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Physiological arousal in processing recognition information: Ignoring or integrating cognitive cues?

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Abstract

The recognition heuristic (RH; Goldstein & Gigerenzer, 2002) suggests that, when applicable, probabilistic inferences are based on a noncompensatory examination of whether an object is recognized or not. The overall findings on the processes that underlie this fast and frugal heuristic are somewhat mixed, and many studies have expressed the need for considering a more compensatory integration of recognition information. Regardless of the mechanism involved, it is clear that recognition has a strong influence on choices, and this finding might be explained by the fact that recognition cues arouse affect and thus receive more attention than cognitive cues. To test this assumption, we investigated whether recognition results in a direct affective signal by measuring physiological arousal (i.e., peripheral arterial tone) in the established city-size task. We found that recognition of cities does not directly result in increased physiological arousal. Moreover, the results show that physiological arousal increased with increasing inconsistency between recognition information and additional cue information. These findings support predictions derived by a compensatory Parallel Constraint Satisfaction model rather than predictions of noncompensatory models. Additional results concerning confidence ratings, response times, and choice proportions further demonstrated that recognition information and other cognitive cues are integrated in a compensatory manner.

Keywords: affect, recognition heuristic, physiological arousal, parallel constraint satisfaction, noncompensatory models.

1 Introduction

Imagine a business trip to a city you have never visited before. Your meetings end later than you had expected and you decide to spend the night. You make a few phone calls and find two hotels with vacancies, both at a similar rate. You know nothing else about these hotels; however, you do recognize the name of one of them. Which hotel would you choose? According to Goldstein and Gigerenzer (1999; 2002), these kinds of probabilistic inferences could be resolved by recognition information alone.

More specifically, according to Gigerenzer and colleagues (Gigerenzer, 2000; Gigerenzer & Goldstein, 1996; Gigerenzer, Todd et al., 1999), individuals are equipped with several tools (i.e., fast and frugal heuristics) that exploit the structure of the environment, some of which rely solely on one piece of information at a time on the road to reaching a decision. The *recognition heuristic* (RH), the simplest and one of the most prototypical tools in this toolbox, suggests that probabilistic inferences about a specific criterion (e.g., which of two cities is more populated), are made on the basis of recognition alone, so that recognized objects (e.g., the name of the city) will be chosen over unrecognized ones.

Indeed, it has been shown repeatedly that people actually prefer recognized objects over unrecognized ones, and that such behavior may lead to rather accurate inferences (e.g., Borges, Goldstein, Ortmann, & Gigerenzer, 1999; Goldstein & Gigerenzer, 1999, 2002; Pachur & Biele, 2007; Pohl, 2006; Reimer & Katsikopoulos, 2004; Serwe & Frings, 2006). Nevertheless, several studies challenge the claim that recognition information is used in a noncompensatory manner[1] as predicted by the RH (e.g., Bröder & Eichler, 2006; Hilbig & Pohl, 2008; McCloy & Beaman, 2004; Newell & Fernandez, 2006;

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[1]Noncompensatory strategies suggest that different cues or attributes of the choice alternative are considered in a specific order, usually in the order of their validity or importance (e.g., the take the best heuristic, TTB). Only one piece of information is being evaluated at a time and cues cannot compensate for deficits in others cues. In contrast, compensatory strategies assume that choices are based on the integration of the available information. Thus, compensation between cues is possible (e.g., the Expected Utility Theory — EUT).

Newell & Shanks, 2004; Oppenheimer, 2003; Pachur, Bröder & Marewski, 2008; Richter & Späth, 2006). For example, in Oppenheimer (2003), Bröder and Eichler (2006), and Richter and Späth (2006), additional information has been found to affect the proportion of choices that followed recognition. While it has been argued that several of these studies suffer from methodological limitations (see Pachur et al., 2008), their findings nonetheless highlight the need for considering a more compensatory integration of recognition information.

Moreover, studies on the RH have focused mainly on choice behavior. Yet, since the choice predictions made by different models often overlap (see Ayal & Hochman, 2009; Glöckner & Betsch, 2008a), it is difficult to draw clear conclusions concerning the underlying cognitive processes. Several recent studies have attempted to address this problem, for example by testing hypotheses concerning process measures such as decision time (Hilbig & Pohl, 2008; 2009; Marewski, Gaissmaier, Schooler, Goldstein, & Gigerenzer, 2010), and by additionally investigating confidence (Glöckner & Bröder, in press). Yet, additional research is needed to disentangle the role of recognition information in decision making, as well as to examine the cognitive processes underlying its use in inferences and choice behavior.

To achieve these goals, we investigated the nature of the processes underlying the use of recognition information in probabilistic inferences, using physiological arousal, choice proportions, decision times, and confidence as dependent measures. We derived concurring predictions on the basis of a noncompensatory perspective, and juxtapose these with contradicting predictions derived from a compensatory model. Specifically, we investigate whether recognition leads to increased physiological arousal, which dominates other cognitive information, as suggested by affect-based noncompensatory models (e.g., Damasio, 1994; Slovic, Finucane, Peters, & MacGregor, 2002). It has been argued that recognition information, like other affective signals, might be generated automatically (Pachur & Hertwig, 2006), and that it may override cognitive information (e.g., Goldstein & Gigerenzer, 2002, Experiment 2; Pachur et al., 2008, Experiment 1). Thus, we examined whether recognition information is affectively encoded during the decision process.

We tested the RH against the compensatory Parallel Constraint Satisfaction (PCS) model for decision making (e.g., Glöckner & Betsch, 2008b). The PCS model was selected because it has been shown to account well for decision times (Hilbig & Pohl, 2009) and confidence (Glöckner & Bröder, in press) in recognition tasks, and because it makes specific predictions concerning physiological arousal. The PCS model assumes that information integration is based on automatic-intuitive processes — akin to perception (Holyoak & Simon, 1999; McClelland & Rumelhart, 1981; Read, Vanman, & Miller, 1997; Thagard, 1989) — by which consistent interpretations of decision tasks are constructed. Available information is taken into account according to its importance, and the advantages of the (emerging) preferred option are highlighted by systematic information distortions (see also Russo, Carlson, Meloy, & Yong, 2008). The formalized PCS model includes four possible steps. First, when presented with a decision task, related information is activated to form a mental representation of the task. Second, automatic processes of PCS lead to maximization of consistency by automatically highlighting information supporting the favored alternative and at the same time suppressing contradicting information. As a result, a consistent representation of the available information is formed. Third, the decision maker evaluates the choice alternatives, and if one alternative clearly dominates the other (i.e., if there is enough information in favor of this alternative), this alternative is chosen. However, if information consistency fails to reach a certain threshold, the decision maker takes a forth step, in which deliberate construction processes are activated to change the structure of the network (e.g., changing the pattern of information search, assigning different weights to the different pieces of information). Among other things, the PCS model is supported by research that shows that unconscious modifications of the available information occur during decision processes (e.g., Glöckner, Betsch, & Schindler, in press; Holyoak & Simon, 1999; Simon, Krawczyk, Bleicher, & Holyoak, 2008; Simon, Snow, & Read, 2004). Furthermore, PCS models have been found to account well for both choices and decision times in probabilistic inference tasks (Glöckner, 2008; Glöckner & Hodges, in press; Glöckner & Bröder, in press; see also Glöckner & Betsch, 2008c).

1.1 Overview of the study

The current study is designed to examine whether recognition information is integrated with other information in a compensatory or noncompensatory manner, and whether recognition information is encoded as a special affective signal. To do so, we examined choice behavior, while participants conducted a city-size task (Goldstein & Gigerenzer, 2002; Richter & Späth, 2006). The city-size task was chosen in order to create an optimal environment for using the RH. Specifically, in this task the criterion (i.e., population size) is not immediately accessible, and inference has to be based on probabilistic cues (Goldstein & Gigerenzer, 2002; Pachur et al., 2008). In addition, recognition is natural rather than experimentally induced, and it is highly correlated with the criterion (Pachur et al., 2008). The selection of this task ensures, according to proponents of the RH, that participants will use the RH and allows us to focus on the processes that underlie the adoption of this heuristic.

Importantly, in order to thoroughly investigate the cognitive processes underlying the use of recognition information, two major methodological considerations must be taken into account. First, choice predictions of different models may overlap, and thus multiple means of investigation are in order (Ayal & Hochman, 2009; Glöckner, 2009, Glöckner & Bröder, in press; for a choice-based approach see also Marewski et al., in press). Here we look at choice patterns, response times, and confidence level. In addition, we focus on autonomic nervous system arousal, which is known to accompany emotional responses to psychological stimuli (Andreassi, 2000; Annoni, Ptak, Caldara-Schnetzer, Khateb, & Pollermann, 2003; Cacioppo, Tassinary, & Berntson, 2007), serving as a physiological marker of behavioral responses (Sokol-Hessner et al., 2009). To measure emotional arousal, we used Peripheral Arterial Tone (PAT) at the fingertip. For further information on the PAT measure, see Hochman, Glöckner, and Yechiam (2010).

Second, to contrast predictions from different models, a sufficient number of diagnostic cases (in which the considered models have contradicting predictions) should be included (Glöckner & Betsch, 2008a). In the current study, several trials will include additional information (in the form of dichotomous cues), which will be either congruent or incongruent with the naturally available recognition information (pointing in the same or the opposite direction, respectively).[2] By focusing on trials in which only recognition information is available versus trials in which additional congruent or incongruent information is presented, we were able to create a sufficient number of such diagnostic cases.

Thus, our methodological design enables us to juxtapose contradicting predictions about the compensatory and noncompensatory use of recognition information. By providing further information about the cities, we deviate from the original domain of choices for which the RH was suggested, namely to account for inferences from memory. Note, however, that inferences that include both given information and information retrieved from memory are rather common and highly relevant in everyday life (for a similar approach see Glöckner & Bröder, in press). Consider, for example, a consumer decision to buy a shampoo. One product is known (e.g., shampoo A), the other one is not (e.g., shampoo B), but when looking at them on a supermarket shelf additional probabilistic cues become immediately available. Such cues might include recommendations of product testing agencies, eco-labels, size and color of the package, etc. Thus, in many real-life situations, accounting for external information is inherent in the evaluation of recognition information. In the current paper we aimed to capture these kinds of situations, and to shed light on the processes underlying the evaluation of recognition and additionally available information.

1.2 Indirect measures of processes and hypotheses

1.2.1 Choice proportion

Choice proportion refers to the proportion of individuals' choices that are consistent with the predictions of a specific decision model (also known as adherence rates). If choice tasks are diagnostic (i.e., if the different models predict different choices), then this measure can be used as an indicator of the underlying processes that lead to the decision (Bröder & Schiffer, 2003; for a discussion of the problems that might result from using choice proportions as predictor for strategy use see also Hilbig, in press).

According to the RH, recognition information is used in a noncompensatory manner. Thus, if a majority of participants applies RH it would be predicted that a high proportion of choices follows recognition in cases in which it is diagnostic (i.e., one option is recognized and the other is not). In addition, this choice proportion should be insensitive to the presence of additional information, whether this additional information is congruent or incongruent with recognition. In contrast, the PCS model (as well as other compensatory models) assumes that all available information is integrated in a compensatory manner. Thus, the PCS model predicts high proportions of choice in line with recognition when recognition information and the additional cue are congruent. However, when only recognition information is available, choice proportion will be lower, and lowest yet if recognition information and the additional cue are incongruent. Since previous research supports a compensatory integration of recognition information and further cues (i.e., the PCS hypothesis), we expected to replicate these findings.

1.2.2 Response time

Response time refers to the time it takes the decision maker to contemplate before making her decision. Short decision latencies are assumed to reflect short processing time and reliance on instantly accessible information, while long decision latencies reflect more deliberate cognitive consideration (Ayal & Hochman, 2009; Betsch,

[2] It should be noted that the use of induced knowledge may highlight the additional information and thus can potentially increase its use in the decision process (see Pachur et al., 2008). To allow for a strong test and to minimize the potential impact of demand effects, the additional cue information had low validity (which was much lower than the validity of recognition information). Furthermore, we tried to support participants' comprehension by explaining that the validity of the cues is only somewhat higher than chance level.

2008; Horstmann, Ahlgrimm, & Glöckner, 2009; Payne, Bettman, & Johnson, 1993).

Since the recognition information used in the current study is natural, it is assumed to be instantly accessible (Pachur & Hertwig, 2006). Thus, the RH (in the implementation suggested by Gigerenzer & Goldstein, 1996) predicts short response times on those cases in which the recognition information is diagnostic. In addition, since this noncompensatory model predicts that recognition is the only information to be considered, this short response time should not be affected by additional (congruent and incongruent) cue information. By contrast, the PCS model suggests that all available information is automatically integrated to form a mental representation. Response time should be shorter when consistency is high, because one alternative is more clearly supported and thus selected more quickly (for a similar prediction see Bergert & Nosofsky, 2007). Thus, response time should be shortest when both available pieces of information (i.e., recognition and cue) are congruent. Response time should increase when only recognition information is available (since the advantage of the preferred alternative is less obvious). Finally, response time should be longest when incongruent information is presented. Note that Hilbig and Pohl (2009) have recently provided convincing evidence for the decision time predictions of the PCS models (and decision field theory; Busemeyer & Townsend, 1993) and we expect to replicate their findings.

1.2.3 Confidence level

The confidence level reflects how confident a decision maker is about her inference. According to the noncompensatory principles, decisions are based solely on the first diagnostic piece of information (e.g., Gigerenzer et al., 1999). Assuming that cues are investigated in order of their validity, decisions should be based on the most valid diagnostic cue. Recognition information has high natural validity in several situations (e.g., Goldstein & Gigerenzer, 2002; Pachur et al., 2008), and is assumed to be the first step in a number of fast and frugal strategies, such as the take-the-best heuristic (Gigerenzer & Goldstein, 1996). Thus, decisions that are based on recognition information alone should lead to a high confidence level which is assumed to be equal to the validity of the recognition cue (Gigerenzer, Hoffrage, & Kleinbölting, 1991; see also Ayal & Hochman, 2009). Furthermore, since the process in these diagnostic recognition cases is assumed to be noncompensatory (i.e., based only on the discriminating information of recognition), this high level of confidence should not be affected by additional information.

On the other hand, compensatory principles suggest that confidence estimations should be based on all available information and on the results of integration of various cues (e.g., Ayal & Hochman, 2009; Erev, Wallsten, & Budescu, 1994). Specifically, confidence level is assumed to depend on the perceived difference between the alternatives (Glöckner & Betsch, 2008c). Accordingly, the PCS model predicts that confidence level will be highest when all information points toward selecting the same option, and lowest when the recognition information and the additional information are incongruent. When less information is available (e.g., only recognition), confidence level is predicted to be intermediate. Based on findings in probabilistic inference tasks (Glöckner & Hodges, in press) and recent findings in recognition based probabilistic inferences (Glöckner & Bröder, in press), we expect to find support for the PCS hypothesis with this measure as well.

1.2.4 Physiological arousal

The sympathetic branch of the autonomic nervous system is responsible for mobilizing bodily resources to allow the regulation and coordination of emotional responses to psychological stimuli (Andreassi, 2000). PAT at the fingertips represents changes in blood volume in response to environmental stimuli (Andreassi, 2000), and is considered a good measure of sympathetic autonomic system activation (Lavie, Schnall, Sheffy, & Shlitner, 2000). The level of sympathetic activation is indicated by a decrease in the transparency of the blood as a function of blood pressure. For each heartbeat, blood pressure varies between systolic and diastolic pressures. The systolic arterial pressure is defined as the peak pressure in the arteries, which occurs near the beginning of the cardiac cycle (when the heart constricts); the diastolic arterial pressure is the lowest pressure (at the resting phase of the cardiac cycle) (Klabunde, 2005). PAT is the difference between the maximum and minimum pressures measured. PAT has been successfully validated by showing high correlations with cortical arousal (Penzel, Fricke, Jerrentrup, Peter, & Vogelmeier, 2002).

Affective responses in humans are accompanied by increased sympathetic activation, indexed by vasoconstriction, i.e., a decreased PAT signal. Thus, autonomic arousal, as indexed by PAT, can be used to examine the way in which recognition information is being treated and integrated during the decision process.

In particular, if recognition represents a natural affective signal, then we should expect an increase in arousal in response to recognized stimuli relative to unrecognized information. Regardless of whether recognition acts as an affective signal, according to the noncompensatory perspective, when recognition differentiates between two alternatives, no changes in arousal should be expected with the presentation of additional information, whether this

Table 1: Competing predictions of the RH and PCS models for each of the measures used in the current study.

Measure	RH predictions	PCS predictions
Choice proportion	Choice proportion aligned with the recognized option will be high, and will not be affected by additional information, whether this information is congruent or incongruent with recognition information.	Choice proportions following recognition will be highest for additional congruent information, and lowest for incongruent information. Intermediate choice proportions are expected when only recognition information is available.
Response time	Response time will be fast if recognition information clearly favors one choice over another, and should not be affected by additional information, whether congruent or incongruent with recognition information.	Response time will be shortest for additional information congruent with recognition information and longest for incongruent information. Intermediate response time is expected when only recognition information is available.
Confidence level	Confidence level will be high if recognition information is available, and should not be affected by additional information, whether congruent or incongruent with recognition information.	Confidence level will be highest for additional information congruent with recognition information and lowest for incongruent information. Intermediate confidence level is expected when only recognition information is available.
Physiological arousal	Recognized city names will be associated with increased physiological arousal relative to unrecognized city names.* In addition, physiological arousal will not be affected by additional information, whether congruent or incongruent with recognition information.	Physiological arousal will be lower for congruent information relative to incongruent information, reflecting increased sensitivity to low consistency versus high consistency.

* Note that this prediction is not directly derived from the original RH-specification of Goldstein and Gigerenzer (1999; 2002). Rather, it represents a proposition put forward in the current study to examine whether recognition information creates an affective signal favoring one option that dominates all other information.

information is congruent or incongruent with the recognition information.

By contrast, if recognition takes no precedence over other cognitive cues, and is integrated with other information, then autonomic arousal should not depend on recognition alone. According to the PCS model, physiological arousal should be dependent on the consistency (vs. conflict) among all available cue information (Glöckner & Hochman, in press). Hence, it should be highest in low consistency situations (i.e., when recognition information and the additional cue are incongruent), and lowest in high consistency situations (i.e., when both types of information are congruent). The current study is the first to investigate the relation between recognition information and physiological arousal in probabilistic inference tasks, and this is the main contribution of this work.

Predictions concerning all dependent variables are summarized in Table 1.

2 Method

2.1 Participants

Twenty-four undergraduates (10 females; mean age = 24.0 years, SD = 2.1) from the Technion — Israel Institute of Technology served as paid participants in the experiment. They received a flat fee of 80 NIS (approx. $21) and had a chance to get an extra bonus of 50 NIS (approx. $13) depending on their performance.

Table 2: Cities used in the experiment.

Recognized cities	Unrecognized cities
Sacramento	Raleigh
Honolulu	Plano
Buffalo	Greensboro
New Orleans	Baton Rouge
Orlando	Amarillo
Salt Lake City	Topeka
Hollywood	Lansing
Ann Arbor	Harrisburg
Cambridge	Jefferson City
Annapolis	Juneau

2.2 Materials

A pilot study was conducted to create appropriate materials. In the pilot study, we assessed the recognition rate of 48 US cities by Israeli participants (N = 20). The 10 most recognized cities (> 75%) and the 10 least recognized cities (< 15%) were chosen (see Table 2). A complete pair-wise combination of city names resulted in a sample of 190 pairs that were used in the experiment. One hundred trials were used as the *critical trials*, in which we expected that participants would recognize one city, but not the other (although the analysis took into account actual recognition rates for each participant). The other 90 trials were used as filler trials that were designed to mask the purpose of the experiment (i.e., trials in which recognition does not differentiate between options). Because we were interested in the influence of the recognition cue alone, we selected cities so that two additional cues that might be potentially used were balanced. That is, in the recognized and unrecognized sample the number of state capital cities and the number of cities with universities were equal. In addition, all cities had medium to small population (ranging from 30,000 to 460,000), in order to avoid ceiling effects of familiarity.

2.3 PAT data acquisition

PAT data were obtained using the SitePAT-200 (Itamar Medical Ltd., Keisaria, Israel), a photo-cell sensor plethysmograph, shaped as a finger cup, which is placed at the end of the first finger of the non-dominant hand (see Karasik et al., 2002). The participant's non-dominant hand was fixed on a hand rest during the whole session. The rate of data acquisition was 100 Hz, averaged to 1 sample per second. Autonomic activity associated with arterial constriction (which indicates arousal) leads to lower values on the PAT measure (expressed by volts).

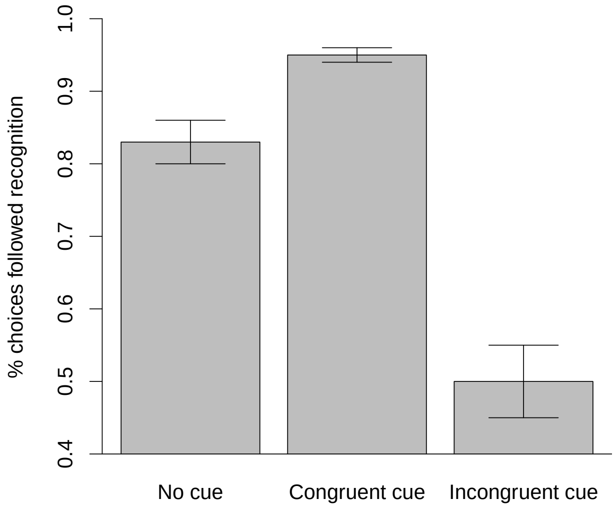
2.4 Design and procedure

Participants were presented with the 190 pairs of cities, and were asked to choose the city with the larger population in each pair. No feedback was provided after choice. A confidence measure appeared right after each selection, and participants were required to state how certain they were about their choice (on a scale from 50% to 100%, in 10% intervals). Reaction time was measured by a computer program, starting from the onset of each pair of cities until the choice response.

In addition, in 91 of the trials (50 in the critical trials in which recognition differentiated), a cue in the form of a +/- sign was presented. This sign constituted the main within-participants manipulation. On average, in half of the critical trials (i.e., the *congruent* cue trials) the cue led to choosing the recognized city (i.e., a plus sign pointing towards the recognized city or minus sign pointing toward the unrecognized city) and hence was congruent with the recognition cue. In the other half of the trials (i.e., the *incongruent* cue trials) the cue pointed towards selecting the unrecognized city. Hence, the additional cue was presented for recognized and unrecognized cities. Participants were informed that this cue represented the prediction of a geography student, who makes a correct prediction about the city with the larger population in 6 out of 10 cases. This reported validity was obtained in the experimental manipulation; namely the additional cue was correct in 60% of the trials. To ensure that participants realized that the cue signified low validity, they were further informed that a validity of 50% in this task (i.e., 5 out of 10 correct) is equivalent to chance level. Half of the cues presented a minus sign, and the other half presented a plus sign. Similarly, half of the minus signs were adjacent to the recognized city and the other half was associated with the other city, and the same was true for the plus signs. Each participant saw all trials, each in a different random order. To motivate good performance, a bonus of 50 NIS was offered to those whose success rate was higher than 75% (across all trials).

Importantly, the 20 cities were presented separately in a different test, and for each city participants were required to state whether they recognize it or not. Half of the participants were given this recognition test prior to the city-size task, and the other half received it after completion of the city-size task. Since order turned out to have no effect, the data were collapsed across these experimental conditions. The inter-trial interval was set to 7 seconds in both phases, so as to minimize residual effects of prior physiological responses.

Figure 1: Mean choice proportions as a function of the type of information available besides recognition.



3 Results

3.1 Recognition and cue validity estimates

On average, participants recognized approximately 9 cities (SD = 1.5; range 5–12). A one-way analysis of variance (ANOVA) revealed that the order of this task (i.e., before or after the experimental task) had no effect on recognition ranks [F (1, 23) = 0.259, p = 0.616]. This result suggests that participants were able to differentiate their experience-based recognition from mere familiarity with the city names that was induced by repeated exposure to the city names in the experiment.

The validity of the recognition cue across all critical trials in which only one city was recognized was 77% (SD = 12.6%), and significantly above chance level [t(23) = 10.724, p < 0.0001 in a one-sample t-test]. This analysis confirms the ecological rationality of using the RH in the current study, establishing the task as a fair test for examining the processes underlying the processing of recognition information. Importantly, the validity of the recognition cue was far above the 60% validity of the additional cognitive cue that was provided in some of the trials (i.e., information from the geography student).

Next, we examined whether the use of recognition information affected choice behavior. To do so, we calculated the proportion of choices that followed the recognition cue, and compared it to chance level. A one-sampled t-test showed that choices were sensitive to the recognition cue in the majority of cases in which only recognition information was available [average = 83.3%; SD = 13%; t(23) = 12.889, p < 0.0001]. In addition, we examined whether response times and confidence level were affected by recognition information. Although the RH makes no specific predictions about cases in which both cities are recognized or unrecognized,[3] RT and confidence level should still systematically differ to cases in which inspecting recognition information alone instantly leads to a decision. More specifically, when other information than recognition has to be considered, we generally expect a slower reaction time and a lower level of confidence. Indeed, these predictions were supported by the findings. When recognition was not diagnostic (i.e., both cities are known) or not available (i.e., both cities are unknown), average response time across participants was 9.03 seconds (SD = 0.93). Response times dropped to 8.48 seconds (SD = 0.88) when recognition information differentiated between options. A within-subject repeated measures ANOVA revealed that this difference was significant [F (1, 23) = 15.781, p = 0.001]. A similar pattern of results was found for confidence ratings. Namely, when recognition was not diagnostic or unavailable, the average confidence level was 60.42% (SD = 6.4). Confidence level increased to 66.3% (SD = 9.4) when recognition information differentiated between options. A within-subject repeated measures ANOVA revealed that this difference was significant [F (1, 23) = 19.178, p < 0.0001].

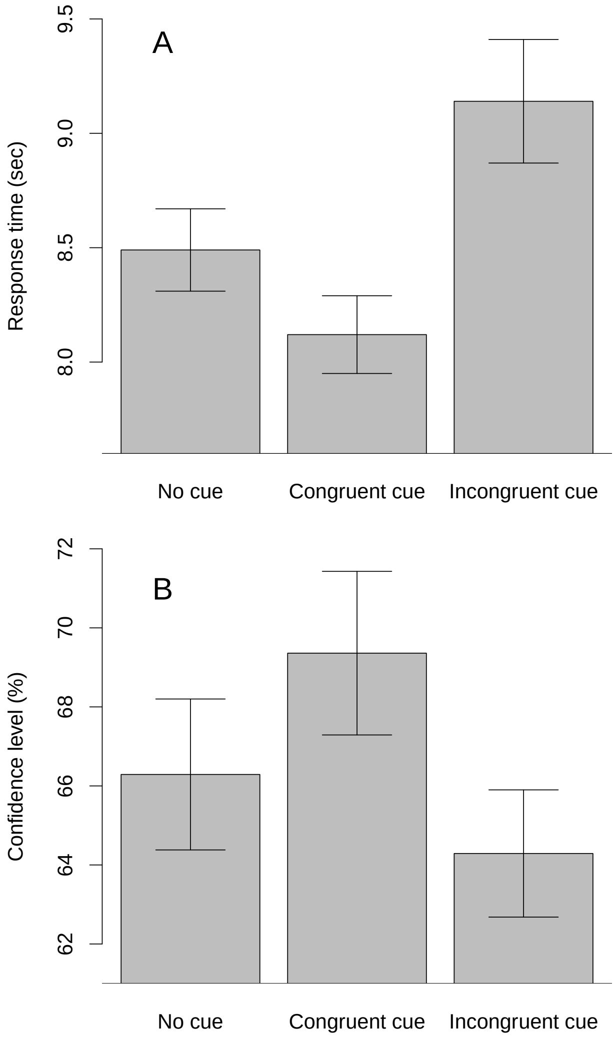
Taken together, these results support the first part of the RH hypotheses according to which diagnostic recognition information leads to high choice proportions that fit the recognition cue, short RT, and a high confidence level (see Table 1). The results also support the validity of our measures in this task.

3.2 Choice proportion analysis

The results of the choice proportion analysis are presented in Figure 1. As mentioned above, participants' choices followed recognition in, on average, 83.3% of the cases in which no information other than recognition was presented. This proportion increased to 95.1% (SD = 6.8%) when a cue congruent with the recognition information was introduced and decreased to 50.1% (SD = 26%) when an incongruent cue was presented. A within-subject repeated measures ANOVA was conducted to test the effect of cue type (i.e., no cue, congruent cue, and incongruent cue) as the independent variable on choices which followed recognition as the dependent variable. This analysis revealed a significant main effect of cue type [(F (2, 69) = 59.26, p < 0.0001). Post-hoc paired-sample analyses demonstrated that the no-cue choices differed significantly from both the congruent and the incongruent cue choices [t(23) = -4.919, p < 0.0001, and t(23) = 7.265, p < 0.0001, respectively].

[3] Since no difference was found between the RTs for either recognized or none-recognized city pairs, these results were collapsed.

Figure 2: A - Mean response time as a function of the type of information available besides recognition. B - Mean confidence level as a function of the type of information available besides recognition. Error bars represent standard errors.



These results replicate previous findings (e.g., Bröder & Eichler, 2006; Oppenheimer, 2003; Richter & Späth, 2006) and support the qualitative predictions concerning changes in choice proportion derived from the PCS model. The results conflict with predictions derived from the RH. Specifically, the results suggest that recognition information is integrated with additional information in a compensatory manner. The claim that recognition information is used as the only information in a noncompensatory manner has to be rejected. Moreover, this pattern of results does not even support a weaker interpretation of the RH (Brandstätter, Gigerenzer, & Hertwig, 2008), which assumes that, while decision makers evaluate all the available information, the final choice is based on only one piece of information in a noncompensatory manner. Instead, the results suggest that participants are sensitive to all information, and base their decisions on its integration.

Partially in contrast to previous findings (e.g., Goldstein & Gigerenzer, 2002; Pachur et al., 2008), it seems that recognition information was completely overridden by other information, even when the additional cue was of low validity and was obtained from a relatively unknown source. In fact, when a cue — with a validity as low as .60 — that was incongruent with recognition was presented, it eliminated the effect of the recognition cue, so that the proportion of choices following recognition dropped to chance level. Thus, in line with most prior research, the current results suggest that recognition information is only one of several cues that are integrated in a compensatory manner. More importantly, our findings suggest that real experience-based recognition information is not significantly stronger than even a low validity cognitive cue.

Finally, as suggested by previous research (e.g., Pachur et al., 2008), individual differences might exists in people's use of recognition information and additional cues. To examine this alternative speculation we calculated, for each individual, the correlation coefficient between proportions of choices that followed recognition and condition (i.e., congruent cue, no cue, and incongruent cue). The median correlation coefficient between choice and condition across participants was –0.95 ($t(23) = -16.406$, $p < 0.05$). Similarly, for 95.6% of the participants the correlation turned out to be highly significant ($p < 0.05$). This pattern of individual results supports the aggregated results and suggests that choice proportions were highest when a congruent cue was presented and lowest when an incongruent cue was presented even at the individual level. Thereby, individual differences cannot easily serve as alternative explanation for our results, as there seems to be only small individual differences in the use of recognition information and additional cues.

3.3 Response time analysis

The analysis of response times is presented in Figure 2A. Overall, the mean response time for cases in which only one city was recognized was 8.48 seconds (SD = 0.88) when no other information was presented. Response time decreased to 8.11 seconds (SD = 0.84) when a congruent cue was introduced and increased to 9.14 seconds (SD = 1.32) when an incongruent cue was presented. A within-subject repeated measures ANOVA was conducted to test the effect of cue type (i.e., no cue, congruent cue, and incongruent cue) on response time as the dependent variable. This analysis revealed a significant main effect of cue type [($F(2, 69) = 17.472$, $p <$

0.0001). Post-hoc paired-sample analyses demonstrated that response times without any cue differed significantly from response times following both the congruent and the incongruent cue [$t(23) = 2.692$, $p = 0.01$, and $t(23) = -3.136$, $p = 0.005$, respectively].

Thus, similar to the choice proportion results, decision time results support the predictions of the PCS model, replicating findings by Hilbig and Pohl (2009). In line with the predictions of the PCS model, our findings demonstrate that when cue predictions are incongruent (i.e., when recognition information points at one choice and the cue points at the opposite choice), response time is increased. Furthermore, we found support for the PCS hypothesis that decision times are decreased if the additional cognitive cue points in the same direction as the recognition cue. This finding is important in showing that more information (i.e., the recognition cue + the cognitive cue) is processed faster than less information (i.e., recognition cue alone). These effects speak against serial models of information integration (e.g., Payne, Bettman, & Johnson, 1988; see also Glöckner & Betsch, 2010).

Moreover, if recognition information were considered in a noncompensatory manner, when no additional cue was presented, response times should have been equal to the other two conditions (either congruent or incongruent cues) or even shorter. Shorter response times for recognition alone could support a weaker interpretation of the noncompensatory viewpoint, in which all available information is scanned but the final decision is based on the best cue alone. In such cases, decision makers would have less information to evaluate and could thus be faster. However, the results provide no support for this weak interpretation of the noncompensatory models. Rather, the pattern of results are in line with PCS models, suggesting that more processing time is required in cases in which it is harder to find a consistent mental representation due to high conflict (i.e., low consistency) between pieces of information.

Finally, as for choice proportions, we calculated, at the individual level, the correlation coefficient between response time and condition. The median correlation coefficient between response times and condition was 0.93 ($t(23) = 9.235$, $p < 0.05$), suggesting that at the individual level response times were highest for incongruent trials and shortest for congruent trials. Similarly, for 86% of the participants, this correlation was highly significant ($p < 0.05$). Thus, as in choice proportions, this result excludes an individual differences account of our data.

3.4 Confidence level analysis

The results of the confidence level analysis are presented in Figure 2B. Overall, the mean confidence level for cases in which only one city was recognized was 66.3% (SD = 9.4%) when no other information was presented. Confidence level increased to 69.4% (SD = 10.1%) when a congruent cue was introduced and decreased to 64.3% (SD = 7.9%) when an incongruent cue was presented. A within-subject repeated measures ANOVA was conducted to test the effect of cue type (i.e., no cue, congruent cue, and incongruent cue) on confidence level as the dependent variable. This analysis revealed a significant main effect of cue type [($F(2, 69) = 25.361$, $p < 0.0001$). Post-hoc paired-sample analyses demonstrated that the confidence level in the no-cue choices differed significantly from the confidence level of both the congruent and the incongruent cue conditions [$t(23) = -4.791$, $p < 0.0001$, and $t(23) = 2.73$, $p = 0.01$, respectively].

Again, the results support the predictions of the PCS model but not the predictions derived from the RH. In particular, our findings suggest that available information is integrated and that it affects confidence level. The analysis of confidence level shows that rather than relying solely on recognition information, decision makers consider recognition to be just one of other cues that are integrated by a compensatory process on the way to reaching a decision.

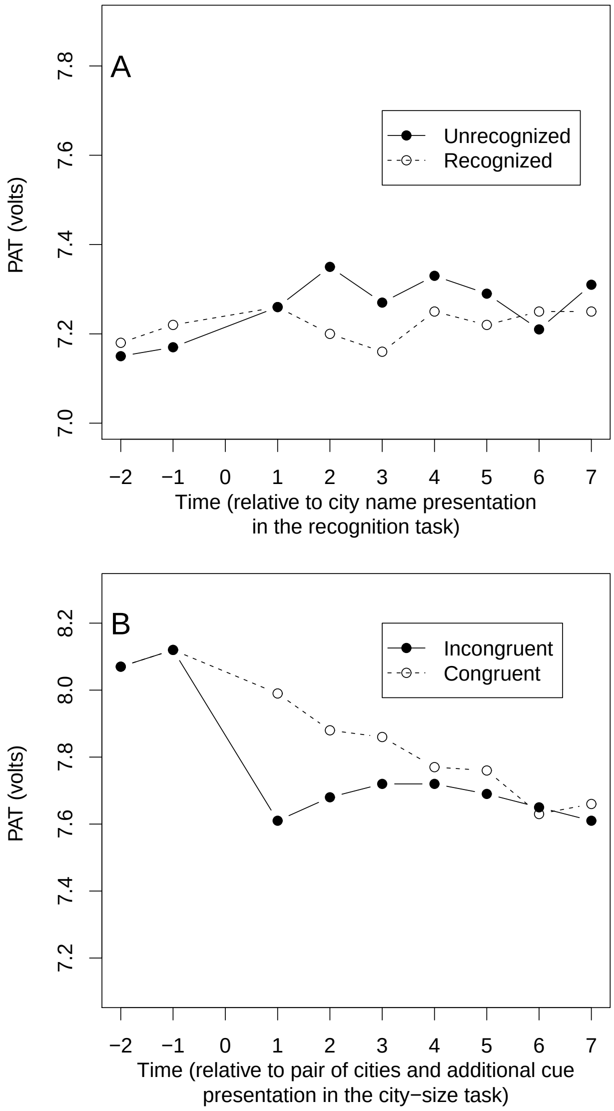
At the individual level, the median correlation coefficient between condition and confidence level across participants was –0.89 ($t(23) = -13.599$, $p < 0.0001$), suggesting that confidence level was highest for congruent trials and lowest for incongruent trials. Similarly, for 92% of the participants this correlation turned out to be highly significant ($p < 0.0001$). Thus, this result adds up to the choice proportions and response times findings, and further support the claim that the current results do not stem from individual differences in the use of recognition information.

3.5 Physiological arousal

3.5.1 Emotional response to recognized stimuli

To evaluate whether recognition information creates an affective signal, we compared physiological reaction, measured for the task in which participants rated whether they recognized the city or not (for single cities). Hence, we measured physiological reaction in response to recognized city names versus unrecognized city names. Note that low PAT measures indicate high arousal. As can be seen in Figure 3A, there was a slight tendency that recognized cities led to higher arousal, particularly 2 to 4 seconds after stimulus onset. However, this tendency was not statistically significant. From 2 seconds prior to city name presentation to 7 seconds after presentation, there was no significant difference between PAT responses to the different types of stimuli. Namely, the average alpha across all within-subject (recognized versus unrecog-

Figure 3: A — Average PAT scores in response to recognized versus unrecognized city names. B — Average PAT scores as a function of information type. Low PAT scores indicate high arousal.



nized) repeated measures ANOVA was 0.51 (SD = 0.25, range 0.18–0.99).[4] We cannot, however, rule out the possibility that the results might be partially due to the relatively small size of our sample. Still, a post-hoc power analysis (for 10 cities within each group, with an assumed correlation of r = 0.3 between observations and assuming a small effect of f = 0.25) indicated an excellent power of 0.91 in this analysis, making it unlikely (i.e., beta-error = 0.09) that an existing effect was merely not detected (Faul, Erdfelder, Lang, & Buchner, 2007).

Although null hypothesis results should be interpreted cautiously, our findings imply that in the current task recognition information does not seem to create an affective signal favoring the recognized city, or it may create a very weak signal which is hard to detect. This conclusion should be further validated in future research.

3.5.2 Physiological response to additional information

To examine physiological response to additional cue information, we compared PAT scores in response to congruent versus incongruent trials.[5] As mentioned above, PAT scores represent vasoconstriction, and low scores therefore indicate increased arousal. As can be seen from Figure 3B, arousal was higher in incongruent trials than in congruent trials (i.e., lower PAT scores). A within-subject repeated measures ANOVA revealed that this difference was significant at one second after the presentation of information [$F(1, 23) = 4.09$, $p = 0.05$].

Thus, in line with the PCS model prediction, arousal increased (i.e., lower PAT scores were obtained) with decreasing consistency between the available information. The arousal data further suggest that additional information is integrated rather than neglected, as would have been predicted by the RH. Specifically, the increased arousal in response to conflicting information (i.e., low consistency), but not in response to recognition information alone, suggests that information is integrated in a compensatory manner and that recognition cues are used as one of several (cognitive) cues.

4 Discussion

The current study aimed to examine the nature of recognition information in human inference tasks, as well as the integration of such information with additional cognitive cues. In particular, we examined two main research questions. First, we tested inferences regarding

[4]The results of the repeated measure ANOVA for the difference between the PAT score for recognized vs. unrecognized cities 2 to 5 seconds after stimulus presentations were $F_{2sec}(1, 23) = 1.941$, $p = 0.18$; $F_{3sec}(1, 23) = 0.933$, $p = 0.34$; $F_{4sec}(1, 23) = 0.727$, $p = 0.40$; and $F_{5sec}(1, 23) = 0.741$, $p = 0.40$. (We did not calculate the test at 1 sec because there was no difference, see Figure 3A).

[5]The PAT score is highly sensitive to cognitive load (Iani, Gopher, Grunwald, & Lavie, 2007; Iani, Gopher, & Lavie, 2004), which is assumed to increase as the task progresses. To control for this effect, we matched for each participant the number of trials in each condition (congruent and incongruent), so that each condition had the same number of trials as the condition with the minimal number of trials (Mean = 17 trials). It should be noted, however, that when we regressed out the time trend (i.e., total trials) from the PAT scores and used regression analysis to predict the PAT score from the type of cue (congruent versus incongruent) we found similar pattern of results, although the effect of cue type was only marginally significant (i.e., the p-value of the model was 0.055; one-tailed test).

population size of pairs of cities, juxtaposing choice proportion, response time, confidence level, and physiological arousal predictions derived from the RH (Goldstein & Gigerenzer, 1999, 2002) and the PCS model (Glöckner & Betsch, 2008b). The RH suggests that, whenever applicable, recognition is used in a noncompensatory manner to govern the decision process, thus dispensing with the idea of compensation by integration. As a result, the RH predicts that none of the measures will be affected by additional information. By contrast, the PCS model postulates that all available pieces of information are taken into account in a compensatory manner. Thus, this model predicts that choice proportions, as well as other measures, will be highly dependent on the consistency of information.

The pattern of results found in all measures supported the PCS model but not the RH predictions. That is, contrary to the RH predictions, we found inferences to be highly sensitive to information other than recognition. These findings suggest that additional information is integrated during the inference process, rather than being neglected. Moreover, in line with the predictions of the PCS model, we found that the proportion of choices of the recognized city increased when congruent information was presented, and decreased when incongruent information was presented. This pattern of results was replicated for response time (shorter in congruent cases), confidence level (higher in congruent cases) and physiological arousal (lower in congruent cases) both at the aggregated and the individual level. It is important to note that the physiological arousal data, used for the first time in this context, support the PCS model view that arousal results from an information-integration processes which operates towards constructing consistency taking into account all available pieces of information. Thus, these data further validate the hypothesis that the construction of consistency is an important factor in human decision behavior (see similar assertions in Ayal & Hochman, 2009; Glöckner & Betsch, 2008b; Russo et al., 2008).

Second, the measure of physiological arousal enables us to test whether recognition information is evaluated at the emotional or the cognitive level. Relying on affect-based models (Damasio, 1994; Slovic et al., 2002), we tested whether recognition information creates an affective signal that leads a person to favor the recognized alternative over other cognitive information, thus explaining the strong influence of recognition cues on choice behavior. However, the results did not support this assumption. Although there was a trend in the predicted direction, no significantly increased physiological arousal in response to recognized versus unrecognized city names (representing an emotional response to environmental stimuli; e.g., Andreassi, 2000; Cacioppo et al., 2007) was observed. It appears, then, that recognition information might be only one of several (maybe cognitive) cues which are integrated by decision makers during the decision process. The fact that the co-occurrence of the recognition cue and the incongruent cue increased arousal suggests that affective signals reflect cue integration rather than attention to recognition alone which is in line with recent findings on decisions from experience (Glöckner & Hochman, in press).

More generally, the current findings add to recent evidence which indicates that the cognitive processes underlying choice behavior are compensatory in nature (Ayal & Hochman, 2009; Glöckner & Betsch, 2008a; see also Bröder, 2003).[6] Moreover, our findings were inconsistent even with modified interpretations of noncompensatory models (e.g., Brandstätter, Gigerenzer, & Hertwig, 2008), which assume that available information is first scanned, and only then are choices made in a noncompensatory manner, on the basis of the best available cue. Hence, response times were not shortest and confidence levels were not highest when recognition was the only available information, but rather when more (congruent) information was available. Thus, a fast and frugal RH model, which assumes that only one piece of information governs choices, cannot account for the current findings. By contrast, these results can be explained by the PCS model, which assumes that the available information is integrated in automatic consistency-maximizing processes which accentuate the best interpretation of the available evidence (e.g., Glöckner & Betsch, 2008b; Holyoak & Simon, 1999; Holyoak & Spellman, 1993; Thagard & Millgram, 1995). The results add to the findings by Glöckner and Bröder (in press), which showed that PCS accounts better for most people's decisions, when these are based on recognition and additional provided information, than noncompensatory models such as RH. It should be noted that a recent study by Marewski et al. (2010) indicates that, when no additional information is provided, RH predicts choices better than other heuristics. However, this study did not include PCS (or similar complex weighted compensatory models). Thus, future research should examine RH vs. PCS in these latter situations.

In sum, the importance of recognition information, as well as the merits of the RH in inspiring interesting debates about decision-making processes, is unquestionable (e.g., Bröder & Newell, 2008; Newell, 2005). Nevertheless, according to our results and the majority of previous findings (e.g., Bröder & Eichler, 2006; Hilbig & Pohl, 2008; McCloy, & Beaman, 2004; Newell & Fernandez,

[6]Of course, this does not preclude that these processes sometimes mimic noncompensatory choices, as it has been repeatedly demonstrated (e.g., Payne et al., 1988). This can be explained in that different thresholds of accumulated evidence give rise to patterns of data that mimic the stopping rules of noncompensatory heuristics (Newell, 2005) or by the usage of noncompensatory cue weighting schemes in integration processes that are conceptually compensatory.

2006; Oppenheimer, 2003; Pachur et al., 2008; Richter & Späth, 2006), this simple heuristic fails to capture the underlying processes of human probabilistic inferences, including the reliance on recognition information.[7]

In line with previous findings (Ayal & Hochman, 2009; Glöckner & Betsch, 2008a), it seems that the predictive power of the noncompensatory models is highly dependent on whether their predictions align with compensatory processes. In situations in which all models make the same prediction (i.e., when recognition and additional congruent information is available) almost all participants prefer the recognized city (i.e., 90% of choices). On the other hand, when incongruent information was available, and the predictions of the RH and PCS were different, the predictive power of the RH decreased to chance level (i.e., 50% of the choices were of the recognized city in the incongruent condition). This adds further support to the argument that high adherence rates (i.e., choices in line with RH) are a necessary but not a sufficient condition to draw sound conclusions concerning strategy use (Hilbig, in press).

The latter finding also implies that natural recognition is considered a cue with moderate validity. Taken together with our physiological data, this indicates that recognition might not have a special status but that it is simply used as another (cognitive) cue. When only recognition information is available, the proportion of choices that followed this cue was substantially higher than the proportion of choices preferring the unrecognized city. However, even contrary cognitive information of low validity (i.e., 0.6) made people indifferent in their choice in that they choose the recognized city in 50% of the cases. It should be noted, however, that, since we used experimentally induced cues, a demand effect (i.e., an increased attention to a cue provided by the experimenter; Pachur et al., 2008) could not be completely ruled out. Nevertheless, the fact that when incongruent information was presented the effects of recognition information on the one hand and the additional cognitive cue on the other hand cancelled each other out (i.e., choice proportion was 0.5) suggests that recognition was taken into account and that the additional cue was not automatically considered to be more valid than the recognition information. Still, further research is needed to investigate the factors influencing the perceived validity of recognition cues in comparison to other cues.

Finally, similar to inferences, research on human preferences has shown that decision makers tend to rely on recognition cues and to prefer what is familiar (e.g., Alba & Hutchinson, 1987; Ballantyne, Warren, & Nobbs, 2006; Macdonald & Sharp, 2000; Sujan & Bettman, 1989; Wood & Lynch, 2002). At the same time, however, decision-makers frequently seek to take the road less traveled (Ariely & Levav, 2000; Ratner, Kahn, & Kahneman, 1999) and tend to diversify their uncertainty pleasures (Ayal & Zakay, 2009; Bawa, 1990; McAlister, 1982) and try innovative products (Cotte & Wood, 2004; Manning, Bearden, & Madden, 1995; Hirschman, 1980; Raju, 1980). In part, this could explain, for instance, how novel brands penetrate the market (Hirschman & Wallendorf, 1982). Our results accord with these tendencies, and suggest that they are not unique to preferences. Specifically, when making inferences, decision makers tend to adhere to recognition and familiarity. However, it seems that alongside this tendency, they are also susceptible to additional information about the alternatives. When additional information supports the recognized alternative it is supposed to increase recognition adherence. However, when the additional information contradicts recognition, it reduces this adherence, and under certain conditions it may even encourage the execution of other heuristics, such as innovation, variety seeking, and diversification (e.g., Chintagunta, 1998; McAlister, 1982; Read & Loewenstein, 1995; Schweizer, 2006). One possible explanation for this tendency could be that traditionally, recognition information was highly ecological, as it reduced the level of uncertainty. However, in our modern life, when many choices aim to maximize utility and pleasures rather than to maximize survival in a threatening environment (see Menon & Kahn, 1995), other cognitive considerations might override recognition to allow us to experience the unknown. From an ecological point of view, this might explain why even in environments in which recognition is highly correlated with the criterion, individuals sometimes tend to give it relatively little weight when integrating it with other cognitive information.

[7]Note that Goldstein and Gigerenzer (2002), as well as other proponents of RH, argue that the consistent findings of relatively high adherence rates with RH (i.e., choices in line with the prediction of the model) support their assumptions concerning the underlying processes. However, this claim was challenged by Hilbig (in press), who showed that adherence rates are necessary but not sufficient conditions for proving a strategy use.

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