits. But of course, citing does not always imply reading; and as outlined above, the term "recognition heuristic" features neither in the title nor in the text of the 1996 article, which contains a section dealing with the "recognition principle" as it was then called. While the 1996 paper is referenced 7 times in the 2002 text, there is no reference to it defining contextual constraints for the recognition heuristic, or being essential reading for understanding under which conditions the heuristic is supposed to work. So, as often with developing theories, it is a question of perspective if the conditions subsumed as mandatory by Gigerenzer and Goldstein (2011, p. 101) had been laid out visibly and explicitly enough.

[5] See also Ayton et al. (2011); but they used givens and information for the unrecognized alternative.

shows that people do *(b)* far more often than *(a)* or *(c)*. It is not so much the case here that available information would be ignored (as with other heuristics from the simple heuristics program): There is just *nothing available* for the unrecognized object for possible comparative integration, compensation, or trade-off, because we know plainly nothing about it.[6] There still remain some quite remarkable effects, such as the less-is-more effect (within this special issue, see Beaman et al., 2010; Davis-Stober et al., 2010; Katsikopoulos, 2010; Smithson, 2010); and it is always easy to brag in hindsight that something ain't spectacular because we knew it all along. But you may agree that the original 1996 setting narrows down the scope, and makes the recognition heuristic somewhat less thrilling, bold, and provocative—less "think big".

Does this mean that all the brouhaha about the perceived *allsatz* was in vain, because the critics just didn't understand the proper definition of the recognition heuristic, and did not read the papers right (or did not read the right papers)? Was it basically all due to a spreading *givens fallacy*? Well, not so fast (and not so frugal). Of course, nobody doubts that definitions are important. (For the debate on what has been defined when, and how clearly and visibly, see above.) But there is no unconditional copyright in science to what a heuristic is, once and for all, and under which (realistic) conditions it is tested. We are all aiming to arrive at meaningful statements about decision making in the wild, after all (see Section 3.5). If the recognition heuristic is limited in the original way (i.e., in the Gigerenzer & Goldstein, 1996, way), then it is no model for all those situations where unrecognized objects are presented together with additional information (as in brochures etc.), or where additional information can be easily obtained or is readily delivered, which are realistic and interesting scenarios, too. It makes excellent sense to extend the idea that recognition is used as a cue that guides decisions to other contexts and domains, and see what role recognition plays when other cues (not from memory) are around. It is still not a settled question if recognition is just "one cue among others" in such conceptually extended settings, or if there is a certain primacy to the recognition cue (sometimes, for some persons, under some conditions) as well. For instance, just think about the fruitful recent extensions into the realm of preferences (e.g., Gigerenzer & Goldstein, 2011, p. 113 ff.; Hauser, 2011; Oeusoonthornwattana & Shanks, 2010).

So the role of the recognition cue in combination with *givens* is neither uninteresting nor unimportant. There are many scenarios where a decision has to be made between two options with one recognized and the other unrecognized (e.g., stocks of companies), and additional information is provided, or can be searched for, or can be purchased at some monetary or non-monetary cost. Consider, for instance, Exp. 1 in B. R. Newell and Shanks (2004), where participants often purchased additional information, and the studies by Ayton et al. (2011), or Zdrahal-Urbanek (2004; Zdrahal-Urbanek & Vitouch, 2006). Especially in the "Age of Google", one may assume that many people would prefer to accumulate some information about unrecognized objects as soon as the decision is important, and there is five minutes time. The question, then, is which role the initial non-recognition plays in exactly that scenario, and if it can override other credible information. As Gigerenzer and Goldstein (2011, p. 101) state themselves:

> This is not to say that studies that test predictions outside the domain are useless; on the contrary, they help to map out the boundary conditions more clearly, as we ourselves and other researchers have done.

In their conclusion, the creators give an extended picture of the recognition heuristic themselves:

> The recognition heuristic is a simple model that can be put to many purposes; describing and predicting inferences and preferences, and forecasting such diverse events as the outcome of sporting events and elections. (Gigerenzer & Goldstein, 2011, p. 114)

Having said all this, a word of caution and a joint prospect should be added. Looking back, we all should care not to fall prey to a specific pattern of conceptual defense: that evidence against the recognition heuristic (especially against its strictly noncompensatory nature) is rebuffed with the argument that it is not the original recognition heuristic that has been tested, while evidence in favor of it is welcome also from innovative contexts quite remote from the original definition (e.g., Berg, Hoffrage, & Abramczuk, 2010). Similar caveats against partisan interpretation of evidence hold for the critics: While the identification of potential loopholes in a theory is important, it may be a better choice to help close the loophole than to shoot the theory. Prospectively, as a common goal, we should just arrive at a more relaxed attitude (including our assumptions), not quarreling about

[6] It is a more complicated and debated question what actually happens in case *(c)*, i.e., how information about the *recognized* object may be used (and potentially integrated, weighted, compared to a threshold, etc.). For comparisons of such candidate models, see Marewski, Gaissmaier, Schooler, et al. (2010) and Marewski and Mehlhorn (in press). The word "gamble" should not imply that decisions sensu *(c)* were irrational, but rather that they usually come along with high uncertainty, as *no direct cue comparisons* are feasible with the (unknown) cue values of the unrecognized object. Also, remember that in case *(b)*, a decision for the recognized object does not necessarily need to be based on recognition, but may be due to other internal processes yielding the same result (see Figure 1 in Section 2.4).

originals and who-said-what at which time, but instead extending the framework and describing which variants of recognition-based heuristics hold under which conditions (see Section 3.1). Or to say it with Abraham Lincoln (see Hauser, 2011): Probably we can show that all of the people use recognition-based heuristics some of the time, and we can even show that most of the people almost always use them under some conditions (namely those of Gigerenzer & Goldstein, 1996), but we cannot show that all of the people use them under all conditions, all of the time. Research would profit from such a common effort.

2.3 What's in a name?

This section briefly digresses into a setting where even less information seems to be in the game than with the original case for the recognition heuristic. Imagine you are confronted with the names of two German cities, and you recognize *neither of them*. There is no more information available to infer which city is larger. What can you do?

Gigerenzer and Goldstein (2011, p. 107) coherently write that "[i]f one has not heard of an object, its cue values cannot be recalled from memory (although the name itself may, quite rarely, impart cue values, much like '80 proof whiskey' reveals its alcohol content)." But are these cases so rare indeed? In 2000, Melanie Drösemeyer, a German psychology student at the University of Münster, finished her yet unpublished master's thesis. From her supervisor, Wolfgang Hell, I [OV] recently learned that Drösemeyer (2000) discovered an intriguing effect about how people can use the length of a city's name to infer its size (W. Hell, personal e-communication, August 30th, 2010). We might baptize this the *brevity cue.*

The theoretical rationale is as follows: There is an old tenet in linguistics that words and names get shorter over long periods of time with frequent use. For instance, Schleicher (1860; cited from Deutscher, 2011) famously compared the Gothic verb form *habaidedeima* with its modern English relative, the monosyllabic *had*, "and linkened the modern form to a statue that has been rolling around on a riverbed and whose limbs have been worn away, so that hardly anything remains but a polished stone cylinder" (Deutscher, 2011, p. 114). "Omnibus", already a brevium itself, meaning "for all" in Latin, becomes "bus", "Vindobona" becomes "Wien" ("Vienna"), "Colonia Agrippina" becomes "Köln" (but as a foreigner, you can take the time to say "Cologne"). Although it is easy to come up with counterexamples (large cities with long names), the correlation seems to be considered an established fact in linguistics.

Drösemeyer (2000) and Hell used the names of smaller German cities, between 45.000 and 60.000 and between 20.000 and 25.000 inhabitants. This resulted in their German participants sometimes having heard of neither of the two, and sometimes just recognizing the two by name, but with no further information available from memory. In the former case, participants correctly chose the larger city in 55% of the pairs, in the latter in 54% of the pairs, both rates significantly different from chance. Although these effects are tiny, they point to an interesting exploitation of information from the mere names, even if both cities are unrecognized.[7]

But there is more. When they asked the subjects about their strategies (and computed the respective ecological validities for their sample of cities), Drösemeyer and Hell found that 19 out of 40 subjects introspectively reported the heuristic "the longer the name, the smaller the city" (with not a single one stating the opposite). So which Austrian city is larger, Graz or Klosterneuburg? You name it. Other cues revealed were that cities with the endings "-stadt" and "-hafen" tend to be large (true for -hafen, indifferent for -stadt), and that the endings -heim / -dorf / -berg / -hausen / -ingen / -bach are characteristic for small cities (true for all six). Participants were divided, however, if "Bad" (spa) before the name was a positive or a negative predictor (it was indifferent), and 9 out of 40 were wrong in assuming that appendices such as "auf der Höhe", "an der Wümme" or "am Rübenberge" (usually used for discriminating between cities of the same name) signify a smaller city, because these actually tended to be larger.

There may be similar, and probably larger, effects if samples with cities from different world regions are used, since the geographic location deduced from the name (e.g., East-Asian vs. Swedish) may allow valid inferences on city sizes. Although the effects reported so far are small and await replication, note that such information usage permits inferences where the recognition heuristic assumes guessing: *both cities unrecognized* or *both cities recognized, no further information retrievable*. A similar, much better established strategy is the *fluency heuristic* (Hertwig, Herzog, Schooler, & Reimer, 2008; Marewski & Schooler, 2011; Schooler & Hertwig, 2005; for a critical view see Hilbig, Erdfelder, & Pohl, 2011), which holds that people introspectively use the recognition memory retrieval times of two recognized city names for inferring that the one that is perceived as having the longer retrieval time is smaller. In sum, there seems to be an entire quiver of cues—fluency, brevity, suffixes, region cues, and the like—, some of them domain-specific, that can jump in instead of guessing in cases which the recognition heuristic cannot decide.

[7] A potential caveat is that recognition statements are often conservative: Participants hesitate to call a city "known", and the hit rate in guessing cases (based on this classification) is slightly above 50% then. Also, fluency effects may play a role.

2.4 A probabilistic revolution?

An eye-catching property of the recognition heuristic is its deterministic formulation—see the *allsatz* considerations in Section 2.2. There is indeed evidence that the recognition heuristic may, under many circumstances and in both its original version and some extended versions, be the single best simple deterministic model available. However, it is an evident question if a *probabilistic* version of the recognition heuristic, and of other simple heuristics, would not be a more appropriate descriptor of both the nature and the actual outcome of mammalian/human decision processes.[8]

In the words of the English statistician Maurice Kendall, at the time of WWII, his probabilistic ilk had "already overrun every branch of science with a rapidity of conquest rivaled only by Attila, Mohammed, and the Colorado beetle" (Kendall, 1942, p. 69; cited from Gigerenzer, 1993, p. 311). As vividly pictured by Kendall's dictum, this "probabilistic revolution in science" (e.g., Gigerenzer et al., 1989) stopped at nothing. Among the most illustrative examples in psychology is Skinner's theory of operant conditioning, or reinforcement learning, which was transformed into a probabilistic theory of learning by Estes (1959). Should the probabilistic revolution come to a late halt, after all, at simple heuristics? It is not easy to see why "probabilistic mental models" (Gigerenzer et al., 1991), as the precursors of simple heuristics were called, must suffer a deterministic process description.

Of course, there are several ways to go probabilistic. If the recognition heuristic per se is not understood as a cognitive process model, but initially just as a *stylized algorithm* or abstract rule, prescribing a certain decision routine, then it need not be probabilistic as such. ("Assume there is this rule, among several; who uses it under which circumstances, and how often, is another issue.") In this case, there subsequently should be a corresponding probabilistic process model, descriptively based on the relative frequency of the heuristic's actual application by real decision makers. However, there is evidence that the recognition heuristic has been designed as a process model (see Section 3.2 in Pohl, 2011), or at least with the intention to be easily transducible into a process model.[9] On general grounds, such a process model should fit reality better, and gain generality, if it were probabilistic. (For recent implementations of process models of recognition-based inference, including the recognition heuristic and various compensatory models that assume probabilistic processes, see Marewski & Mehlhorn, in press.)

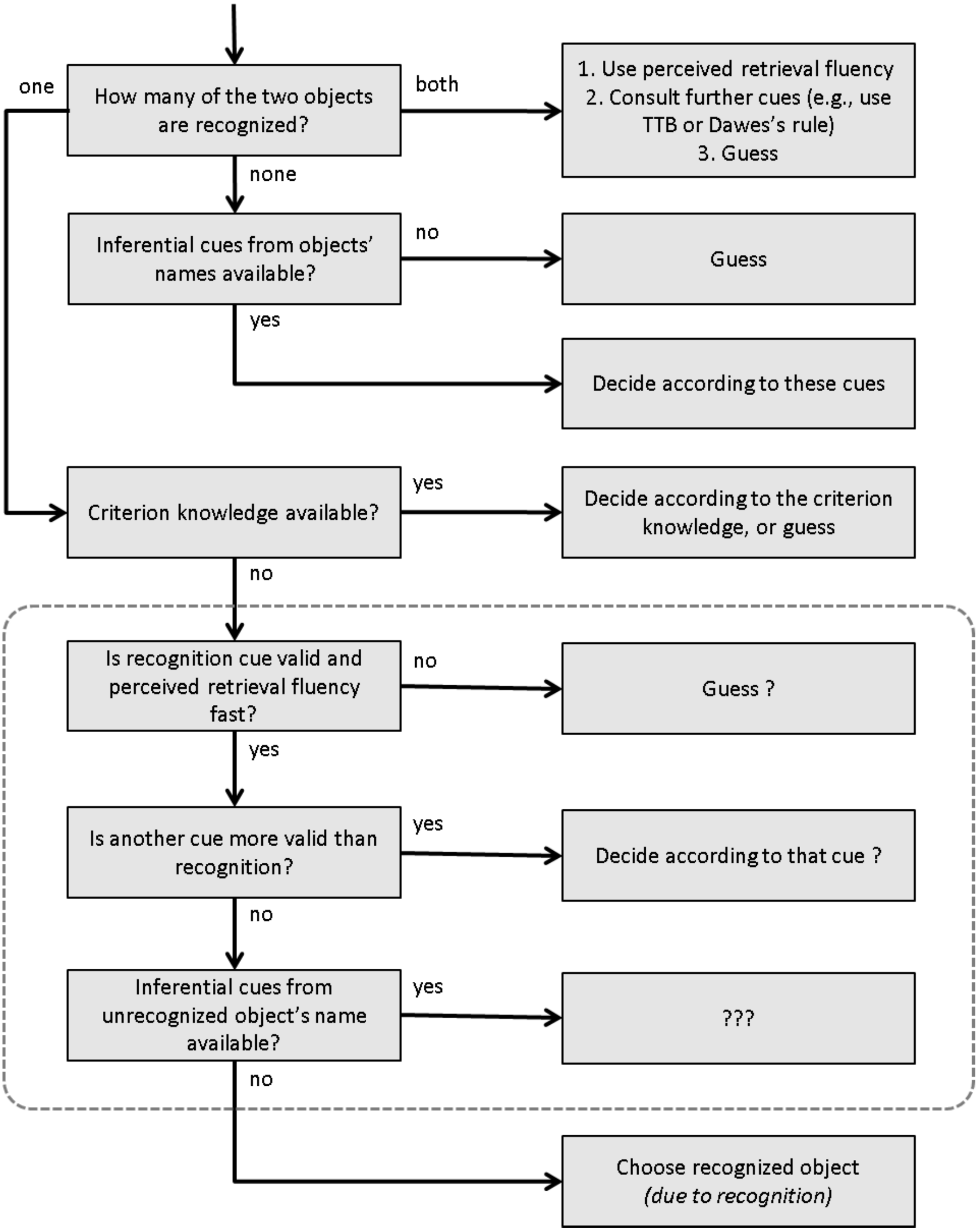
This topic is linked to a more general as-if problem in judgment and decision making research, namely the *monotony* or *uniformity assumption*. Researchers often act as if it were granted that their participants apply the same decision routine in every single trial, without any strategy variation at all. This is usually due to methodical constraints, making models only identifiable under this assumption. However, there are several evolution-based arguments for why strategy variation is not only real, but also rational: (A) Environments may change without notice; (B) a certain share of exploration may be advantageous even if one thinks to have adopted the optimal, or a very good, strategy; and (C) uniform behavior can be most easily (and, in the worst case, most deadly) exploited by opponents in game-theoretical settings. Argument C relates to the evolutionist case for *protean behavior* (adaptively unpredictable behavior; e.g., Miller, 1997), which makes the next move unpredictable even for the protagonist himself, and therefore also for a predator or competitor. Having said this, while both the reasons for strategy variation and its actual benefits may contextually vary, its mere existence should be beyond question: See, for instance, Pachur's (2011) conclusion from the data of Pachur and Hertwig (2006) suggesting that "the decision of whether to use the recognition heuristic or not is made for each individual pair of objects rather than for an entire environment" (Pachur, 2011, p. 418). For recent methodological attempts to tackle this problem, see Marewski and Mehlhorn (in press) and Marewski and Schooler (2011).

Finally, it has repeatedly been argued that the recognition heuristic is not really a (satisfying) process model (e.g., B. R. Newell, 2011), because if it were, it had to include steps for deciding whether the heuristic should be applied in a given setting. Hence, an accurate process model had to contain more information than just the recognition/non-recognition information. As considered in this editorial, further bits of information may play a decisive role within a typical recognition setup, too. Figure 1 aims to give an extended flow-chart model of recognition-related decision processes, trying to integrate several facets discussed in this triple special issue, some of them hypothetical, into one graphic display. The chart has, due to the nature of the subject, some core parallels to Figure 1 from Pohl (2011), but tries to further expand his model.

[8]Kudos to Bartosz Gula, who has recently brought this topic to my [OV] attention.

[9]Gerd Gigerenzer has always been a fierce critic of "as-if models" in economics (for a recent example, see Berg & Gigerenzer, 2010), and an advocate for accurate process models which do not just model the behavioral output, but the underlying cognitive routines leading to this very output on a step-by-step basis. I [OV] therefore always understood fast and frugal heuristics as process models, or process model candidates, for actual human decision making.

Figure 1 [OV and RFP]: Extended recognition heuristic process model. Setting: Pair of objects (forced choice); all cues retrieved from memory (but object names given). The sketched decision flow includes both an evaluation step ("Is recognition a valid cue in this domain and/or with this specific pair of objects?") and specific knowledge states (e.g., perceived retrieval fluency; cue knowledge and use) of the individual decision maker. The dashed area depicts the evaluation stage. Note that the chosen sequence of steps is largely speculative, and not intended to exclude modes of parallel processing. TTB = take-the-best heuristic.



2.5 Synopsis: From psychophysics to metaphysics—and beyond

The recognition heuristic, as initially postulated, seemed to have an almost psychophysical quality: It had the simplicity and determinism of a classic psychological law, just as from the dusk of the 19th century, from the days of Fechner, Ebbinghaus, and Wundt. What followed was a longsome debate on whether the cognitive world could be so physicalistically simple. As typical for such debates, it was difficult in the long run to completely abstain from metaphysics. For instance, Gigerenzer and Goldstein (2011), in their "Misunderstanding # 2", hold that "(direct) knowledge" essentially differs from cue-based inference. However, the example they provide is that we all know that Bernie Madoff is a fraudulent bankrupt. But do we indeed *know* this, in a way that would have halfway satisfied the British Empiricists, or do we infer it from statements in the media of our choice (which are rather cues than stone-carved facts)? The border between secure knowledge and probabilistic inference is a foggy site (see the section "Cues, information & knowledge" in B. R. Newell, 2011). Consider that Goldstein and Gigerenzer (2002, p. 76) stated themselves that "It is also easy to think of instances in which an object may be recognized for having a small criterion value. Yet even in such cases the recognition heuristic still predicts that a recognized object will be chosen over an unrecognized object", which does not properly fit to their segregation of inference and "local" knowledge.

On a hopefully more material level, it is a general question if recognition and valence can be essentially separated. From an evolutionary perspective, a major function of recognition should be to guide one's behavior towards either approaching (if recognized as positive/pleasant) or avoiding (if recognized as negative/aversive) the recognized entity. So recognition memory without memory for valence seems rather one-eyed. One of the major theories of human emotion and affect, the *component process model* (CPM; Scherer, 1987, 2001, 2009), assumes a dynamic sequence of stimulus evaluation checks, with the earliest checks being automatically processed. Step 1, the *novelty check* (known/unknown), is immediately followed by a *valence check* ("intrinsic pleasantness") in Step 2. While it seems to make adaptive sense to have valence intimately coupled to recognition, to attach a "valence label" to things you have encountered before and therefore recognize, novelty and valence appraisals indeed seem to happen with distinct, sequential timelines (Delplanque et al., 2009), with novelty being processed as soon as 100 ms after stimulus presentation with olfactory stimuli and valence being processed at a latency of 400 to 500 ms. Zdrahal-Urbanek and Vitouch (2006) found that most participants would not give virtual votes to populist right-wing politicians from foreign European countries, and would not erroneously take them for the prime ministers, even if these are the only ones they recognize due to international media publicity; so recognition and valence memory usually seem to inseparably go along.[10]

In a nutshell, assumptions from the fast and frugal heuristics program have sometimes been perceived as apodictic by skeptics of central tenets of the approach. On the creators' side, critique has been perceived as being based on misreadings and misconceptions. What is *hors de question* in any case, and admirable as even the most inveterate critics must admit, is the amount of creative research that has been inspired and triggered by this program, and especially by the recognition heuristic.

Taking all evidence together, recognition effects seem to play an important role in everyday decision making, in a variety of settings, and with both inferences and preferences. Just think of the famous pick-up scene in *Vicky Cristina Barcelona*, where Javier Bardem approaches the table of Rebecca Hall (Vicky) and Scarlett Johansson (Cristina) and forthrightly suggests that the three of them fly to Oviedo in one hour, see a sculpture, spend the weekend, and make love together. *"I'm not going to Oviedo. First off, I never heard of Oviedo"*: Name recognition is the first cue that Vicky produces, then supported by two further arguments. (Well, they eventually *do* go to Oviedo, but that's another story.) In this fine emblematic case of applied dyadic decision-making under considerable uncertainty, Woody Allen seems to have gotten the cognitive basics quite right.

3 Outlook: The thorny road towards theory integration *[Julian N. Marewski]*

In the introduction to Part I of this special issue, we have pointed out that the debate on the recognition heuristic much resembles what is known from the traditional schools of psychology (like, e.g., psychoanalysis, behaviorism, or gestalt psychology), in which theoretical convictions were turned into dogmas that had to be defended by all means. One goal of this special issue was to re-

[10]Having said this, I recently had an experience challenging this *recognition + valence* view. Together with my little son, I repeatedly played a French *massive multiplayer online role-playing game* (MMPORG) called *Dofus* (www.dofus.com), which in addition to a "player vs. monster" mode (PvM) also has a "player vs. player" mode (PvP) with the option to spontaneously "aggress" other characters. I actually made the strange experience that I practically always remembered if I had fought a certain player before (by character name recognition), but did *not* always remember who had won the fight. You will not be surprised to learn, however, that my 8-year-old knew perfectly well whether we should fight or flee.

solve some of the controversies on which contemporary recognition heuristic research has centered; for instance, by bringing researchers with different theoretical viewpoints together in the editorial and reviewing teams of submitted articles. In what follows, we will give four recommendations that we believe may help to further bridge the various competing theoretical viewpoints and foster theory integration. While we formulate our recommendations specifically for future recognition heuristic research, we expect for at least some of them to also apply more broadly to other areas of judgment and decision making research, including research on other heuristics that have been developed in the fast and frugal heuristics research program.

3.1 Build cumulative theories

Recently, Katsikopoulos & Lan (submitted) pointed to our adversarial collaboration as an illustration of how researchers coming from different theoretical perspectives are sometimes classified as "proponents" or "critics" of a certain approach. In their view, such divisions are harmful for theory integration, as they give importance to *who* said what instead of *what* has originally been said. We agree. Recognition heuristic research should be about data and models, and not about people.

We would like to add another point to Katsikopoulos and Lan's (submitted) observation. As editors, it has been a striking experience for us to actually learn *how much* of the recognition heuristic controversy focuses on *what* has originally been said about the recognition heuristic. For instance, as pointed out in Section 2.2, in 1996, Gigerenzer and Goldstein introduced the recognition principle as a mechanism for making decisions when all available information has been retrieved from memory. They labeled the corresponding paradigm inferences from memory. The recognition principle was later renamed into the recognition heuristic (Goldstein & Gigerenzer, 1999, 2002). Even though the recognition heuristic's memory-based paradigm had thus been specified,[11] as we have witnessed, a part of the current controversies *still* centers on whether the recognition heuristic has originally been specified as a model for inferences from memory, or whether this heuristic is additionally applicable to non-memory-based paradigms. This has been an important distinction, for instance, (a) to those researchers who have set out to test and potentially refute the recognition heuristic as a model of behavior, or (b) to those researchers who were interested in establishing what are likely to represent fair and/or strong tests of the heuristic, or (c) to those researchers whose goal it was to evaluate whether the results of memory-based tests of this heuristic are likely to generalize to non-memory-based settings.

Importantly, from our perspective it is neither useful nor relevant how the domain of the recognition heuristic has originally been specified more than a decade ago. After all, scientific theories evolve over time, and change in the course of their development in order to be able to account for empirical findings. This process is called cumulative theory development. By this token, it is more of historical importance whether the recognition heuristic was originally specified only as a model for memory-based inferences or whether the intended applicability of the model exceeded that domain; what *is* relevant is the fact that the current empirical evidence suggests that the recognition heuristic is a good model of behavior for inferences from memory. That is, in our view, current theorizing about the recognition heuristic specifies this heuristic as a model of memory-based inference, and contemporary research should start from there, rather than focus on producing yet another test of this heuristic that establishes the heuristic to be an inadequate model of behavior outside of its domain. For instance, as we will elaborate in Section 3.4 below, it is important that contemporary recognition heuristic research continues to explore the boundary conditions of recognition heuristic use in inferences from memory (e.g., Pachur & Hertwig, 2006; Pohl, 2006), ideally specifying corresponding computational models that allow predicting when people are likely to rely on the heuristic in memory-based inference and when not. Much the same—quarrelling about what additional assumptions about the recognition heuristic have been specified, and what not—can be said with respect to other controversies that populate the recognition heuristic literature (see Pohl, 2011).

In short, rather than being largely motivated by what has originally been said about the recognition heuristic, studies on this model of behavior should draw their motivation from refining the current knowledge and theorizing about recognition-based inference.

3.2 Build computational process models, using cognitive architectures

Where does the focus on who has said what, and what has been said come from? We wonder if a part of the problem can be attributed to the following observation: While much of the rather uncontroversial recognition heuristic research that focuses on prescriptive, normative questions or the less-is-more effect makes use of formal methods such as mathematical or simulation-based modeling (e.g., Davis-Stober et al., 2010; Katsikopoulos, 2010; Pachur, 2010; Pleskac, 2007; Reimer & Katsikopoulos, 2004; Schooler & Hertwig, 2005; Smithson, 2010), most descriptive and more controversial studies on this heuris-

[11] See also Figure 1 in Gigerenzer and Goldstein (1996) and Figure 2–1 in Goldstein and Gigerenzer (1999) for graphic visualizations of the recognition heuristic's memory-based domain.

tic have not made use of corresponding tools. Formal simulation and mathematical methods can help dissolving ambiguities in theory specification. For instance, ideally, the entire recognition heuristic theory were cast into computer code, and this code would also specify when the heuristic ought to be able to describe people's behavior, say in memory-based inferences, and when not. If the code were applied to experimental paradigms for which it has not been designed it would, ideally, be unlikely to run, obliterating the need to exchange unfruitful arguments about how the model had originally been specified. At the same time, for those interested in the historical stages of theory development, changes in the code, made to accommodate new findings or to extend the recognition heuristic's domain of applicability to new experimental paradigms, can be detected by comparing older and newer model codes.

Besides helping to avoid unfruitful controversies, formal simulation and mathematical approaches can also aid ameliorating a more serious problem most descriptive studies on the recognition heuristic have suffered from: As mentioned above, this heuristic represents a model of how people make inferences when all available information has to be retrieved from memory. Memory processes, such as whether an object (e.g., a car brand) is recognized or not, provide input to the heuristic's decision rule (i.e., to infer recognized objects to be larger than unrecognized ones). While memory processes thus obviously play a role in the way how people make recognition-based inferences, other cognitive processes are also likely to be involved in the use of the recognition heuristic. These include, for instance, perceptual processes (e.g., reading a car brand's name), intentional processes (e.g., having the intention to make inferences about car quality quickly rather than accurately), motor processes (e.g., pressing a key in a computer-based consumer choice experiment), as well as the interplay of these processes with the environment (e.g., which car brand names are advertised in the environment and hence ready to be memorized) to name just a few.

It has been pointed out elsewhere why it is important for a theory to provide an integrative, encompassing account of the various aspects of behavior (see A. Newell, 1990), and why also contemporary behavioral recognition heuristic research warrants such an integrative, encompassing approach (see Dougherty et al., 2008; Tomlinson et al., 2011). Rather than repeating the arguments that have been made, we would like to point to one tool that is available for building such an approach: *cognitive architectures*. A cognitive architecture is a quantitative theory that applies to a broad array of behaviors and tasks, formally integrating theories of memory, perception, action, and other aspects of cognition (for an introduction to cognitive architecture, see Gluck, 2010). Implementation of models within a cognitive architecture lends further precision and breadth to the corresponding theory. For instance, it is possible to specify when the recognition heuristic will be used by people and when not, say, in memory-based inferences about city size or spatial navigation in driving.

Among the architectures developed to date (e.g., *EPIC*, Meyer & Kieras, 1997; *Soar*, A. Newell, 1992), the *ACT-R cognitive architecture* (e.g., Anderson, et al., 2004) provides perhaps the most detailed account of the various perceptual, memory, and decision processes that may play a role in recognition-based inference, making ACT-R especially suitable to study the recognition heuristic. At the same time, ACT-R is sufficiently broad to allow for modeling recognition-based decision processes beyond the two-alternative forced choice task that has been the focus of most studies on the recognition heuristic. To illustrate this, ACT-R has been applied to flying (Gluck, Ball, & Krusmark, 2007), driving (Salvucci, 2006), or the teaching of thousands of children in U.S. high schools (Ritter, Anderson, Koedinger, & Corbett, 2007).[12] Specifically, ACT-R consists of a set of modules, each of which is devoted to a different activity. For example, the *declarative module* allows information storage in and retrieval from declarative memory (e.g., whether a city is recognized or not, what a person knows about a city), the *intentional module* keeps track of a person's goals (e.g., infer city size), and the *imaginal module* holds information necessary to solve the problem currently in the focus of attention. A *visual module* for perception and a *manual module* for motor actions (e.g., pressing a key on a computer keyboard) are used to simulate interactions with the world. These modules are coordinated by a production system. The production system consists of production rules (i.e., if-then rules) that serve to model procedural knowledge (i.e., knowing how), and that allow implementing decision making mechanisms such as the recognition heuristic.

With ACT-R researchers can derive predictions of at least three kinds of behavioral data: (i) overt behavior, such as the outcomes of decisions; (ii) the temporal aspects of the behavior, such as time involved in making a decision; and (iii) the associated patterns of neuronal activity in the brain, as measured with functional magnetic resonance imaging (fMRI) scanners. For instance, by modeling decision processes side by side with perceptual, memory, intentional, and motor processes, Marewski and Mehlhorn (in press) were able to test 39 detailed competing quantitative predictions about people's decisions and

[12] ACT-R also represents a good example of successful theory integration and cumulative theory building over time. Over the past decades, ACT-R has been repeatedly adapted to be capable of accounting for previously unexplained phenomena, a fact that is also reflected in the changes in the architecture's name (e.g, HAM, ACT*; Anderson, 1983; Anderson & Bower, 1973).

the associated decision times in recognition-based inferences from memory. The corresponding models not only predict which of two objects will be chosen, but also how different pieces of information will be processed to derive a decision. In doing so, the models quantitatively predict at what point in time which processes (e.g., memory, decision, motor, etc.) occur in parallel and which do not. In the memory paradigm, it seems difficult to derive such detailed predictions without a formal, architectural approach.

Until today, only a few studies have investigated the recognition heuristic by specifying this model within a cognitive architecture, or a similarly formalized, architectural system. Most of these studies do not actually test the heuristic as a model of behavior (e.g., Dougherty et al., 2008; Gigerenzer, Hoffrage, & Goldstein, 2008; Pachur, 2010; Schooler & Hertwig, 2005; for such tests see Marewski & Mehlhorn, in press; Marewski & Schooler, 2011; see also Glöckner & Bröder, 2011, for a formal test conducted without specifying the heuristic in a cognitive architecture). Put differently, the architectural modeling of recognition-based inference still represents a largely unexplored territory.

We can think of at least three reasons for this state of affairs. A first reason is perhaps that one appeal of studying the recognition heuristic, namely its stunning simplicity, appears to get lost when embedding this simple mechanism in a detailed cognitive framework (see Pohl, 2011, for corresponding arguments). Yet, it is not necessarily the recognition heuristic that becomes more complex when implemented in a cognitive architecture; rather it is the case that studying even simple decision making mechanisms warrants formulating detailed theories about how these simple mechanisms interact with other components of cognition.[13] A second reason, is perhaps, disciplinary segregation: A portion of decision making research continues to be mostly concerned with formulating verbal, that is, informal hypotheses about cognition, ignoring the formal tools that have been developed by mathematical psychologists, computer scientists, and machine learning and artificial intelligence researchers, to name a few. A third reason may actually be a product of the second one: If precision and level of detail is a major virtue of architectural approaches to cognition, these features can also become a curse. With respect to much of the verbal, informal contemporary recognition heuristic theorizing (e.g., Hilbig, Scholl, & Pohl, 2010; Marewski, Gaissmaier, Schooler, et al., 2009; Newell & Fernandez, 2006; Pachur et al., 2008; Pohl, 2006; Volz et al., 2006) modelers need to decide how to bridge the gaps between informal verbal descriptions of hypotheses and their respective architectural implementations. If it is not clear *a priori* which of many potential formal implementations of a verbal hypothesis are adequate, a large proliferation of formal implementations can be the result, warranting large-scale (and hence labor-intensive) competitive tests of these implementations in order to identify the best one. For instance, when modeling recognition-based inferences with ACT-R, Marewski and Mehlhorn (in press) faced this problem, leading them to implement a total of 39 different quantitative models of recognition-based inference in ACT-R.[14] Another problem modelers face is that bridging the gap between verbal, informal hypotheses and their architectural implementations can lead to unintended discrepancies between the hypotheses and their architectural, formal counterparts, a problem that is also known as the *irrelevant specification problem* (see Lewandowsky, 1993).

In short, the recognition heuristic is arguably a simple mechanism of decision making. However, this simple decision making mechanism comes embedded into a rich cognitive system, and understanding the complexities of the interplay among the various mnemonic, perceptual, intentional and decisional components of this system and the simple recognition heuristic mechanism is a challenging task, warranting a formal, architectural approach to cognition. We propose that future recognition heuristic research should tackle this challenge and get a handle on these complexities of recognition-driven cognition. Tackling this challenge by means of formal, architectural approaches will most likely also help to shift the focus of the current controversies from what-has-been-said-by-whom to which computer code predicts behavior, and which computer code does not (or does not even run).[15]

[13]Obviously, corresponding theories need to be simple enough to be useful. In overly complex models, a problem may arise that is known as the *Bononi paradox*: When models become more realistic and more complete they also become less comprehensible (see Dutton & Starbuck, 1971). For example, adding more and more detailed assumptions about the workings of the brain to a model of the brain may finally result in a model that is no more understandable than the workings of an actual brain. (As the saying goes, the most accurate map of France ever available has been published recently. The only problem is that it is just as large as France.)

[14]Originally Marewski and Mehlhorn had, in fact, implemented 25 quantitative models of recognition-based inference in ACT-R (see Mehlhorn & Marewski, 2011). As many more models could be derived from the literature, they finally ended up with 39. However, based on the literature, it likely is possible to implement even more quantitative models. As long as the descriptive theories and hypotheses about recognition-based inference remain largely verbal, such a proliferation of candidate models seems inevitable, warranting large-scale competitive model tests—at least until a reasonable set of candidate models has been identified.

[15]Let us add that the formal (architectural) route to understanding behavior does not come without its complications, and is also not a useful route to take for all research questions (see Marewski & Olsson, 2009, for a discussion). Moreover, sometimes it is useful for the testing of informal (e.g., verbal) hypotheses to temporarily precede modeling approaches. This may well have been the case for past recognition heuristic research.

3.3 Falsifying a model is not enough: Conduct competitive model tests

There are different ways in which the recognition heuristic can be implemented in ACT-R or other architectures. Likewise, there are different ways in which competing (e.g., compensatory) models of decision making can be implemented. Regardless of the implementation chosen, there are at least three reasons why it is important to test corresponding models comparatively.

First, research on the recognition heuristic should not be about testing just this model in isolation, proclaiming whether it fits the data or not. Rather, research should be about identifying better models of behavior than those that already exist. This implies that research on the recognition heuristic should strive to develop new, alternative models, or strive to extend existing models, much like some researchers have done (see Erdfelder et al., 2011). At this stage of recognition heuristic research, falsificationism that comes without specifying an alternative theory is not enough. We hasten to add that the division of labor that characterized some of the past recognition heuristic research actually helps us to call for a research strategy shift today: Without past attempts to test and refute the recognition heuristic (but that did not propose alternative models), we would not know as much about recognition-based inference as we do today.

Second, formal model comparisons establish yardsticks for evaluating the descriptive adequacy of competing models, with the models being each other's benchmarks in model evaluation. When just one model is tested, a discrepancy between the model's predictions and the observed data might lead a researcher to reject that model. In contrast, with a comparison, the researcher may find that all models suffer (e.g., due to noise in the data), enabling her to find out which model suffers least. Paraphrasing Box (1979), all models are incorrect, but some models are useful, and model comparisons can help to find out which models are more useful than others.[16]

Third, there may often exist many different models, all of which are equally capable of reproducing and explaining data—a dilemma that is also known as the *identification problem* (see Anderson, 1976). As a result it appears unreasonable to ask which of many process models is more truthful; rather, one needs to ask which model is better than another given a set of criteria, and one such criterion is for a model to outperform others in predicting behavior. In short, we propose that future research on the recognition heuristic should shift towards competitive model tests. First steps in this direction—in and outside of memory-based inferences—have been taken by Glöckner and Bröder (2011), Marewski, Gaissmaier, Schooler, et al. (2009, 2010), Marewski and Mehlhorn (in press), and Pachur and Biele (2007).

[16]Obviously it can be the case that all models suffer so much that none can be considered useful.

3.4 Move from binary questions to the building and testing of models of strategy selection

"Psychology ... attempts to conceptualize what it is doing. ... How do we do that? Mostly ... by the construction of oppositions—usually binary ones. We worry about nature versus nurture, about central versus parallel, and so on", wrote A. Newell in 1973 (p. 285). Almost forty years later, much of contemporary judgment and decision making research is still organized around binary oppositions, such as System I versus System II, intuitive versus deliberative, simple versus complex, and so on. Also research on the recognition heuristic has centered on dichotomies such as compensatory versus noncompensatory processes. What do psychologists gain from working with such binary oppositions? Possibly thinking and analyzing data in terms of dichotomies is easy, and corresponding ideas facilitate communication?

We do not know the answer. However, one lesson we all have learned to agree on during our adversarial collaboration is that recognition heuristic research would benefit if such dichotomous questions were replaced by what one may call *when-questions*, or the questions about processes. For instance, in our view it is not a fruitful endeavor to ask the dichotomous question *whether* recognition is always processed in either a compensatory or a noncompensatory fashion: Given the existing experimental evidence, neither of these extremes is likely to be true. Rather, we believe it makes more sense to ask the question *when* recognition will be used in a compensatory fashion[17] (i.e., as one piece of information among others), and *when* the recognition heuristic will come into play, with recognition being used in a noncompensatory fashion. Corresponding challenges to investigate the boundary conditions of recognition heuristic use have been formulated in the literature (e.g., B. R. Newell, 2011; Tomlinson et al., 2011); and indeed a number of studies provide insight with respect to these conditions (e.g., Ayton et al., 2011; Bröder & Eichler, 2006; Erdfelder et al., 2011; Hertwig et al., 2008; Hilbig, Scholl, et al., 2010; Hochman et al., 2010; Marewski, Gaissmaier, Schooler, et al., 2009, 2010; Newell & Fernandez, 2006; Oppenheimer, 2003; Pachur et al., 2008, 2009; Pachur & Hertwig, 2006; Pohl, 2006; Volz et al., 2006). However, until recently, there has been little attempt to integrate the findings from these studies into an overarching theory of

[17]This question is also the one that naturally follows from the fast and frugal heuristics framework, which assumes that people adaptively select between different decision making mechanisms, including both compensatory and noncompensatory ones.

strategy use (but see Gigerenzer & Goldstein, 2011; Pohl, 2011).

Ideally a corresponding theory of strategy use would be sufficiently precise in order to be implemented in computer code, quantitatively predicting when the recognition heuristic will be used and when not. As of writing this text, we know of only one such computational model of strategy selection. This model has been developed within the aforementioned cognitive niche framework (Marewski & Schooler, 2011; see Section 2.2) and has been built by using the ACT-R cognitive architecture.[18] According to the cognitive niche framework, heuristic use emerges as a function of how cognitive capacities such as memory or time perception represent and transform the structure of the environment into *affordances* (see Gibson, 1979) for heuristic use. With respect to the recognition heuristic, the model quantitatively predicts, for instance, that a person will be more likely to be able to quickly and effortlessly execute this heuristic when that person has additional knowledge about the recognized object. In this situation, the heuristic is also most likely to help the person to make a correct inference. Likewise, the heuristic is likely to help a person make accurate judgments when the person perceives the recognition times for the recognized object to be fast. These model predictions are derived from environmental data, such as how often a person will have read an object's name on the internet or in other media.

Building such models of strategy selection is important for behavioral research on the recognition heuristic—otherwise researchers may fall prey of what we would like to call the *strategy selection trap*: Rejecting a model of a heuristic simply because it does not predict behavior in a certain situation is problematic, because there are two potential reasons for this (see Newell & Fernandez, 2006). One is that the strategy is generally not a good model of behavior and warrants to be rejected, another is that the strategy is not used because people (or the corresponding selection mechanisms) *choose* not to use it in a particular situation. Disentangling these two explanations for a heuristic's failure warrants a model of strategy use.[19] In short, we would like to encourage future recognition heuristic researchers to shift from simply binary oppositions to testing computational models of strategy selection.

3.5 Don't just stay in the lab: Also go out into the wild

Marked by the publication of Woodworth's (1938) classic textbook *Experimental Psychology*, the methodological dictate of mainstream experimental psychology—systematic design—has prescribed the isolation and manipulation of a few independent variables whereas all others are kept constant or varied randomly (Dhami, Hertwig, & Hoffrage, 2004). This has led to the widespread acceptance of tightly controlled experimental tasks, often entailing solely a few impoverished, artificial stimuli that yield a maximum of control, for example, of participants' pre-experimental exposure to the stimuli. Ecological theorizing, however, has motivated criticism of this methodology. Brunswik (1955) suggested that it destroys the natural covariation of variables in the organism's habitat, making it hard to generalize from such experiments to the conditions under which the organism actually performs in its environment. In the real world, people hardly ever interact with only a few impoverished stimuli. People, newspaper ads, or features of cars rarely come in isolated packages; rather, they are often accompanied by a wealth of other information, such as the contexts in which we encounter other humans, read ads, or look at cars. Real-world, natural recognition, as has been hypothesized to be at play when the recognition heuristic is relied upon, comes with such a wealth of information.

Importantly, while there has been controversy with respect to how the domain of the recognition heuristic has actually been originally specified, there is little controversy that it has been an ecological model of decision making from the start. In fact, a number of studies has focused on investigating how useful recognition is as a forecasting tool for predicting real-world events, such as the outcomes of sports events (Herzog & Hertwig, 2011; Pachur & Biele, 2007; Scheibehenne & Bröder, 2007; Serwe & Frings, 2006), the results of political elections

[18] Challenges to develop models of strategy selection have also been formulated with respect to other decision strategies (cf, Glöckner & Betsch, 2010; Marewski, 2010). However, it is important to realize that the strategy selection problem is a stumbling block for theories in different disciplines, ranging from economics to machine learning, where the problem presents itself in terms of the selection between algorithms, routines, productions, parameters, or actions, to name a few. It is a non-trivial task to build unsupervised models of strategy selection that are applicable to a wide range of different tasks (e.g., choices between two consumer goods, or spatial navigation when driving).

[19] For instance, before Marewski and Schooler (2011) modeled strategy selection for the fluency heuristic (see Section 2.3) within the aforementioned cognitive niche framework, it was reasonable to assume that the fluency heuristic is equally applicable in situations when no knowledge about two objects (e.g., two cities) is available and when knowledge can be retrieved (see Hertwig et al., 2008, who did not distinguish between these situations; see Marewski, Schooler, & Gigerenzer, 2010). Comparative model tests in which these situations are not examined separately would have shown that knowledge-based strategies predict people's decisions systematically better than the fluency heuristic does. Yet, it would have been mistaken to then conclude that the fluency heuristic is not a good model of behavior (see Hilbig et al., 2011): In several computer simulations and experiments, Marewski and Schooler provided evidence that the interplay between memory and the environment constrains the choice between this heuristic and knowledge-based strategies such that the fluency heuristic can most likely be relied upon when knowledge is sparse or unavailable, representing an instance of strategy selection.

(e.g., Gaissmaier & Marewski, 2011), the performance of stocks (e.g., Borges, Goldstein, Ortmann, & Gigerenzer, 1999), or whether a sense of recognition can be used to build automated recommender systems for literature selection in the library sciences (van Maanen & Marewski, 2009), to name just a few. Yet, only a handful of studies have explored how people might exploit a sense of recognition for making decisions in the wild, say when it comes to decide in which neighborhood to live (Berg et al., 2010). At the same time, there appears to be a number of phenomena that would lend themselves to corresponding investigations; including, for instance, social contact seeking among scientists at major conferences; as well as the broad field of marketing research (see Goldstein, 2007; Hauser, 2011).

In short, the recognition heuristic is an ecological model of decision making. However, surprisingly little research has actually gone out into the wild, examining how people exploit a sense of prior encounter when making real-world decisions. Perhaps, debating over the various recognition heuristic controversies has largely kept us from asking questions that are of immediate relevance to the world—an unsatisfactory state of affairs. We hope that, through helping to resolve these controversies, this special issue contributes to changing this in the future.

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