On the adaptive nature of memory-based false belief

Hidehito Honda (hitohonda.02@gmail.com)
Graduate School of Arts and Sciences, The University of Tokyo
3-8-1, Komaba, Meguro-ku, Tokyo, 153-8902

Toshihiko Matsuka (matsukat@muscat.L.chiba-u.ac.jp)
Department of Cognitive and Information Science, Chiba University
1-33, Yayoi-cho, Inage-ku, Chiba-shi, Chiba, 263-8522, Japan

Kazuhiro Ueda (ueda@gregorio.c.u-tokyo.ac.jp)
Graduate School of Arts and Sciences, The University of Tokyo
3-8-1, Komaba, Meguro-ku, Tokyo, 153-8902

Abstract

Previous studies have shown that people's memories are changeable, and systematic incorrect memories (e.g., false memory) can be created. We hypothesize that people's beliefs about the real world can be changed similarly to the way systematic incorrect memories and systematic incorrect beliefs (which we call memory-based false belief) are generated. We also predict that since memory-based false beliefs are consistent with abstract knowledge that is consisted with prototypical patterns and organization found in the real world, false beliefs work adaptively in making inferences about environmental information in the real world. We conducted behavioral and simulation studies in order to examine our hypotheses on people's beliefs and inferences about the real world. The results showed that participants had systematic false beliefs about cities' attributes (e.g., whether they have a professional baseball team), and that such false beliefs worked adaptively in making inferences about population size.

Keywords: memory-based false belief; inference about real world; ecological rationality

Introduction

One of the most studied topics in human decision making has been how human cognitive characteristics affect adaptive decisions. Many studies have shown that people rely on heuristics, which result in various cognitive biases (Kahneman, Tversky, & Slovic, 1982; Kahneman, 2011). Contrarily, other studies have shown that human cognitive limitations do not necessarily lead to maladaptive decisions because people's cognitive limitations are systematic and people can take advantage of such systematic limitations (Gigerenzer, Todd, & The ABC Research Group, 1999; Todd, Gigerenzer, & The ABC Research Group, 2012). In the present study, we provide new evidence that systematic cognitive limitations work adaptively in making inferences.

One interesting finding on the relationship between cognitive limitations and adaptive inferences is that limitations of human memory do not always result in maladaptive inferences. For example, consider the following question: "Which city has a larger population, Tokyo or Chiba?" Who can make the most accurate inference to answer this question, people who know both Tokyo and Chiba or people who know only Tokyo? Intuitively, the amount of knowledge should correlate with the correctness of inferences. Thus, the more knowledge people have, the more accurate inferences people should make based on their knowledge. Thus, our intuition is that people who know both Tokyo and Chiba can make more accurate inferences than people who know only Tokyo. However, studies have shown that this is not always true: people who know only Tokyo can make more accurate inferences in this situation (e.g., Gigerenzer & Goldstein, 1996; Goldstein & Gigerenzer, 2002; Schooler & Hertwig, 2005). This superficially counter-intuitive phenomenon occurs because people have systematic cognitive limitations. For example, imagine the limitation in the amount of knowledge such that people do not know about some cities in Japan. Generally, missing knowledge about Japanese cities is systematic. For example, people are more likely to recognize cities that have larger populations than smaller ones. Thus, systematic limitations in the amount of knowledge do not always result in maladaptive inferences about cities' population sizes.

Previous studies have mainly examined how the amount of knowledge affects adaptive inferences. In other words, previous studies have focused on the limitation of quantity in memory. However, people have another limitation in memory; the quality of memory. Studies on human memory have shown that a simple experimental manipulation can make people have false memories (e.g., Roediger, & McDermott, 1995). The formation of false memories is not limited to experimental manipulations, and false memories can be generated in the real world (Loftus, 2005; Roediger & DeSoto, 2016). Based on these considerations, we predict that people have incorrect beliefs about real world information. We refer to such incorrect belief as *memory-based false belief*. Then, how do false beliefs affect inferences? Few previous studies have examined this issue. We conducted behavioral and simulation studies to examine this issue. In the following sections, we first introduce our hypotheses about memory-based false belief. Then, we report our behavioral and simulation studies for examining our hypotheses.

Memory-based false belief

Findings in memory research indicate that people can have false belief about the real world. There are noteworthy findings about false memories. One of the most straightforward manipulations for generating false memories (DRM paradigm, Roediger, & McDermott, 1995) is as follows. (1) Participants hear a list of words such as "table," "sit," "legs," "seat," "desk," "arm," "sofa," and so on. (2) After a short interval, the participants complete a recognition task where they are presented with a list of words. The list comprises "old" words that participants heard in (1) and some "new" words that participants did not hear in (1). The most typical results are that participants answer "old" for semantically associated new words (e.g., "chair") and seldom answer "old" for unrelated new words (e.g., "cat"). Although some factors are involved in the processes of generating a false memory, the findings suggest that false memory is generated with a systematic way (e.g., Roediger, Watson, McDermott, & Gallo, 2001). Specifically, the false recognition for the related new words occurs by means of a strong association between the memory for the old words and the related new words that were not actually presented in (1). According to these findings, we predict that people have false beliefs about the real world and that such false beliefs are systematic like false memory.

People are predicted to form abstract knowledge that is consisted with prototypical patterns and organization found in the real world (Rosch, & Mervis, 1975). Hereafter, we refer to this type of knowledge as the prototypical knowledge. For example, people may have prototypical knowledge about characteristics of big cities, such as "there is a professional football team," "there is an international airport," "it's a state capital," and so on. Imagine that there is no professional football team in city "X" which happens to have a large population. People may have a false belief such that there is a professional football team in city X based on prototypical knowledge. That is, a strong association between professional football teams and big cities may produce a false belief. Hereafter, we call this false belief *false positive belief* (FPB). In contrast, imagine a small city "Y" where there is a professional football team. For city Y, people may have a false belief such that there is no professional football team since the association between professional football teams and small cities is weak. Hereafter, we call this false belief *false negative belief* (FNB). We predict that people have two kinds of systematic false belief, which are generated by the associations between prototypical knowledge and the target object (in this case, a city).

How does systematic false belief affect inferences about the real world? Intuitively, false belief seems to deteriorate inferences about the real world. We predict that false belief deteriorates inferences if it is generated in a non-systematic way. However, the systematic nature of false belief described above may work adaptively in making inferences. When there is a correlation between an attribute of a city (e.g., whether it has a professional football team) and criterion for inferences (e.g., population size), inferences based on the attribute are generally accurate (e.g., when there is a professional football team in city X, but not in city Y, this implies that the population of city X is larger than city Y; e.g., Gigerenzer & Goldstein, 1996). Therefore, if false belief is systematically generated by prototypical knowledge about the real world, the false belief will function adaptively in making inferences.

In sum, our hypotheses about false belief are the followings:

Hypothesis 1: People have false belief consistent with prototypical knowledge. For the attributes associated with big cities, people have more FPB for cities with large populations than those with small populations. In contrast, people have more FNB for cities with small populations than for those with large populations.

Hypothesis 2: Systematic false belief functions adaptively in making inferences, although non-systematic false knowledge deteriorates accuracies of inferences. Thus, inferences about cities' population sizes based on systematic false beliefs (i.e., the belief people tend to possess) are more accurate than those based on non-systematic false beliefs.

Behavioral study: Examination of Hypothesis 1

In order to examine Hypotheses 1, we conducted a behavioral study about people's knowledge about cities, and examined the nature of false beliefs in the real world.

Method

Participants Japanese undergraduates (N = 25) from Aoyamagakuin University participated as part of course work**.**

Tasks, materials, and procedure Participants performed a knowledge task about Japanese cities. In this task, participants were presented with one city name and an attribute such as "professional baseball team." The question is "Is there a professional baseball team in this city?" The participants were asked to answer "yes," "no," or "I don't know" depending on their subjective knowledge.

We selected the top 100 Japanese cities ("shi") based on population size in 2011. The top five cities are "Yokohama," "Osaka," Nagoya," "Sapporo," and "Kobe" (see the Appendix for examples). We asked about five attributes of a city; "professional baseball team," "prefectural capital," "high court," "station of bullet train," and "capital area." We selected these attributes based on the following procedure. First, we conducted a pilot study about the cues used in making inferences about population size. In this study, 37 participants were asked "What is a valid cue when making an inference about which city has a larger population size for the presented two cities." Based upon the answers in this pilot study, we selected the five attributes showing actual validity for inferring population size. We examined the validity of the attributes in making inferences based on Gigerenzer and Goldstein (1999). Here, validity

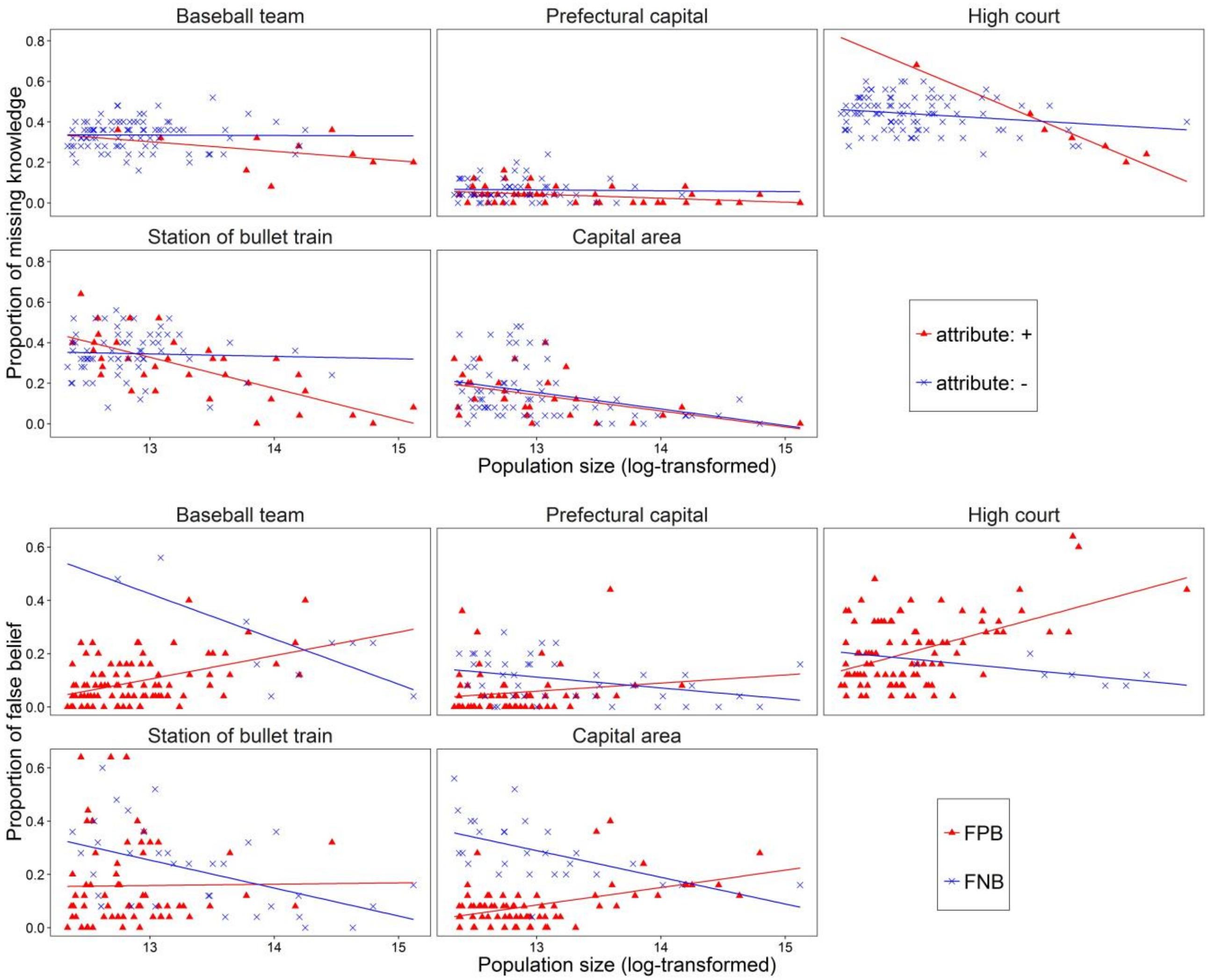

Figure 1. Relationship between population size and proportion of missing knowledge or FPB and FNB for five attributes.

Table 1. Correlation coefficients between proportion of missing knowledge, FPB, or FNB and population size.

Attribute	Missing knowledge				False knowledge			
	Attribute: +		Attribute: -		FPB		FNB	
Baseball team	-0.378		-0.012		0.444	***	-0.733	*
Prefectural capital	-0.345	*	-0.030		0.137		-0.372	*
High court	-0.981	***	-0.210	*	0.482	***	-0.642	
Station of bullet train	-0.718	***	-0.045		0.013		-0.488	**
Capital area	-0.445	*	-0.354	**	0.477	***	-0.354	**

* p < .05, **p <.01, ***p <.001

reflects how often a cue leads to correct inferences. Using the 4950 pairs (100 * 99 / 2) for the 100 cities used in the behavioral experiment, the validity of the attributes for inferences was calculated by A_c / (A_c + A_i). A_c denotes the number of pairs for which an attribute could discriminate between two cities (e.g., in a pair of cities X-Y, X has the attribute and Y does not) and the use of the attribute information resulted in the correct inference (i.e., X actually has a larger population). A_i denotes the number of pairs for which the attribute could discriminate the two cities but the use of attribute information resulted in an incorrect inference (i.e., Y actually has larger population). The validities for the five attributes were 0.902 (professional baseball team), 0.671 (prefectural capital), 0.923 (high court), 0.710 (station of bullet train), and 0.503 (capital area). Thus, although people tend to believe that all these attributes are valid cues for making inferences, their actual validities vary from high to low.

Participants were tested individually using a computer. They were asked to answer the questions for all 500 attributes (5 attributes * 100 city names).

Results and discussion

We analyzed participants' subjective knowledge about the 100 cities from the relationship between the cities' population sizes and (1) missing knowledge (i.e., the response of "I don't know"), or (2) the FPB and FNB.

First, we examined the relationship between missing knowledge and population size, although this analysis was not our focus. Previous studies have shown that a city's population size is correlated with the number of times the city is referenced in media such as newspapers, and that the number of the city's references is correlated with recognition rate and familiarity (Goldstein & Gigerenzer, 2002; Honda, Matsuka, & Ueda, accepted). Thus, we predicted that the proportion of missing knowledge decreases as population sizes increase. In order to examine this prediction, we calculated the proportion of missing knowledge for every city and attribute, and conducted correlation analyses for every attribute. In particular, we calculated correlation coefficients between proportions of missing knowledge and log-transformed population sizes. Since an attribute is categorized into "+" (the city actually has the attribute) or "-" (the city does not actually have the attribute) and missing knowledge may differ between these attributes, we conducted a correlation analysis for each attribute. The upper panel of Figure 1 denotes the relationships between log-transformed population size and proportion of missing knowledge, and the left panel of Table 1 shows the correlation coefficients. Although the results depend on the attributes, there was a general relationship between the proportion of missing knowledge and population size: As population size becomes larger, the proportion of missing knowledge decreases. This result supports our prediction.

Next, we analyzed the relationship between FPB (or FNB) and population size in order to evaluate Hypotheses 1. As in the analysis of missing knowledge, we calculated the proportions of FPB and FNB for every city and attribute, and conducted correlation analyses for every attribute. In particular, we calculated correlation coefficients between proportions of FPB (or FNB) and log-transformed population sizes. The lower panel of Figure 1 denotes the relationship between log-transformed population size and proportions of FPB or FNB, and the right panel of Table 1 shows the correlation coefficients. Although the results varied among the attributes, as was also the case for missing knowledge, we found apparent tendencies. The proportion of FPB increases as the population size increases. In contrast, the proportion of FNB decreases as the population size increases. These results corroborated our Hypothesis 1. Figure 2 denotes the individual data on false beliefs and missing knowledge (proportion out of 500 attributions). We found that there were large individual differences.

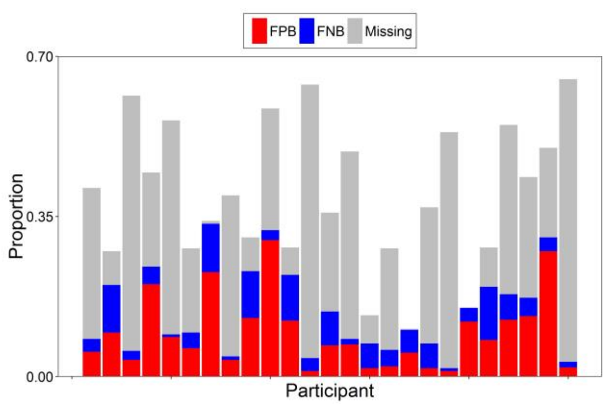

Figure 2. Individual differences in false belief and missing knowledge.

Taken together, people's knowledge about real world cities is correlated with their population sizes. The proportion of missing knowledge decreases as the population size increases. For false beliefs, the proportion of FPB (FNB) increases (decreases) as the population size increases. These results are consistent with Hypothesis 1.

Simulation study: Examination of Hypothesis 2

The results of our behavioral study showed that people have systematic false beliefs, which is consistent with Hypothesis 1. Hypothesis 2 predicts that such systematic false beliefs will function adaptively in making inferences in the real world. We examined this hypothesis by using computer simulations.

Method

We conducted computer simulations of binary choice population inference tasks based on the empirical data collected in our behavioral study. There were a total of 50 simulated participants. Among the 50 simulated participants, half of Systematic condition (hereafter Syst condition; Syst1, Syst2, …, and Syst25) was designed to possess exactly the same knowledge as the 25 participants in the behavioral study. That is, for example, simulated participant Syst1's knowledge about the five attributes for 100 cities was identical to that of empirical participant 1. The remaining 25 simulated participants in Non-Systematic condition (hereafter, Non-Syst condition; Non-Syst1, Non-Syst2, …, and Non-Syst25) possessed the same amounts of FPB, FNB, and missing knowledge as the empirical participants but the patterns were randomly reconstructed. Thus simulated participants in the Syst condition were assumed to possess systematic false beliefs while those in the Non-Syst condition were assumed to possess non-systematic false beliefs. The simulated participants were presented with two cities and asked to infer which city has a larger population. They answered all of the 4950 pairs (100 * 99 / 2) of the cities used in the behavioral study. They were set up to make inferences based on their knowledge. In the present simulation, we compared three inference strategies in order to examine the efficacy of systematic false beliefs regardless of what strategy was used (specific algorithms of inference strategies are shown in Table 2). Among the three strategies, two were knowledge-integration strategies and the third was a heuristic-based strategy. For the heuristic strategy, we

Table 2. Simulated inference strategies.

Strategy	Content of inference: Which city has a larger population, city A or B?
Take-the-best	Consider attributes in the order of their validities. Participant makes an inference based on the first attribute where one city has a positive value and the other has unknown or negative value.
Tally 1	Add up the number of positive cue values and subtract the number of negative values for Cities A and B. A participant makes an inference such that the city with the higher summation has a larger population.
Tally 2	Add up the number of positive cue values for Cities A and B. A participant makes an inference that the city with the higher summation has a larger population.

Note. Here, "positive (negative) value" means that a participant thinks a city has (does not have) the attribute. "Unknown" means that the participant does not have knowledge about the attribute (i.e., missing knowledge).

used "Take-the-best" (Gigerenzer & Goldstein, 1996). As integration models, we used Tally 1 and 2 (Marewski, & Schooler, 2011).

The correctness of an inference was defined as follows. We assigned 1 (or 0) to a pair where an inference strategy led to a correct (or incorrect) inference. When an inference strategy could not discriminate a pair, 0.5 was assigned to the pair. We calculated the mean correctness of inferences for 4950 pairs and regarded this value as the proportion of correct inferences.

For the simulated participants in the Syst condition, we calculated the proportion of correct inferences for each of the three inference strategies. For the Non-Syst condition, we made 100 sets of randomly reconstructed knowledge for every 25 participant, and we calculated the proportions of correct inferences using the three inference strategies for every 100 sets. We regarded the average proportion of correct inferences for the 100 sets as the proportion of correct inferences for each strategy.

Results and discussion

Figure 3 shows the performance on the inference task. As is apparent, the proportion of correct inferences was higher for the simulated participants in the Syst condition than for those in the Non-Syst condition for all of the three inference strategies. Since the amounts of missing knowledge, FPB, and FNB for Syst1, Syst2, …, and Syst25 corresponded to those for Non-Syst1, Non-Syst2, …, and Non-Syst25, we compared the proportion of correct inferences for each pair. Using the Take-the-best and Tally 2 strategies, 24 of the 25 participants in the Syst condition showed higher performance. Using the Tally 1 strategy, 23 of the 25 participants in the Syst condition did better. These results indicate that the systematic nature of human false beliefs about cities functioned adaptively in making inferences about cities' population sizes regardless of inference strategies. Furthermore, given that there were large individual differences in false beliefs and missing knowledge (see Figure 2), the effect of memory-based false belief on inferences is robust regardless of individual differences.

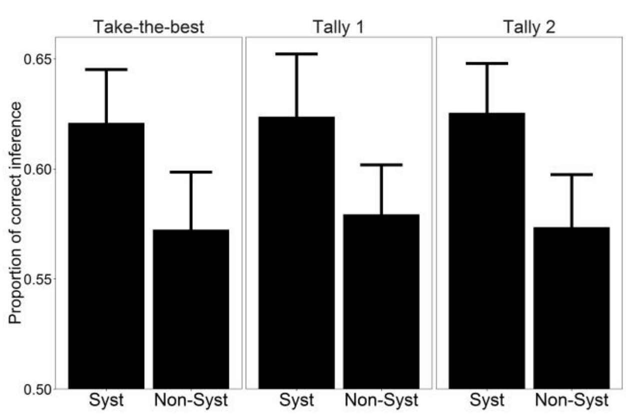

Figure 3. Proportion of correct inferences in the simulation task. Error bars denote standard deviation.

Taken together, the results of computer simulations for binary choice inference task show that the systematic nature of memory-based false beliefs functioned adaptively in making inferences, corroborating Hypothesis 2.

General discussion

In the present study, we examined the nature of people's false beliefs about the real world. The results of a behavioral study showed that participants had systematic false beliefs. In particular, the nature of their false beliefs correlated with environmental structure (i.e., cities' population sizes). For large cities, people tend to falsely recognize that there is an attribute which is associated with large cities (e.g., there is a professional baseball team). In contrast, for small cities, people tend to falsely recognize that there is no such an attribute. We also conducted a simulation study and examined how the memory-based false belief affected inferences about the real world. We found that the systematic nature of false beliefs functioned adaptively in making inferences.

Previous studies have discussed how limitations in the amount of knowledge affect adaptive inferences. For example, Gigerenzer and Goldstein (1996) examined two forms of limited knowledge. One was inability to recognize objects and the other was inability to recognize attributes of recognized objects. Schooler and Hertwig (2005) examined how forgetting aids inferences based on the recognition heuristic. These studies both showed that a limited amount of knowledge (i.e., the number of recognized objects or cues) does not necessarily lead to maladaptive inferences. Rather, a limited amount of knowledge can enhance adaptive inferences. In the present study, we examined the effect of limitations of memory in terms of systematic incorrectness. We found that the systematic nature of memory-based false belief can enhance accuracies of inferences. This provides new evidence about the relationship between cognitive limitations and adaptive inferences.

Pleskac (2007) theoretically examined the recognition heuristic in terms of signal detection theory. He showed that false alarms and misses in recognition processes affected the performance of the recognition heuristic. Thus, he examined the relationship between accuracy of recognition and adaptive inferences. Here, we note two differences between Pleskac (2007) and our present study. First, Pleskac focused on recognition of objects and examined how false recognition affected the usage of the recognition heuristic. The present study focused on the nature of memory-based false belief (i.e., cities' attributes) and how false belief affected knowledge-based inferences. Hence, Pleskac and the present study examined basically different domains. Second and more importantly, we conducted not only a theoretical study (i.e., computer simulation), but also a behavioral study. In particular, we clarified the nature of false beliefs about the real world. We provided evidence that people had systematic false beliefs about the real world using a behavioral study, and showed how such memory-based false beliefs affected inferences by using computer simulations. Therefore, although our study and Pleskac were analogous in that they both examined how accuracy of memory affected adaptive inferences, our findings provide new insights about the relationship between limitations of memory and adaptive inferences.

In sum, we provided new evidence that limitations in human memory can enhance adaptive inferences. We believe that the present findings make a substantial contribution toward understanding the relationship between adaptive inferences and cognitive limitations.

Acknowledgments

This research was supported by Grants-in-Aid for Scientific Research (A, 16H01725; B, 25280049; C, 25330167) and Young Scientists (B, 16K16070).

References

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

Gigerenzer, G., & Goldstein, D. G. (1999). Betting on one good reason: The take-the-best heuristic. In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 75–95). New York: Oxford University Press.

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

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

Honda, H., Matsuka, T., & Ueda, K. (accepted). Memory-based simple heuristics as attribute substitution: Competitive tests of binary choice inference models. *Cognitive Science*.

Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan Magazines Ltd.

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

Loftus, E. F. (2005). Planting misinformation in the human mind: A 30-year investigation of the malleability of memory. *Learning & Memory, 12*, 361–366.

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

Pleskac, T. J. (2007). A signal detection analysis of the recognition heuristic. *Psychonomic Bulletin and Review, 14*, 379–391.

Roediger, H. L., & DeSoto, K. A. (2016). Recognizing the presidents: Was Alexander Hamilton president? *Psychological Science, 27*, 644–650.

Roediger, H. L., & McDermott, K. B. (1995). Creating false memories: Remembering words not presented in lists. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*, 803–814.

Roediger, H., Watson, J., McDermott, K., & Gallo, D. (2001). Factors that determine false recall: A multiple regression analysis. *Psychonomic Bulletin & Review, 8*, 385–407.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology, 7*, 573–605.

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

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

Appendix. List of city names and attributes used in the present study (Four examples).
"+ (-)" indicates that there is (is not) the attribute in that city.

	City name (shi)	Population size	Baseball team	Prefectural capital	High court	Station of bullet train	Capital area
1	Yokohama	3,689,603	+	+	-	+	+
2	Osaka	2,666,371	+	+	+	+	-
…	…	…	…	…	…	…	…
99	Chigasaki	235,140	-	-	-	-	+
100	Yamato	228,180	-	-	-	-	+