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When the Brain Decides: A Familiarity-Based Approach to the Recognition Heuristic as Evidenced by Event-Related Brain Potentials

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Abstract

Humans can make fast and highly efficient decisions by using simple heuristics that are assumed to exploit basic cognitive functions. In the study reported here, we used event-related potentials (ERPs) to disclose the psychological mechanisms underlying one of the most frugal decision rules, namely, the recognition heuristic. According to this heuristic, whenever two objects have to be ranked by a specific criterion and only one object is recognized, the recognized object is ranked higher than the unrecognized object. Using a standard recognition-heuristic paradigm, we predicted participants' decisions by analyzing an ERP correlate of familiarity-based recognition occurring 300 to 450 ms after stimulus onset. The measure remained a significant predictor even when later ERP correlates were taken into account. These findings are evidence for the thesis that simple heuristics exploit basic cognitive processes. Specifically, the findings show that familiarity—that is, recognition in the absence of recollection—contributes to decisions made on the basis of such heuristics.

Keywords

decision making, memory, event-related potentials

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In the realm of decision making, researchers have sometimes regarded cognitive heuristics as poor replicas of statistical procedures that are often too complicated for the uneducated mind to compute (Kahneman & Tversky, 1996). However, other researchers have emphasized that cognitive heuristics represent adaptive strategies that are ecologically rational (Gigerenzer, 1996; Gigerenzer & Gaissmaier, 2011; Gigerenzer & Goldstein, 2011; Goldstein & Gigerenzer, 2002). According to this latter view, it is assumed that cognitive heuristics evolved in tandem with basic psychological mechanisms. One well-known heuristic, namely the recognition heuristic, exploits the vast and reliable capacity of the human brain for recognition. According to this heuristic, whenever two objects have to be ranked by a specific criterion and only one object is recognized, then the recognized object is ranked higher than the unrecognized object.

In environments in which recognition is positively correlated with the decision criterion, inferences on the basis of mere recognition will lead to good results with the least amount of effort and time. A famous example illustrating how the recognition heuristic works is the city-size comparison task. Participants have to decide which of two cities has more inhabitants. Intriguingly, most participants indeed decide as if they adhere to the recognition heuristic: When a known and an unknown city name are presented, participants choose the known city, as verified by questionnaires employed before or after the experiment, in approximately 90% of the cases (Goldstein & Gigerenzer, 2002). The recognition heuristic leads to performance highly above chance (i.e., it is ecologically rational), because city size and recognition are mediated via the number of times a city has been mentioned in the news. Thus, the larger a city, the more often it is cited in the news, and the better it is recognized (Fig. 1). The recognition heuristic also functions well in other domains, such as predicting the outcome of tennis matches or the success of stock trades (Borges, Goldstein, Ortmann, & Gigerenzer, 1999; Serwe & Frings, 2006).

One argument against the recognition heuristic is that it can be inferred only indirectly from postexperiment questionnaires,

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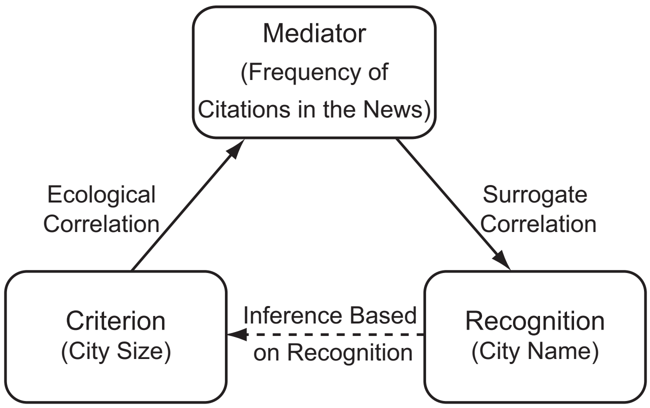

Fig. 1. Schematic illustrating the operation of the recognition heuristic in the city-size comparison task (adapted from Goldstein & Gigerenzer, 2002). The unknown criterion, city size, is correlated with a mediator variable, frequency of citations in the news, such that the larger a city, the more often it is mentioned in the news. This increased publicity in turn leads to increased recognition of a city name. Consequently, favoring a recognized city name over an unrecognized city name leads to highly above-chance correct identification of the larger of two cities in the task.

so that the possibility cannot be excluded that participants used criterion-related knowledge or other sources of knowledge instead of mere recognition. In a study that is so far unique, Volz et al. (2006) investigated the neural correlates of the recognition heuristic with event-related functional MRI (fMRI). Volz and her colleagues revealed increased activation within the anterior frontomedian cortex, precuneus, and retrosplenial cortex when participants followed the recognition heuristic, as compared with when they did not follow the heuristic. Nevertheless, the study did not provide any information about what kind of recognition processes participants might have used to make their decision. In the study reported here, we took a new approach to investigating the recognition heuristic by employing psychophysiological methods. By measuring recognition-related brain electrical activity, we predicted participants' decisions on-line even before they actually made those decisions.

In the dual-process perspective of recognition memory, a distinction is made between an initial sense of knowing (familiarity), which is fast and context free, and a second, slower, and more effortful process (recollection), by which contextual details of a prior episode can be retrieved (Eichenbaum, Yonelinas, & Ranganath, 2007; Yonelinas, 2002). These two memory processes have been extensively studied in behavioral experiments (Yonelinas, 2002), as well as with brain imaging (Yonelinas, Otten, Shaw, & Rugg, 2005) and electrophysiological methods (and, particularly in the latter case, by the analysis of event-related potentials, or ERPs; Rugg & Curran, 2007). Because of the millisecond time-resolution of ERPs, familiarity-based recognition and recollection-based recognition can be temporally differentiated. Furthermore, the two recognition processes are associated with different ERP scalp topographies. Familiar stimuli elicit more positive-going ERP waveforms than do unfamiliar stimuli at fronto-central recordings sites between 300 to 500 ms after stimulus presentation, whereas recollection is associated with a parietal maximal ERP modulation having an onset of around 450 ms after stimulus presentation (Jäger, Mecklinger, & Kipp, 2006). In support of the view that familiarity reflects a continuous index of memory strength, the midfrontal old/new effect (the difference between ERPs in response to studied and unstudied items) was found to covary with the level of familiarity, as indexed by response confidence during recognition judgments (Woodruff, Hayama, & Rugg, 2006).

The characteristics of familiarity-based memory make it an ideal mechanism for exploitation by the recognition heuristic: Familiarity typically arises early after stimulus onset, thereby preventing extensive comparisons or evaluations using other knowledge sources. Also, in the case of the city-size comparison task, as familiarity reflects a continuous index of memory strength and because city size is highly correlated with the number of prior encounters in the media, familiarity should also be highly diagnostic even for an inaccessible criterion, such as city size.

In the current study, we linked neurocognitive research with the field of decision making. We reasoned that the benefits of this linkage would be twofold. First, a well-known heuristic would be associated with a basic memory process and its widely accepted neural correlate (Rugg & Curran, 2007). Second, familiarity could be measured directly and on-line, independently of postexperiment questionnaires. This approach opens in turn the intriguing possibility of predicting behavioral decisions by means of electroencephalography (EEG) data: If the recognition heuristic exploits familiarity when two objects are compared, then the object that elicits the larger ERP correlate of familiarity should be chosen. Thus, the ERP data would predict the subject's decision even before the decision was made. To investigate this intriguing possibility, we recorded EEG data while subjects performed a city-size comparison task.

Method

Participants

Twenty-one volunteers (12 female, 9 male), ranging in age from 21 to 31 years (mean age = 24.9 years), took part in the experiment. Data from 1 subject had to be excluded from the analysis because of technical artifacts. All participants were students at Saarland University. Participants were informed about the procedure of the experiment and gave their written consent for taking part in it.

Materials

We used the names of 60 well-known and 60 little-known cities in France, Italy, Spain, and Great Britain. The average recognition rates of these cities were known from a previous study (Pachur, Bröder, & Marewski, 2008). In our experiment, each well-known city had at least an average recognition rate

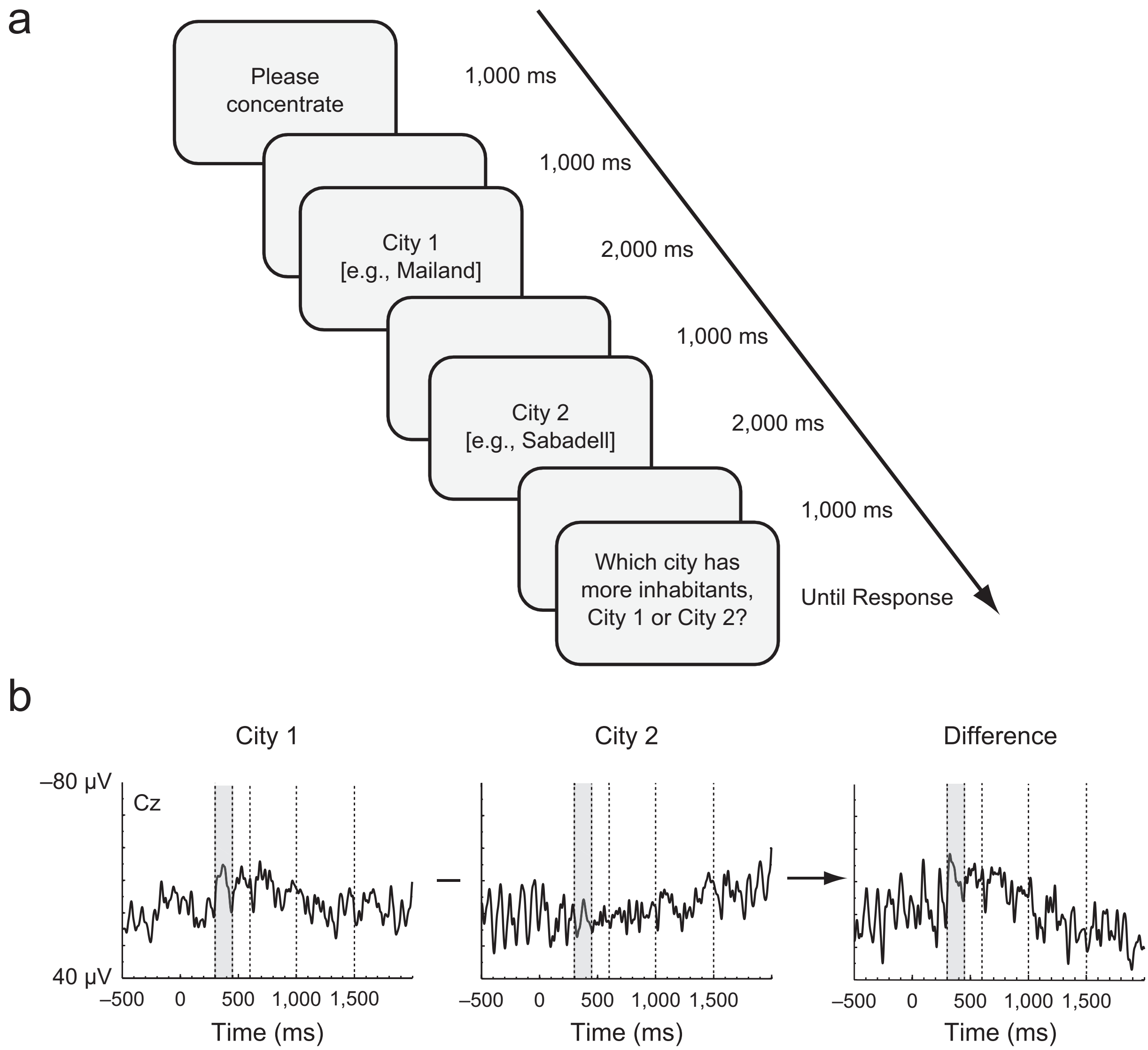

Fig. 2. Sample sequence (a) and analysis (b) of a single trial. Each trial began with a 1,000-ms interval in which participants were asked to concentrate. Next, participants saw two consecutively presented city names (one well-known city and one little-known city) for 2,000 ms each. Participants were then prompted to indicate which of these two cities has more inhabitants by pressing a button. The four display screens were separated by 1,000-ms interstimulus intervals. The electroencephalography (EEG) data for each trial were segmented into two 2,500-ms epochs, one for each city. Each epoch covered the time window from 500 ms prior to the presentation of the city name to the offset of the city name (data from the Cz recording site are shown here). Amplitude differences between the two epochs of each trial (see the bottom row for an illustration) were entered as predictors into the binary logistic regression analysis. The gray shading indicates the early time window (300–450 ms) during which familiarity-based recognition effects are known to occur. Dotted vertical lines indicate the four time windows of interest between 350 and 1,500 ms. Event-related potentials (ERPs), as displayed in Figure 3, were derived by averaging the epochs for the well-known and little-known cities; such averaging is a standard procedure for analyzing EEG data.

of 80% or higher, whereas each little-known city had an average recognition rate not exceeding 15%.

Procedure

Participants performed a city-size comparison task while EEG data were recorded. A sample trial sequence is illustrated in Figure 2a. In each trial, participants saw four screens. On the first screen, they were asked to concentrate. The next screen presented a city name, and the following screen presented a different city name. The final screen prompted participants to decide which of the two cities had more inhabitants. Participants indicated their decision by pressing a button (no time limit), and they did not receive feedback. In each trial, a well-known and a little-known city were randomly chosen to optimize the use of the recognition heuristic. Cities were paired such that the average probability that the well-known city had more inhabitants than the little-known city was 83.8%, and the average probability that the little-known city had more inhabitants than the well-known city was 16.2%. Stimuli were presented sequentially for 2,000 ms each, and the four screens were interleaved with interstimulus intervals lasting 1,000 ms. The order of known and little-known cities was counterbalanced during the experiment. Each of the city names was presented twice during the experiment.

Electrophysiology

Elastic caps (Easycap, Herrsching, Germany) with 58 embedded Ag/AgCl EEG electrodes were attached to the subjects' heads. Electrode locations in these caps are based on an extended 10-20 system (10-10 system). EEG data were continuously recorded, referenced to the left mastoid. In addition, electroocular activity was recorded from two pairs of electrodes placed at the outer canthi and below and above the right eye. Data were sampled at a rate of 500 Hz and filtered on-line from 0.016 Hz (time constant = 10 s) to 250 Hz. Electrode impedances were kept below 5 kΩ.

Data were filtered off-line from 0.1 Hz to 35 Hz (48 dB), with an additional notch filter added to suppress line activity, and rereferenced to linked mastoids. The impact of eye movements and blinks on EEG activity was eliminated by a correction algorithm implemented in the analysis tool (Vision-Analyzer 2.01, Brain Products, Gilching, Germany); this algorithm was based on an independent component analysis (ICA). Subsequently, EEG data were segmented into epochs of 2,500-ms duration, including a 500-ms baseline, and baseline corrected. Trials with EEG activity falling outside the range of –100 to +100 μV were excluded.

In a first step, ERPs in response to well-known and little-known city names were obtained for each individual subject and then averaged across participants without regard for the subjects' responses. For each subject, ERPs were based on an average of 118 trials (range = 99–120) for well-known city names and 119 trials (range = 102–120) for little-known city names. Mean amplitude values from 300 to 450 ms (covering familiarity-based recognition effects), 450 to 600 ms (covering recollection-based recognition effects), 600 to 1,000 ms, and 1,000 to 1,500 ms were extracted and entered into an analysis of variance with city publicity (well-known, little-known), anterior-posterior electrode (F, FC, C, CP, P), and lateral-medial electrode (8, 4, z, 3, 7) as within-subjects factors. ERP difference values were calculated by subtracting ERPs in response to little-known city names from ERPs in response to well-known city names. Then, the topographic change in the recognition effects from the first to the second time window was tested in an analysis of variance on these ERP difference values with anterior-posterior electrode (F, FC, C, CP, P), lateral-medial electrode (8, 4, z, 3, 7), and time window (300–450 ms, 450–600 ms) as within-subjects factors. These difference values are depicted as maps in Figure 3b. Greenhouse-Geisser correction for nonsphericity was applied when necessary and is indicated by referring to the ε value.

In the second step of data analysis, single-trial data from the electrodes Fz, Cz, and Pz were exported. For each single trial, we quantified the mean EEG amplitudes between 300 to 450 ms, 450 to 600 ms, and 1,000 to 1,500 ms after the onset of the first city name and the onset of the second city name at three electrodes (Fz, Cz, Pz), and amplitudes in response to City 2 were subtracted from amplitudes in response to City 1, as schematically illustrated in Figure 2b. For each subject, difference values of on average 116 trials (range = 93–120) were entered into the analysis. Subsequently, we used these voltage differences to predict the behavioral decision in each trial. All decisions of all participants were entered into binary logistic regression models with participants' decisions as the criterion and the voltage differences as predictors. Three models were calculated (Fig. 4): In Model 1, Fz and Cz data during the time window of 300–450 ms were used as predictors. In Model 2, differences in activation on Pz during the time window 450–600 ms were added, and the nonsignificant predictor of Model 1 (Fz data from 300–450 ms) was removed. In Model 3, differences in activation at Fz, Cz, and Pz during the time window 1,000–1,500 ms were added.

Results

Participants selected the well-known city name 90.5% of the time, correctly identifying the larger of the two cities in 79.3% of trials. When participants chose the well-known city name, 84.9% of the responses were correct. In contrast, only 26.4% of the responses were correct when the little-known city name was chosen.

In the first step of the analysis, ERPs in response to well-known and little-known city names were compared in order to reveal the general effects of publicity. This comparison showed pronounced differences in the ERPs during the 300- to 450-ms, 450- to 600-ms, and 1,000- to 1,500-ms time windows (Fig. 3a). From 300 to 450 ms, well-known city names elicited more positive-going waveforms than little-known city names did, $F(1, 19) = 25.15$, $p < .001$, particularly at fronto-central electrodes. From 450 to 600 ms, the ERPs in response to well-known city names continued to be more positive, $F(1, 19) = 23.30$, $p < .001$, with the largest differences in this time window found over parietal electrode sites. The anterior-posterior distribution of the publicity effect (well-known city name vs. little-known city name) changed significantly from the 300- to 450-ms to the 450- to 600-ms time windows, $F(4, 76) = 6.18$, $p = .016$, $\varepsilon = .303$ (Fig. 3b). In the late time window (1,000–1,500 ms), the polarity of the main effect was reversed, such that ERPs in response to well-known city names were more negative-going than ERPs in response to little-known city names, $F(1, 19) = 32.10$, $p < .001$, with a maximum difference over posterior electrode sites.

In the second step of the analysis, in line with the main goal of the current study, we constructed three models to predict the participants' responses on the basis of single-trial EEG data. All three binary logistic regression models were significant (i.e., the single-trial data predicted the participants' decisions), and all included voltage differences of the early time window

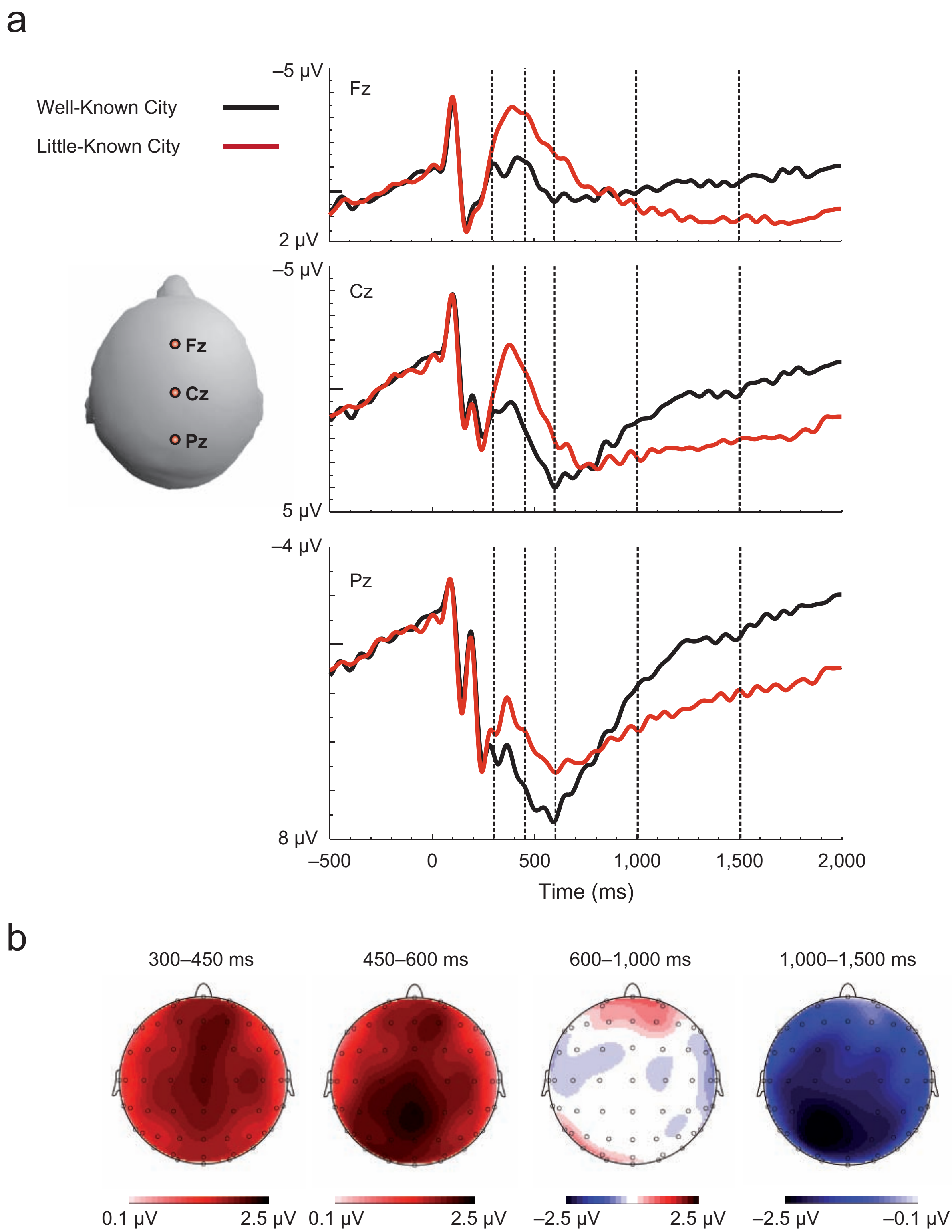

Fig. 3. Event-related potentials (ERPs) averaged across responses to well-known city names and little-known city names. ERP waveforms at Fz, Cz, and Pz (a) are shown for the 2,500-ms time window ranging from 500 ms prior to stimulus presentation to the end of stimulus presentation. The four time windows of interest (300–450 ms, 450–600 ms, 600–1,000 ms, and 1,000–1,500 ms) are indicated by dotted vertical lines. Topographic maps showing the difference in responses to well-known city names and little-known city names (b) were created for the four time windows of interest. Amplitudes are color-coded.

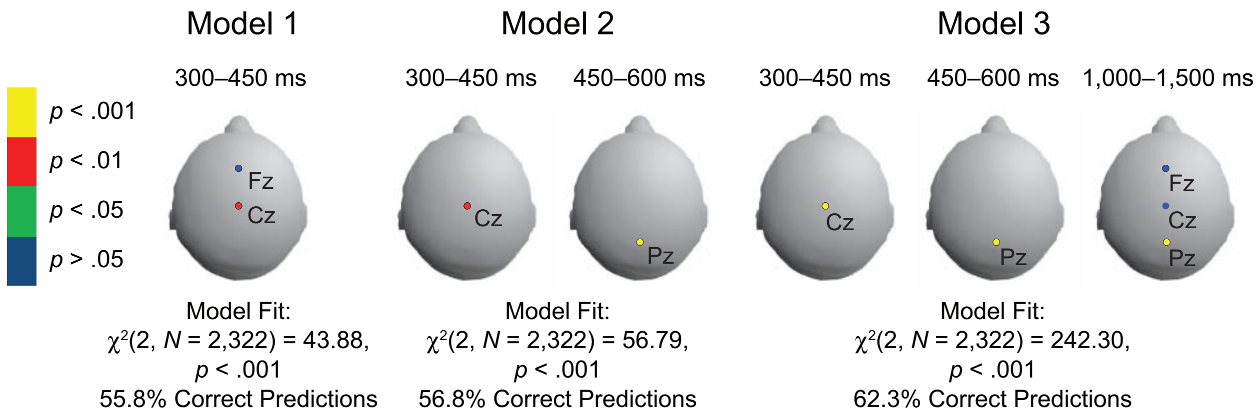

Fig. 4. Time windows and electrodes used in the three logistic regression models created for predicting participants' decisions. Single-trial differences in activation at electrodes Fz, Cz, and Pz during the time windows spanning 300 to 450 ms (covering familiarity), 450 to 600 ms (covering recollection), and 1,000 to 1,500 ms (covering the usage of knowledge and possible strategies) were used as predictors. The chosen predictors directly follow from event-related potential effects significant at the group level. In Model 1, Fz and Cz data during the 300- to 450-ms time window were used as predictors. In Model 2, differences in activation at Pz during the 450- to 600-ms time window were added, and the nonsignificant predictor of Model 1 (Fz data from 300 to 450 ms) was removed. In Model 3, differences in activation at Fz, Cz, and Pz during the 1,000- to 1,500-ms time window were added.

(300–450 ms) as predictor. In the first model, only voltage differences of the early time window at the electrodes Fz and Cz were entered as predictors. The model was significant, $\chi^2(2, N = 2,322) = 43.88$, $p < .001$ (Fig. 4, Table 1),[1] showing that participants' decisions could be predicted by EEG data solely from this early time window, which comprises the ERP correlate of familiarity-based recognition (Jäger et al., 2006; Rugg & Curran, 2007; Woodruff et al., 2006). In this model, the voltage differences at Cz but not at Fz were a significant predictor of participants' decisions. This pattern of results is congruent with the topography of the early ERP effect, which was most pronounced at central electrodes.

In the second model, the voltage differences at Pz in the time window from 450 to 600 ms were added as predictors. At parietal electrode sites in this latency range, recollection-based processes are observed in ERPs (Rugg & Curran, 2007; Rugg et al., 1998; Wilding, 2000). Inclusion of data from this later time window slightly improved predictions of the participants' decisions, $\chi^2(2, N = 2,322) = 56.79$, $p < .001$ (Fig. 4, Table 1). Note that in this model, the EEG data from the early time window remained a significant predictor of participants' decisions.

This pattern held true in the third model, when activation differences of later time windows (1,000–1,500 ms), presumably reflecting participants' usage of other knowledge sources, their response preparation, or both of these possibilities, were added as predictors. The amount of correctly predicted decisions increased to 62.3%, $\chi^2(2, N = 2,322) = 242.30$, $p < .001$ (Fig. 4, Table 1), and the voltage differences of the early time window remained a significant predictor.

To further corroborate the validity of using EEG data for predicting decisions, we investigated the predictive validity of all three models in a cross-validation analysis. The data sample of each participant was randomly split into two subsamples, and one subsample was used for estimating the logistic regression functions with which we then predicted the decisions of the other subsample. All three models significantly predicted the behavioral decisions, leading to 58.1% correct predictions for the first model, $\chi^2(1, N = 1,177) = 32.13$, $p < .001$; 56.4% correct prediction for the second

Table 1. Results From the Three Regression Models: Wald Statistics for Each Electrode and Time Window

Model and statistic	Fz: 300–450 ms	Cz: 300–450 ms	Pz: 450–600 ms	Fz: 1,000–1,500 ms	Cz: 1,000–1,500 ms	Pz: 1,000–1,500 ms
Model 1						
Wald statistic	1.40	9.36	—	—	—	—
p	.24	.002	—	—	—	—
Model 2						
Wald statistic	—	8.35	14.17	—	—	—
p	—	.004	< .001	—	—	—
Model 3						
Wald statistic	—	23.97	76.95	0.03	3.57	51.68
p	—	< .001	< .001	.86	.06	< .001

model, $\chi^2(1, N = 1{,}177) = 20.53$, $p < .001$; and 64.4% correct predictions for the third model, $\chi^2(1, N = 1{,}177) = 97.87$, $p < .001$.

Discussion

In the study reported here, we asked participants to perform a city-size comparison task. The amount of correct responses (79.3%) was clearly above chance level. This relatively high level of task performance can be explained by the fact that participants adhered to the recognition heuristic. In approximately 90% of the trials, they chose the well-known city instead of the lesser-known city as being the larger one. This percentage of trials is close to values reported by other studies using the city-size comparison task (Goldstein & Gigerenzer, 2002; Volz et al., 2006). In contrast to trials in which participants adhered to the recognition heuristic, performance was below chance level when participants chose the little-known city name (26.4% correct responses). This performance level is, nevertheless, slightly better than one would expect from the average probability that a little-known city was the larger one ($p = .16$). Thus, criteria other than the recognition of a city name might in some cases have provided valid clues about the city size, but on average the participants would have performed better if they had ignored any criteria other than whether they recognized the name of the city.

The ERPs in response to well-known and little-known city names differed significantly between 300 to 450 ms, 450 to 600 ms, and 1,000 to 1,500 ms. The early midfrontal ERP effect is likely to reflect familiarity-based recognition processes, which are fast acting and relatively automatic (Rugg & Curran, 2007). These processes arise before extensive comparisons or evaluations of city names can take place based on other knowledge sources and, thus, correspond to what Goldstein and Gigerenzer (2002, p. 77) called "mere recognition." As outlined, the early midfrontal ERP effect reflects a continuous index of memory strength, which was found to covary with the level of city familiarity, as indexed by response confidence during recognition judgments (Woodruff et al., 2006).

In contrast, the parietally distributed ERP effect at 450 to 600 ms is assumed to reflect a more effortful retrieval process that gives rise to consciously accessible information (Jäger et al., 2006; Rugg & Curran, 2007). The effect is influenced among other things by the depth of encoding (Rugg et al., 1998) and the correctness of source judgments (i.e., judgments about the context in which one has encountered a memorized item; Wilding, 2000). What kind of information was recollected when a well-known city name was presented is difficult if not impossible to assess. It could in principle be any kind of available information associated with the city name.

The ERP findings indicate that both familiarity-based and recollection-based recognition took place when participants encountered the well-known city names. However, at the group level, the ERP responses do not provide any evidence that mere recognition contributed to the participants' decisions. In principle, names of well-known cities might have elicited familiarity effects, but subjects might have made their decision only on the basis of consciously assessable information, like the city size itself or (if this information was not available) indirect indicators of the city size, such as whether the named city has an airport, a soccer team in the premier league, or an exhibition center (Goldstein & Gigerenzer, 2002).

With the second step in the data analysis, we aimed to predict the participants' decisions by using single-trial EEG data to evaluate the impact of familiarity-related processes on the decision processes. The results of this analysis showed that EEG data from the early time window (reflecting familiarity-based recognition) were indeed predictive of the participants' decisions. Note that we could predict the size judgment as early as 300 to 450 ms after the presentation of the city name and, thus, well before the participants actually made their decisions. The inclusion of EEG data of later time windows (reflecting conscious recollection and other cognitive processes) in the regression analysis improved the amount of correctly predicted decisions, but EEG data from the early time window remained a significant predictor of participants' decisions. Our findings indicate that early familiarity-based processes had a fundamental impact on the participants' decisions, even though participants appeared to use other kinds of information for their decisions as well.

A final note concerns the fact that even when EEG data from later time windows were included in the regression model, the prediction of participants' decisions was still worse than the participants' accuracy. This finding can primarily be explained by the inherently low signal-to-noise ratio of single-trial EEG data. Furthermore, it should be noted that we did not seek to minimize prediction error by using the whole range of recorded EEG data (e.g., by decomposing the EEG signal into its spectral contents) or by using more sophisticated pattern-classifier techniques (e.g., as described by Newman & Norman, 2010). Instead, we focused our single-trial analysis on commonly accepted electrophysiological correlates of familiarity- and recollection-based recognition processes in the ERP domain (Jäger et al., 2006; Rugg & Curran, 2007). Nevertheless, findings show that, alongside ERP and event-related fMRI studies, single-trial EEG analysis offers an intriguing possibility for understanding the neural basis of decision making.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Note

1. In our principal analysis, we used a nonhierarchical logistic regression model, meaning that we did not differentiate between the level of participants and the level of single trials. We acknowledge that hierarchical linear models might be a valid alternative way of analyzing the data. To rule out a potential impact of the currently employed regression model on the current findings, we computed a hierarchical multiple regression with the single trial as the individual-level factor (Level 1) and the participant as the group-level factor (Level 2). The dependent variable was participants' decisions, which were coded as 0 or 1 (cf. Myers & Broyles, 2000, for applying regression coefficient analysis in a repeated measures design with a binary criterion). The analysis with this hierarchical linear model revealed essentially the same major findings as reported here for the nonhierarchical logistic regression model; most important in this additional analysis, the amplitude difference at Cz in the 300- to 450-ms time window remained a significant predictor and did not significantly vary at the level of participants.

Furthermore, we computed logistic regression functions for each individual participant. Again, results of this analysis were in line with results of the reported main analysis. For example, for Model 1, the best-fitting regression model for 18 out of 20 participants was in line with the regression model for the pooled data. In addition, for 14 out of 20 participants, the amplitude difference at Cz from 300 to 450 ms was a significant predictor in these individual regression functions.

References

Borges, B., Goldstein, D. G., Ortmann, A., & Gigerenzer, G. (1999). Can ignorance beat the stock market? In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 59–72). New York, NY: Oxford University Press.

Eichenbaum, H., Yonelinas, A. P., & Ranganath, C. (2007). The medial temporal lobe and recognition memory. *Annual Review of Neuroscience*, *30*, 123–152.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman and Tversky. *Psychological Review*, *103*, 592–596.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*, 451–482.

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

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

Jäger, T., Mecklinger, A., & Kipp, K. (2006). Intra- and inter-item associations doubly dissociate the electrophysiological correlates of familiarity and recollection. *Neuron*, *52*, 535–545.

Kahneman, D., & Tversky, A. (1996). On the reality of cognitive illusions. *Psychological Review*, *103*, 582–591.

Myers, L., & Broyles, S. T. (2000). Regression coefficient analysis for correlated binomial outcomes. *Journal of Applied Statistics*, *27*, 217–234.

Newman, E. L., & Norman, K. A. (2010). Moderate excitation leads to weakening of perceptual representations. *Cerebral Cortex*, *20*, 2760–2770.

Pachur, T., Bröder, A., & Marewski, J. N. (2008). The recognition heuristic in memory-based inference: Is recognition a non-compensatory cue? *Journal of Behavioral Decision Making*, *21*, 183–210.

Rugg, M. D., & Curran, T. (2007). Event-related potentials and recognition memory. *Trends in Cognitive Sciences*, *11*, 251–257.

Rugg, M. D., Mark, R. E., Walla, P., Schloerscheidt, A. M., Birch, C. S., & Allan, K. (1998). Dissociation of the neural correlates of implicit and explicit memory. *Nature*, *392*, 595–598.

Serwe, S., & Frings, C. (2006). Who will win Wimbledon 2003? The recognition heuristic in predicting sports events. *Journal of Behavioral Decision Making*, *19*, 321–332.

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.

Wilding, E. L. (2000). In what way does the parietal ERP old/new effect index recollection? *International Journal of Psychophysiology*, *35*, 81–87.

Woodruff, C. C., Hayama, H. R., & Rugg, M. D. (2006). Electrophysiological dissociation of the neural correlates of recollection and familiarity. *Brain Research*, *1100*, 125–135.

Yonelinas, A. P. (2002). The nature of recollection and familiarity: A review of 30 years of research. *Journal of Memory and Language*, *46*, 441–517.

Yonelinas, A. P., Otten, L. J., Shaw, K. N., & Rugg, M. D. (2005). Separating the brain regions involved in recollection and familiarity in recognition memory. *Journal of Neuroscience*, *25*, 3002–3008.