The use of familiarity in inferences: An experimental study

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Abstract

In the *recognition heuristic* (Goldstein & Gigerenzer, 2002), people's knowledge of objects is defined as "recognized" or "not recognized." Thus the subjective knowledge levels for recognized objects are regarded as identical. However, subjective knowledge levels for recognized objects can differ, based on differences in their familiarity. In the current study, we assume that subjective knowledge levels for recognized objects differ in familiarity, and we examine effects of familiarity on inference. Results of an experimental study show that participants infer on the basis of familiarity, and that participants adopt some inference strategies depending on the situation.

Keywords: recognition heuristic; familiarity-based inference; knowledge-based inference; fluency heuristic; ecological rationality

Introduction

Many researchers in the area of judgment and decision making have tried to clarify various heuristics people use in deciding and judging. For example, in the research project, *heuristics and biases program*, many studies have shown that people use several different heuristics (e.g., availability, representativeness, anchoring and adjustment), and that reliance on these heuristics frequently results in biased judgments and decisions (cf. Gilovich, Griffin, & Kahneman, 2002; Kahneman, Gilovich, & Tversky, 1982; Kahneman & Tversky, 2000). These studies have thus focused on the drawbacks of heuristics, indentifying the conditions under which the heuristics produce biases.

Recent research has also focused on another side of heuristics, their adaptive function. One of the most notable heuristics in this research stream is the r*ecognition heuristic* (Goldstein & Gigerenzer, 2002). The recognition heuristic has been proposed as one of the fast and frugal heuristics (see Gigerenzer, Todd, & The ABC Research Group, 1999). As applied to the binary choice problem, the recognition heuristic is described as follows:

> "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)

Consider a population inference problem such as "Which city has a larger population, Kyoto or Chiba?" For this problem, the recognition heuristic predicts that someone who recognizes Kyoto but not Chiba should infer that Kyoto has the larger population.

According to Goldstein and Gigerenzer (2002), inference based on the recognition heuristic is very simple because it is necessary to consider only a small amount of information (i.e., whether an object is recognized or not). Experimental evidence suggests that people actually use the recognition heuristic in the proposed manner (e.g., Goldstein & Gigerenzer, 2002; Pachur & Hertwig, 2006; Reimer & Katsikopoulos, 2004; Volz, Schooler, Schubotz, Raab, Gigerenzer, & Cramon, 2006; Snook & Cullen, 2006).

Familiarity-Based Inference in Binary Choice

In most of the previous studies on the recognition heuristic, people's knowledge about objects has been classified as "recognized" or "not recognized". This implies that their subjective levels of knowledge about the recognized objects have been regarded as identical. However, this classification might be too simplistic, because knowledge levels about recognized objects can be different, rather than identical. For example, although most Japanese can recognize both Tokyo and New York, their knowledge levels about the two cities are different: Most Japanese should know Tokyo better than New York.

In this paper, we regard the subjective knowledge levels for recognized objects as unequal, and we examine the effect of these knowledge levels on inferences. Specifically, we examine the effect of familiarity for objects. The familiarity means the subjective sense of how much one knows about an object. For example, when one knows just the name of an object, the familiarity would be very low. In contrast, the familiarity would be very high when s/he has many pieces of information about an object.

We think that it is very important to examine the effect of familiarity on inferences, for the following two reasons. The first is to provide additional clarification of the cognitive processes of the recognition heuristic in terms of familiarity. Recent findings by Pohl (2006, Experiment 2, see also Hilbig, Pohl, & Bröder, in press) imply that the familiarity of recognized objects affects use of the recognition heuristic. Using a binary choice task requiring a population inference, Pohl found that in pairs in which one of two cities is recognized and the other is not (hereafter, we call this the recognized/not-recognized pair), the recognized city was inferred to be more populous. This tendency was observed more often when participants had knowledge about the city in addition to recognition than when they merely recognized the city. This result implies that familiarity influence the use of the recognition heuristic. However, this finding does not fully clarify the effect of familiarity, because Pohl' classification of recognized objects was either "mere recognition" or "recognition plus additional knowledge." Therefore it is necessary to systematically examine the effect of familiarity.

The second reason to examine the effect of familiarity on inference is to clarify the cognitive processes of inference in cases in which both of two objects are recognized (hereafter, we call these the recognized/recognized pair). Some heuristics have already been proposed for this case (e.g., *take the best heuristic*, Gigerenzer & Goldstein, 1996; *fluency heuristic*, Hertwig, Herzog, Schooler, & Reimer, 2008). However, compared to the research on the recognition heuristic, little research has explored the cognitive processes of inferences in the recognized/recognized pairs. By treating the subjective knowledge level about recognized objects as familiarity, it is possible to examine the cognitive processes of inferences in these cases. Further, it is possible to compare differences in inferences between recognized/recognized pairs and recognized/not-recognized pairs.

Overview of the Present Study

In the present study, we investigate the effect of familiarity on inferences. Based on the findings by Pohl (2006), our hypothesis is that participants who are more familiar with a city will infer that the city is more populous.

In order to examine this hypothesis, we conducted a binary choice task of population inference. Consider the situation in which cities A and B are presented, and city A is more familiar than city B. Our hypothesis predicts that the greater the difference in familiarity between two cities, the more often the city A will be chosen as more populous.

Experiment

Method

Participants. Eighty one undergraduates (81 women) from Japan Women's University participated in this experiment as a course requirement.

Tasks and Materials. We conducted two tasks, a binary choice task of population inference and a measurement of familiarity.

In the binary choice task, the question was "Which city has a larger population?" Participants were presented with two city names and answered the question. For this task, we used two lists, Lists A and B (see Table 1). Each participant was presented with all combinations (i.e., 105 pairs) for both lists.

Lists A and B were constructed using the following procedure. In making List A, we first chose the most populous cities ("shi") from each of the 47 prefectures[1] in Japan, then selected top 15 cities from these 47 cities. The List B consisted in the same way as List A except that we first chose the second most populous city from each of the 47 prefectures. We conducted a pilot study of recognition test for these 30 cities. Twenty-five undergraduates were asked whether they knew each of the 30 cities. The mean numbers of recognized cities were 13.40 (SD=2.18) for List A and 8.16 (SD=3.18) for List B. From these results, we predict that most of the pairs in List A will be recognized/recognized pairs. In contrast, List B will include some recognized/not-recognized pairs.

In the measurement of familiarity, participants were asked whether they knew each of the 30 cities presented in the binary choice task, and if they knew the city, how well they knew it.

Table 1. Two lists used in the experiment.

List A	List B
Yokohama-shi	Kawaguchi-shi
Osaka-shi	Machida-shi
Nagoya-shi	Kohriyama-shi
Sapporo-shi	Takasaki-shi
Kobe-shi	Tsu-shi
Kyoto-shi	Sasebo-shi
Fukuoka-shi	Hachinohe-shi
Hiroshima-shi	Matsumoto-shi
Sendai-shi	Hitachi-shi
Chiba-shi	Yamaguchi-shi
Niigata-shi	Takaoka-shi
Hamamatsu-shi	Imabari-shi
Kumamoto-shi	Miyakonojo-shi
Okayama-shi	Ogaki-shi
Kagoshima-shi	Ashikaga-shi

Procedure. The two tasks were conducted individually using a computer. Participants first performed the binary choice task, followed by the measurement of familiarity. We conducted the two tasks in the same order for all participants[2].

In the binary choice task, participants were presented with two city names on a computer screen and answered the question by using the mouse to select a choice button on the screen. In choosing a city, the participants could take as long as they wished to respond. Half of participants received pairs from List A first, and then pairs from List B. The other participants were given the lists in the opposite order.

In the measurement of familiarity, participants were presented with a city name on a computer screen. When participants did not know a presented city, they used the mouse to push the button representing "not recognized" on the screen. When they knew the city, they reported their familiarity using a scale on the screen. This scale was labeled "just

[1] The prefecture corresponds to the state in the U.S.

[2] Goldstein and Gigerenzer (2002) and Pachur and Hertwig (2006) reported that the order of two tasks, inference task and recognition test, did not have a significant effect on responses. In the recognition test in Goldstein and Gigerenzer (2002) and Pachur and Hertwig (2006), participants were asked whether they knew each of objects presented in inference task. We assumed that there were no essential differences between the recognition test and the measurement of familiarity.

know the name" on the far left and "know a lot about the city" on the far right. The participants' responses for familiarity were recorded over 100 points (1-100).

The two tasks took about 30 minutes to complete.

Results and Discussion

For each pair of cities, the two cities can be ordered by their actual populations, and we name them accordingly. For example, if cities X and Y are presented, and the city X has a larger population than city Y, we call city X the "larger city," and city Y the "smaller city."

In the following analyses, we operationally define familiarity of a city based on participants' responses to the measurement of familiarity. If a participant recognized a city, familiarity for the city was defined as the corresponding value in the measurement of familiarity. If the participant did not recognize the city, familiarity was defined as 0.

In pairs in which neither city was not recognized, it can be assumed that participants answered by guessing. Hence we deleted the data of such pairs from the analyses.

Analysis of Aggregated Data. To conduct an analysis of aggregated data, we calculated mean rates of the larger city choice and mean differences in familiarity for each of the 105 pairs in Lists A and B. When we calculated the difference in familiarity, the familiarity rating of the smaller city was subtracted from that of the larger city. Thus, a difference greater than 0 means that participants were more familiar with the larger city, and a difference less than 0 means that participants were more familiar with the smaller city. Figures 1 and 2 show the relationship between the mean choice rates of the larger city and the mean differences of familiarity for List A and List B.

To examine the effect of familiarity on population inferences, we proposed a model representing the choice rates of the larger city on the log odds scale:

$$\log \frac{p_{MCL}}{1-P_{MCL}} = aX_{Mdiff} + b \qquad (1)$$

where P_{MCL} represent the mean choice rate of the larger city, X_{Mdiff} represents mean difference in familiarity, and a and b denote free parameters for weight and intercept, respectively. This model assumes that the choice rates shift depending on the difference in familiarity. We assessed the fit of equation (1) by regressing P_{MCL} in log odds units on the difference in familiarity. Table 2 presents the results of the regression analyses, displaying regression coefficients for *a*, *b*, and R^2. The regression lines are shown in Figures 1 and 2 as a function of P_{MCL} that is transformed from the equation (1).

These results indicate that for both lists, the familiarity of cities influenced inferences about population. Specifically, the results suggest that participants who are more familiar with a city infer that the city is more populous. Therefore the aggregated data support our hypothesis about the effect of familiarity on inferences.

It should be noted that there was a substantial difference in the estimated intercepts for the two lists. This difference is noteworthy at the point where the difference in familiarity is 0. At this point, the participant is equally familiar with presented cities. Therefore, in a strict sense, if the participant makes an inference on population based on familiarity, the choice rate for the larger city should be 50%. However, the predictions of the choice rate at this point from the estimated models were 67.0% for the List A and 56.0% for the List B.

These results imply that in responding to List A, participants used certain knowledge about cities' populations, in addition to familiarity. This possibility is reasonable based on the characteristics of the cities in the two lists. List A consisted of very famous cities, so the possibility is high that participants could access the certain knowledge about their populations. Previous studies have shown that when participants can easily access certain knowledge about the populations of recognized objects, they use it in making inferences (e.g., Oppenheimer, 2003; Newell & Fernandez, 2006; Richter & Späth, 2006). Therefore the findings for List A are consistent with those of the previous studies. On the other hand, the possibility of accessing certain knowledge about populations might be rather low in responding to the List B. In this case, participants would rely on the difference in familiarity to infer the populations.

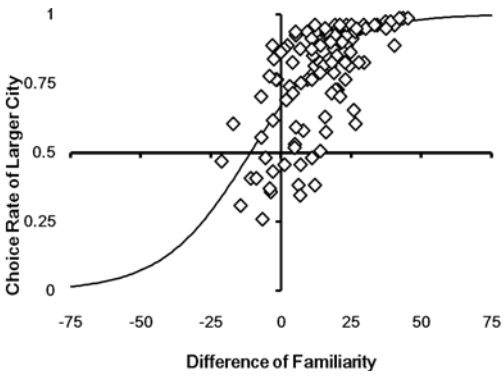

Figure 1. The relationship between the mean choice rates of the larger city and differences in familiarity in List A.

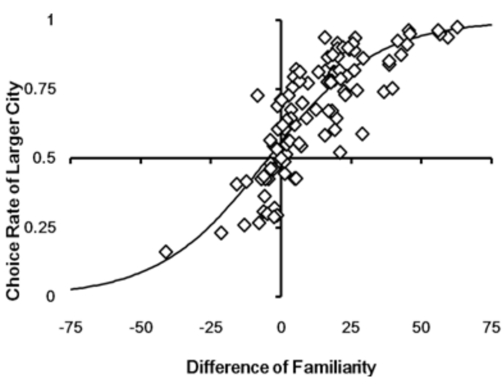

Figure 2. The relationship between the mean choice rates of the larger city and differences in familiarity in List B

Table 2. Results of regression analyses for aggregated data.

List	a	b	R^2
List A	0.065*	0.707*	0.496
List B	0.052*	0.241*	0.707

*p<.001

Analysis of Individual Data. Next, we analyze individual data to examine two points that have not been clarified in the aggregated data analysis.

First, the analysis based on aggregated data implies that participants' inference patterns shift between the two lists. Individual data analysis can be explored in detail to examine this shift.

Second, and more important, we can examine the difference between the inferences for recognized/not-recognized pairs (in which participants can use the recognition heuristic) and those for recognized/recognized pairs. In the aggregated data analysis, inference patterns were analyzed based on differences in familiarity. Thus this analysis did not distinguish the inference patterns for recognized/recognized pairs from those for recognized/not-recognized pairs. The literature on the recognition heuristic, however, has argued that recognition has a special status, because when a person does not recognize an object, s/he cannot use any cues in inference (Pachur & Hertwig, 2006; Pachur, Todd, Gigerenzer, Schooler, & Goldstein, in press). Thus, the inference patterns for recognized/not-recognized pairs might be different from those for recognized/recognized pairs. We examine this issue by proposing a model that distinguishes recognized/recognized pairs from recognized/not-recognized pairs in the individual data.

In the analysis of individual data, we carry out logistic regression analyses. We propose three models that represent the choice rates of the larger city. The first model is:

$$\log \frac{P_{CL}}{1-P_{CL}} = aX_{diff} + b \qquad (2)$$

where P_{CL} represents the choice rate for the larger city, X_{diff} represents the difference in familiarity, and *a* and *b* denote free parameters for weight and intercept, respectively. This model is basically the same as equation (1).

The second model is:

$$\log \frac{P_{CL}}{1-P_{CL}} = aX_{diff} + bX_{recog} + c \qquad (3)$$

The unique aspect of this model is that the dummy variable X_{recog} is added. X_{recog} is the variable for cases in which only one of the two cities is recognized. When only the larger city is recognized, X_{recog} equals 1. In contrast, when only the small city is recognized, X_{recog} equals -1, and when both of the cities are recognized, X_{recog} equals 0. Hence X_{recog} is an operational representation of the recognition heuristic, such that inference patterns in the recognized/not-recognized pairs are different from those in the recognized/recognized pairs. *a*, *b*, and *c* denote free parameters for weights and intercept, respectively.

The third model is:

$$\log \frac{P_{CL}}{1-P_{CL}} = aX_{recog} + b \qquad (4)$$

This model assumes that a participant only considers recognition, and does not use the difference in familiarity in making inferences, suggesting that inference patterns in recognized/recognized pairs are constant. *a*, *b* denote free parameters for weight and intercept, respectively.

Using these three models, we conducted a logistic regression analysis. For List A, 75 of the 81 participants recognized all of 15 cities, 5 participants recognized 14 cities, and one participant recognized 12 cities. There were thus few cases in which the recognition heuristic could be applied to pairs in List A. Therefore we analyzed only recognized/recognized pairs, and regressed equation (2) on individual data for List A. For List B, the mean number of recognized cities was 10.71 (SD=2.32). This result shows that List B included some recognized/not-recognized pairs. So the three models, equations (2), (3), (4), were regressed on individual data[3].

The purpose of the analysis of List A is to explore whether the model of equation (2) can explain the data. So in this analysis, we first assessed goodness of fit of the model using deviance (Agresti, 1996), and then examined whether the effect of difference in familiarity was present in the model using the likelihood ratio test (Agresti, 1996). When the effect of difference in familiarity was significant, we regarded the equation (2) as the best model for the data. When the effect was not significant, we regarded the intercept model as the best model, suggesting that inference patterns are constant irrespective of difference in familiarity. According to this procedure, we selected the best model for each individual's data. Table 3 shows the results of this analysis.

These results indicate that more than 60% of the individual inference patterns are well explained by equation (2), suggesting that the differences in familiarity influenced inferences. At the same time, the intercept model explained more than 30% of individual inference patterns. All of the estimated coefficients for the intercept were positive values, indicating that these participants used certain knowledge about population instead of the difference in familiarity. On the whole, the results of the individual data analysis are consistent with those of aggregated data analysis.

The purpose of the analysis of List B is to explore which model can best explain the data. In this analysis, we followed the same procedure as in the analysis of List A, except that when more than one model showed a good fit, we selected one model using the AIC. Table 4 presents results of this analysis.

The results show that approximately 60% of the individual data were well explained by equations (2) and (3), indicating that familiarity influenced inferences. It is notable that equation (3) explained almost 50% of the individual

[3] 3 of the 81 participants recognized all of the 15 cities. We regressed only equation (2) on data for these 3 participants.

data. Furthermore, around 30% of the individual data were well explained by equation (4), which represents the recognition heuristic in the strictest manner. These results indicate that inference patterns in the recognized/not-recognized pairs are different from those in the recognized/recognized pairs, and are not explained simply by the difference in familiarity.

Compared to the results for List A, the intercept model did not well explain the individual data (only that of 1 out of 81 participants). As discussed above, the intercept model assumes that participants use certain knowledge about population, beyond the difference in familiarity, when they infer. This result therefore indicates that in responding to List B, participants did not access certain knowledge about population, but based their inferences upon differences in familiarity or the recognition heuristic.

Taken together, the findings of the individual data analysis are as follows. First, participants actually rely on the familiarity of cities when they make inferences about population.

Second, inference patterns in the recognized/not-recognized pairs cannot be simply explained by the difference in familiarity. This indicates that inferences in recognized/not-recognized pairs have unique features, as some previous studies have claimed (e.g., Pachur & Hertwig, 2006; Pachur et al., in press).

Third, participants do not use a single inference strategy, but adopt some strategies depending on the situation. In particular, our findings suggest that when people have certain knowledge about population, they do not base their inferences on familiarity. Some researchers have argued that people do not always use the recognition heuristic. Pachur and Hertwig (2006) and Pachur et al. (in press) have claimed that the recognition heuristic is used to make inferences under uncertainty, that is, when certain knowledge about the criterion is not available. Given that inference based on familiarity is a kind of heuristic, our findings provide empirical evidence for this claim.

Table 3. Results of analysis of individual data for List A.

Model	Eq. (2)	Intercept	N.S.
N	52	25	4
%	64.2	30.9	4.9

Note. "N.S." means none of the models can explain the data well.

Table 4. Results of analysis of individual data for List B.

Model	Eq. (2)	Eq. (3)	Eq. (4)	Intercept	N.S.
N	10	37	22	1	11
%	12.3	45.7	27.2	1.2	13.6

Note. "N.S." means none of the models can explain the data well.

Is it worth exploiting familiarity in making inferences?

So far, we have demonstrated that participants use familiarity in making inferences. As previously suggested, inference based on familiarity can be assumed a kind of heuristic strategy. In discussing heuristics, one of the most interesting issues is whether or not a heuristic has an adaptive function. Thus we ask if making inferences based on familiarity has an adaptive function, or if it can result in irrational inferences.

Figure 3 shows the relationship between familiarity and population for the 30 cities that were used in the experiment. The figure shows that familiarity is correlated with population; that is, the more familiar participants are with the cities, the more populous the cities are (r=.796, p<.001). This suggests that inferences based on familiarity have an adaptive function, just as the recognition heuristic and the fluency heuristic do. This function has been called *ecological rationality* (Goldstein & Gigerenzer, 2002; Hertwig, et al., 2008).

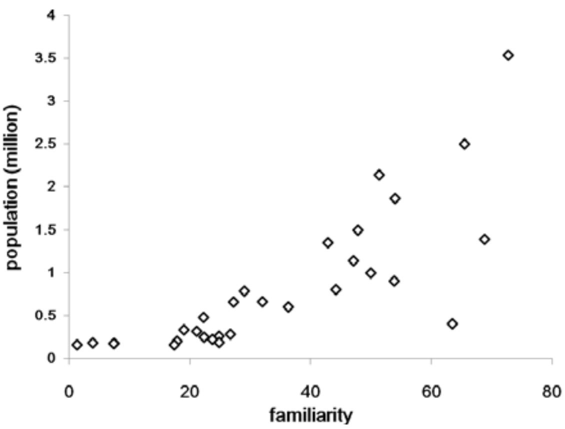

Figure 3. The relationship between population and familiarity in 30 cities that were used in the experiment.

Conclusions

In the present study, we investigated the effect of familiarity of objects on inferences. Participants used the familiarity of objects in making inferences, and this use of familiarity has an adaptive function, a form of ecological rationality. However, participants did not always make inferences on the basis of the familiarity; they also used other inference strategies, such as the recognition heuristic or knowledge-based inference. This shift of inference strategies can be explained by situational factors in which participants were able to access certain knowledge about the criterion in making inferences.

We point out that inference based on the familiarity of objects is analogous to previously proposed heuristics such as the recognition heuristic (Goldstein & Gigerenzer, 2002) or the fluency heuristic (Hertwig, et al., 2008; Schooler & Hertwig, 2005). In particular, we think that the familiarity-based inference has many links to the fluency heuristic. The fluency heuristic is described as follows:

> "If two objects, a and b, are recognized, and one of two objects is more fluently retrieved, then infer that this object has the higher value with respect to the criterion." (Hertwig et al., 2008, p.1192)

Although we have not obtained empirical evidence, we predict that the greater the familiarity of an object, the more fluently the object will be retrieved.

Hence, familiarity-based inference and the fluency heuristic will predict the same inference in the same situation. More importantly, the cognitive processes of experiencing familiarity or fluency would influence each other. In their discussion, Hertwig et al. (2008) pointed out the possibility that familiarity for objects is involved with processes of the fluency heuristic. At this point, the differences between these two inference strategies are not obvious, and this is a limitation in the current research. Hence it is necessary to clarify the relationship between fluency and the familiarity for objects, and how these factors affect inferences.

Acknowledgments

This work was in part supported by the Japan Society for the Promotion of Science KAKENHI (Grant No. 20700235) and the Support Center for Advanced Telecommunications Technology Research (SCAT).

References

Agresti, A. (1996). *An introduction to categorical data analysis*. New York: John Wiley & Sons, Inc.

Gigerenzer, G., & Goldstein, D. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review, 103*, 650-669.

Gigerenzer, G., Todd, P., & The ABC Research Group. (1999). *Simple heuristics that make us smart*. New York: Oxford University Press.

Gilovich, T., Griffin, D. W., & Kahneman, D. (Eds.). (2002). *Heuristics and Biases*. New York: Cambridge University Press.

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review, 109*, 75-90.

Hertwig, R., Herzog, S. M., Schooler, L. J., & Reimer, T. (2008). Fluency heuristic: A model of how the mind exploits a by-product of information retrieval. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*, 1191-1206.

Hilbig, B. E., Pohl, R. F., & Bröder, A. (in press). Criterion knowledge: A moderator of using the recognition heuristic? *Journal of Behavioral Decision Making*.

Kahneman, D., Slovic, P., & Tversky, A. (Eds.). (1982). *Judgment under uncertainty: Heuristics and biases*. New York: Cambridge University Press.

Kahneman, D., & Tversky, A. (Eds.). (2000). *Choices, values, and frames*. New York: Cambridge University Press.

Newell, B. R., & Fernandez, D. (2006). On the binary quality of recognition and the inconsequentiality of further knowledge: Two critical tests of the recognition heuristic. *Journal of Behavioral Decision Making, 19*, 333-346.

Oppenheimer, D. M. (2003). Not so fast! (and not so frugal!): Rethinking the recognition heuristic. *Cognition, 90*, B1-B9.

Pachur, T., & Hertwig, R. (2006). On the psychology of the recognition heuristic: Retrieval primacy as a key determinant of its use. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 32*, 983-1002.

Pachur, T., Todd, P. M., Gigerenzer, G., Schooler, L. J., & Goldstein, D. G. (in press). Is ignorance an adaptive tool? A review of recognition heuristic research. In P. M. Todd & G. Gigerenzer & The ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world*. New York: Oxford University Press.

Pohl, R. F. (2006). Empirical tests of the recognition heuristic. *Journal of Behavioral Decision Making, 19*, 251-271.

Reimer, T., & Katsikopoulos, K. V. (2004). The use of recognition in group decision-making. *Cognitive Science, 28*, 1009-1029.

Richter, T., & Späth, P. (2006). Recognition is used as one cue among others in judgment and decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 32*, 150-162.

Schooler, L. J., & Hertwig, R. (2005). How forgetting aids heuritic inference. *Psychological Review, 112*, 610-628.

Snook, B., & Cullen, R. M. (2006). Recognizing national hockey league greatness with an ingnorance-based heuristic. *Canadian Journal of Experimental Psychology, 60*, 33-43.

Volz, K. G., Schooler, L. J., Schubotz, R. I., Raab, M., Gigerenzer, G., & von Cramon, D. Y. (2006). Why you think Milan is larger than Modena: Neural correlates of the recognition heuristic. *Journal of Cognitive Neuroscience, 18*, 1924-1936.