Research Article

Parallel Constraint Satisfaction in Memory-Based Decisions

Andreas Glöckner[1] and Sara D. Hodges[2]

[1]Max Planck Institute for Research on Collective Goods, Bonn, Germany, [2]University of Oregon, Eugene, OR, USA

Abstract. Three studies sought to investigate decision strategies in memory-based decisions and to test the predictions of the parallel constraint satisfaction (PCS) model for decision making (Glöckner & Betsch, 2008). Time pressure was manipulated and the model was compared against simple heuristics (take the best and equal weight) and a weighted additive strategy. From PCS we predicted that fast intuitive decision making is based on compensatory information integration and that decision time increases and confidence decreases with increasing inconsistency in the decision task. In line with these predictions we observed a predominant usage of compensatory strategies under all time-pressure conditions and even with decision times as short as 1.7 s. For a substantial number of participants, choices and decision times were best explained by PCS, but there was also evidence for use of simple heuristics. The time-pressure manipulation did not significantly affect decision strategies. Overall, the results highlight intuitive, automatic processes in decision making and support the idea that human information-processing capabilities are less severely bounded than often assumed.

Keywords: memory-based decision making, parallel constraint satisfaction, fast and frugal heuristics, automatic information integration, intuition

Decision making entails integrating probabilistic information. Empirical evidence indicates that individuals employ multiple different strategies to accomplish this (Payne, Bettman, & Johnson, 1988). Some of these strategies are more effortful such as the weighted additive rule (WADD) of utility theory. Others, such as the lexicographic rule (LEX, Fishburn, 1974), elimination-by-aspects (Tversky, 1972), or the equal weight rule (EQW, Fishburn, 1974), involve considerably fewer computational steps. Considering deliberate processes only, it is reasonable to assume that the mental effort for a decision strategy can be approximated by the number of computational steps to apply the strategy (Payne, et al., 1988). Therefore, the application of a WADD strategy should be much more effortful and time consuming than the application of, for instance, a LEX or an EQW heuristic and it has been shown that people are aware of this fact (Chu & Spires, 2003).

Interestingly, recent studies in neuroscience indicate that "rational" principles like weighted sums might be naturally computed by certain brain regions (e.g., Glimcher, Dorris, & Bayer, 2005; Platt & Glimcher, 1999). In a similar vein, findings in probabilistic inference decisions (Glöckner & Betsch, 2008c) and preference decisions under risk (Glöckner & Betsch, 2008a) indicate that individuals are able to apply WADD strategies very quickly. Decision times are far below the times that would be necessary for a sequence of deliberate calculations. These findings indicate that individuals might apply intuitive-automatic decision strategies that partially rely on automatic processes (e.g., Kahneman & Frederick, 2002) and approximate weighted additive information integration without a deliberate calculation of weighted sums (Hammond, Hamm, Grassia, & Pearson, 1987). Glöckner and Betsch (2008b) have argued that the underlying cognitive processes can be modeled using parallel constraint satisfaction (PCS) networks (Holyoak & Simon, 1999; McClelland & Rumelhart, 1981).

In the current paper, we investigate specific predictions of the PCS model (Glöckner & Betsch, 2008b) in memory-based probabilistic inference decisions concerning choices, decision times, and confidence ratings. First, studies of memory-based decisions are reviewed and critically evaluated. Then, the PCS model is briefly introduced and hypotheses are derived. Three studies are reported in which we test these hypotheses against hypotheses derived from the take-the-best (TTB) heuristic (Gigerenzer & Goldstein, 1996), the EQW heuristic, and a WADD strategy. This is the first study to investigate how well the automatic-intuitive PCS model can account for choices, decision times, and confidence in memory-based probabilistic inferences compared to classic heuristics. We also investigate the influence of time pressure on strategy selection in memory-based decisions. Small effects of increased time pressure would add further support for the automatic-processing assumption underlying PCS. As a third issue, we aim to explore whether the previously found (and often cited) predominant application of TTB in memory-based decisions holds in the classic city-size task.

Research on Memory-Based Probabilistic Inference Decisions

Much research on probabilistic inference decisions has been conducted using the city-size task (Gigerenzer & Goldstein,

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1996). In this task individuals have to decide which of two cities has more inhabitants. Assuming they do not already know the exact number of inhabitants, people might use information about the cities that have a certain predictive power for estimating the size of the cities (*cues*). Individuals could try to remember, for instance, if one of the cities is a state capital, given that state capitals are on average larger than noncapitals.

To solve probabilistic inference tasks, individuals may have to consider probabilistic information from multiple cues. Research has focused mainly on cues with dichotomous cue values (i.e., yes/no). Individuals might take into account *cue validities*, that is, the estimated predictive power of the cues (sometimes defined as the conditional likelihood of a positive criterion value given a positive cue value; e.g., Gigerenzer & Goldstein, 1996). According to a TTB heuristic (a special case of LEX), individuals only retrieve information on the most valid cue and select the option that scores higher on this cue. The second cue is retrieved only if the first cue does not differentiate between options, and so on for the third cue, etc. The EQW heuristic assumes that people only add up positive and negative cue values of both options and choose the option with the higher sum. The deliberate WADD strategy assumes that individuals calculate the weighted sum of cue values and cue validities for each option and select the option with the higher weighted sum.

If the information about the city (*cue value*) is directly presented to the person, for instance on a computer screen, this would be considered an inference from the givens (Bröder & Schiffer, 2003b; Gigerenzer & Goldstein, 1996). In contrast, if cue values have to be retrieved from memory this is referred to as inferences from memory. In contrast to a large body of evidence on decisions from given information (e.g., Bergert & Nosofsky, 2007; Bröder, 2000, 2003; Bröder & Schiffer, 2003b; Glöckner & Betsch, 2008c; Newell, Weston, & Shanks, 2003), only a few studies have been conducted to investigate strategies of memory-based probabilistic inference decisions. In one of the first investigations of memory-based decisions, Bröder and Schiffer (2003b) developed a research paradigm in which participants learned information about target people. Participants used this information later on to decide which of these targets committed a certain crime. The experiments revealed that the majority of participants used simple heuristics, particularly TTB. A significant shift in decision strategies was observed between memory-based decisions and decisions from given information. In memory-based decisions a higher proportion of TTB users and a lower proportion of WADD users were observed. Furthermore, the representation format of the cues had an influence on decision strategies. In the "learning phase," attributes of the target people (e.g., type of jacket and shirt color) were presented either verbally or in the form of a picture of the person which showed the various attributes. The latter was meant to induce an image-based representation format and led to a higher percentage of WADD users, something that Bröder and Schiffer explained by incorporating automatic processes as suggested in image theory (Beach & Mitchell, 1996) which might result in weighted compensatory information integration.

Bröder and Gaissmaier (2007) further investigated decision strategies in memory-based decisions by conducting a reanalysis of five earlier studies (Bröder & Schiffer, 2003b, 2006), plus one new experiment, all of which used essentially the same procedure as the studies reported above. The reanalysis revealed that the majority of participants used simple heuristics instead of more effortful weighted compensatory strategies (198 TTB users, 83 EQW users, 90 WADD users, and 44 participants who appeared to guess randomly). Furthermore, decision times indicated that for TTB users, decision times increased with the number of cues needed to differentiate between the options when using this strategy. This provided converging evidence for the strategy classification. It was further interpreted as support for the general claim that information is serially processed and that the number of necessary calculations determines decision time (cf. Payne et al., 1988).

For several reasons we suspect that these results might not generalize to other settings. The criminal case materials used in these studies incorporated several specific features that might crucially influence the results. First, the cues used were not intended to have any natural predictive power (cue validity) for the decision criterion (guilty vs. not guilty) and they were conceptually not binary cues (a cue such as shirt color could have numerous possible values, whereas whether a city is a state capital or not is a yes/no question). Individuals were explicitly informed about cue validities, but only after they had learned the cue values. Individuals learned, for instance, that Anne wore a white shirt and were then later informed that four eyewitnesses had seen the perpetrator wearing a white shirt. Therefore, the decision task was rather demanding: Individuals first had to remember the cue validities and then had to retrieve the cue values they had learned earlier. In contrast, in other settings, like the city-size decisions, cues have a priori cue validities which are readily meaningful and they are often binary. This might facilitate the application of automatic processing. Hence there is evidence demonstrating the use of TTB as a common strategy in memory-based decisions, but perhaps only under specific circumstances in which retrieval is particularly effortful.

The PCS Model for Decision Making

In contrast to the previously mentioned deliberate strategies, PCS models assume that persons do not use stepwise calculations in reaching a decision. Instead, automatic processes akin to perception are activated that operate toward identifying the preferred interpretation considering the overall constellation of information. This interpretation is highlighted and people construct best interpretations given the evidence. For instance, in legal or moral judgments people might construct the preferred solution to a highly complex task involuntarily and within

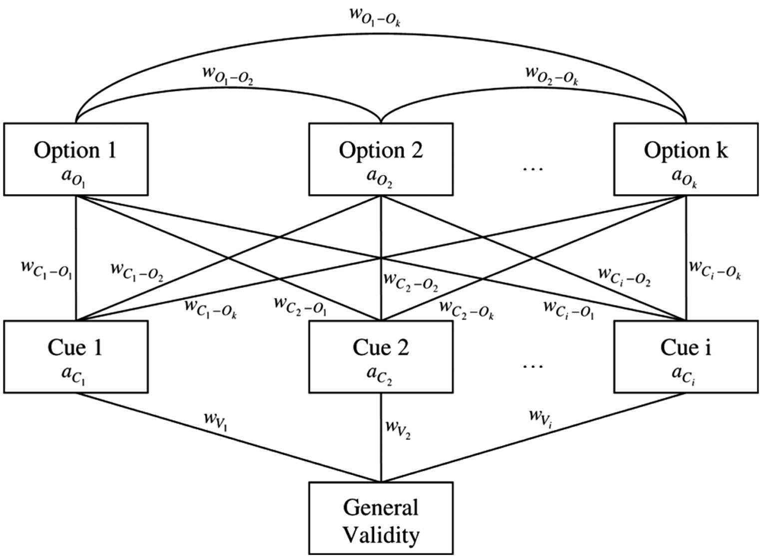

Figure 1. The picture shows the structure of a general PCS network model for probabilistic inferences as postulated by PCS. Boxes represent nodes, for which activation *a* is changed in the process of PCS. Lines represent links between nodes which can have different strength *w* and can be excitatory and inhibitory.

the blink of an eye. Glöckner and Betsch (2008b) have suggested to model the cognitive processes by PCS networks (for earlier PCS approaches to judgment and decision making, see Holyoak & Simon, 1999; Thagard, 1989). The suggested PCS model consists of three (or possibly four) steps: When individuals encounter a decision situation, they first activate associated and salient information in memory and form a mental representation that incorporates any given information, plus information stored in memory. In the second step, automatic processes of PCS take place that lead to the maximization of consistency in the representation. Consistency in this context means that pieces of information do not contradict each other. Consistency in a decision situation can mainly be reached by dominance structuring (cf. Montgomery, 1989), which occurs by modifying information so that one option clearly dominates the other(s). By spreading activation, inconsistency between pieces of information is reduced and a consistent (or balanced) mental representation is formed. In the third step, the decider consults the resulting mental representation in which one option usually clearly dominates chooses this option. If the consistency of the resulting mental representation is below a certain threshold, deliberate construction processes are activated, constituting a fourth step. Deliberate constructions are used to change the structure of the network. However, for pragmatic reasons, the simulation reported below only considers the first three steps.

In the following section, we present results from simulations of the model that were calculated to derive specific decision time and confidence predictions for the later reported empirical tests.

Simulations

The Model and the Updating Algorithm

For the simulation the network structure presented in Figure 1 and an iterative activation updating mechanism (PCS algorithm; McClelland & Rumelhart, 1981) were used (Glöckner & Betsch, 2008b). Boxes represent nodes with variable activations. Lines represent (fixed) links between nodes and are all bidirectional. Connection weights can range from -1 to +1 and are labeled *w.* Connections between options and cues represent cue information, indicating a positive or negative predictive weight of the cue for the respective option. Links between the general validity node and the cues represent a priori cue validities that might result from learning. The general validity node is used to activate the network but has no specific psychological meaning. Using the iterative updating algorithm, consistency (also referred to as coherence) is produced in the network by changing activations (*a*) of the nodes.[1]

The iterative updating algorithm uses a sigmoid activation function proposed by McClelland and Rumelhart (1981):

$$a_i(t+1) = a_i(t)(1 - decay) + \begin{cases} if \quad input_i(t) < 0 \quad input_i(t)(a_i(t) - floor) \\ if \quad input_i(t) \geq 0 \quad input_i(t)(ceiling - a_i(t)) \end{cases} \tag{1}$$

where $a_i(t)$ represents the activation of the node *i* at iteration *t*. The parameters *floor* and *ceiling* stand for the minimum and maximum possible activation (in our model set to -1 and +1, respectively). $Input_i(t)$ is the activation node

[1] Note that PCS networks take the network structure as given and simulate only the ad hoc interpretation given this evidence structure (Shultz & Lepper, 1996). Changes in the structure of the network (i.e., in the link weights) that might be caused by long-term learning are not part of model (cf. supervised or unsupervised learning models).

Table 1. Cue patterns used in the simulation and in Experiments 1–3

	Pattern 1		Pattern 2		Pattern 3		Pattern 4		Pattern 5		Pattern 6	
	A	B	A	B	A	B	A	B	A	B	A	B
Cue 1	+	–	+	–	–	–	+	–	+	–	+	–
Cue 2	–	+	–	–	+	–	–	+	–	+	+	–
Cue 3	–	–	–	+	–	+	–	+	+	–	–	+
	Decision time predictions PCS											
Cycles	212.1 (4.9)		166.5 (2.1)		215.0 (0.6)		286.2 (15.2)		186.3 (2.9)		135.0 (1.1)	
Estimate	0.5		−1.5		0.5		3.5		−0.5		−2.5	
	Confidence predictions PCS											
a_{o1}-a_{o2}	0.251 (.007)		0.361 (.004)		0.274 (.0003)		0.141 (.021)		0.324 (.005)		0.472 (.003)	

Note. A and B represents the two options. Cue 1 is the most valid cue, cue 2 is the second most valid cue, and cue 3 is the least valid cue. Decision time and confidence predictions for the cue patterns are shown in the lower part of the table. Cycles mean iterations in the PCS simulation. They were averaged over 525 simulations per cue pattern (i.e., 21 × 5 × 5). The *SD* for 21 average values for each level of initial validity of cue 1 is given in parentheses. Estimate is a rough transformation of cycles to a scale of contrast weights that add up to zero.

i receives at iteration *t*, which is computed by summing up all products of activations and connection weights w_{ij} for node *i* (Equation 2). *Decay* is a constant decay parameter.

$$input_i(t) = \sum_{j=1 \to n} w_{ij}\, a_j(t). \tag{2}$$

According to previous simulations we expected choices to approximate a weighted compensatory cue-integration, decision times should decrease and confidence should increase with increasing superiority of one option over the other (e.g., Glöckner, 2010; Glöckner & Herbold, in press). Finally, the posterior cue validity (i.e., activation of cue nodes in the resulting mental representation) should not be stable but should be indirectly influenced by other cues indicating information distortions (cf. DeKay, Patino-Echeverri, & Fischbeck, 2009; Russo, Carlson, Meloy, & Yong, 2008; Simon, Snow, & Read, 2004).

Method

In the simulation, the differences between initial cue validities were systematically manipulated. Separate simulations were run for the six cue patterns depicted in Table 1 (top). The cue patterns represent all possible cue patterns in decision tasks with two options and three cues in which each option has at least one positive cue and no cue has positive values for both options.

In the simulation we used parameters roughly oriented on the ones used by McClelland and Rumelhart (1981). We used parameters that were very similar to the ones used in our other publications (Glöckner, 2006, 2009, 2010; Glöckner, Betsch, & Schindler, in press; Glöckner & Bröder, in press) which are presented in Table 2. Differences are due to general developments of the PCS model (and specifically the fact that the here reported work was conducted some years before most of the other studies mentioned above). They are not due to post hoc data fitting.[2] One important conceptual difference is that in this paper we do not run simulations for each individual but generated an overall PCS prediction for all participants (see Table 1). This average modeling approach has the major advantage that it puts PCS and the other strategies on equal footing and avoids the issue of overfitting. Specifically, we manipulated cue validities in a certain parameter range and used the average prediction in this range as the PCS prediction for all participants. This means that PCS predictions ignore difference in individuals' cue validities (e.g., whether a person relies twice as much on one cue than on another) but takes into account participants' cue hierarchy (i.e., their subjective ordering of cues according to validity). It, however, also has the downside of neglecting individual differences which might lead to underestimating PCS use. We nevertheless decided to use this simplified method for pragmatic reasons.

In the PCS simulations, according to Figure 1, cue information (links between cues and options, e.g., $w_{c1\text{-}o1}$) was represented by link weights of +0.01 and −0.01. The inhibition between the options was represented by a strongly negative link $w_{o1\text{-}o2} = -0.10$ and the decay parameter was set to 0.10.[3] The stability criterion used for terminating the

[2] In Glöckner (2006) we used exactly the same parameters. In the other simulations that were run later we mainly used a slightly lower decay (.05) and a somewhat stronger inhibitory connection (−.20). In several (unpublished) robustness checks of PCS we found that such slight changes in decay and in the inhibitory connection do not change PCS predictions qualitatively (see also Footnote 3, below).

[3] For simplicity, inhibitory links between options were assumed to be equal in all comparisons. Alternatively, one might assume that the strength of inhibitory links decreases with increasing similarity between options. Previous simulations have shown that changes in inhibitory strength mainly influence the size of information distortions (see Table 2) but do not change the pattern of results qualitatively.

Table 2. Parameters used in the PCS simulation

	Value	Comment
Decay	0.10	Decay parameter for node activation; influences the overall activation level of the nodes, the higher the value the lower the final activation level.
$w_{\text{o1-o2}}$	−0.10	Inhibitory connection between options; influences the size of coherence shifts; the stronger the inhibitory connection the stronger the coherence shifts.
$w_{\text{c-o}}$	0.01/−0.01	Connection between cues and options representing positive or negative predictions.
w_{v}	w_{v1} = 0.40 to 0.60 w_{v2} = 0.10 to 0.14 w_{v3} = 0.01 to 0.05	Links between general validity node and cues representing a priori cue validity. Cue validities range from 0 to 1 and were manipulated.
Ceiling/floor	1/−1	Upper and lower limit for activations of nodes.
Stability criterion	10^{-6}	The network was considered having reached a stable solution if there was no energy change in the network for 10 iterations which exceeded 10^{-6}.

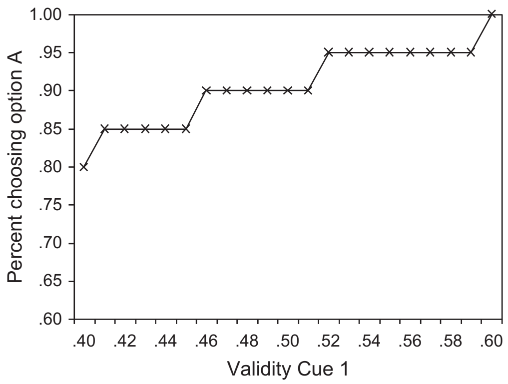

Figure 2. Choice predictions for cue pattern 4.

process was 10 cycles with no energy changes[4] bigger than 10^{-6}. In the simulation, the validity weight of cue 1 w_{v1} was manipulated from 0.40 to 0.60.[5] With this manipulation, the advantage of cue 1 over the other cues was systematically increased. For each level of cue 1, w_{v3} was varied from 0.01 to 0.05 and w_{v2} was varied from 0.10 to 0.14 in order to add some variation on each level of w_{v1} and to reduce the impact of a number-specific outlier in decision time predictions. All analyses are based on the average of the resulting 25 crossed constellations for each level of w_{v1}. Overall, we simulated a total of 525 cue validity constellations per cue pattern.

Results and Interpretation

Choices

Choice predictions were calculated by comparing the activation of the two option nodes after the network stabilized. In cue patterns 1, 2, 3, 5, and 6, all predicted choices were for option A.[6] In cue pattern 4, predicted choice for option A increased with increasing validity of cue 1 (Figure 2). Thus, as we expected the model's predictions are in line with the predictions of weighted additive models.[7] Further simulations with different parameters showed that (when assuming similar cue hierarchies) the general patterns for all dependent variables are relatively robust (see also Glöckner, 2009).

Decision Time

Decision time predictions were calculated from the number of iterations (cycles) that were necessary to construct

4 The overall Energy at time-step (iteration) t is calculated by multiplying all pairwise activations a_i and a_j and connection weights w_{ij} of both:

$$Energy(t) = -\sum_i \sum_j w_{ij} a_i a_j.$$

Energy changes are determined by comparing Energy over time-steps.

5 Note that link weights (which represent initial validity parameters in the model) are not numerically identical with cue validities, defined as conditional probabilities. A link weight of zero represents the fact that a cue has no predictive power and is equivalent to a cue validity of .50.

6 In the simulation of PCS, for simplicity, no error model was incorporated. Hence, PCS predicts choice probabilities of 1 plus an unspecified flexible component which is due to variations in the transformation of values into weights.

7 The question of how different cue validities should be transformed into cue weights in PCS network models and WADD is discussed elsewhere (Glöckner, 2010).

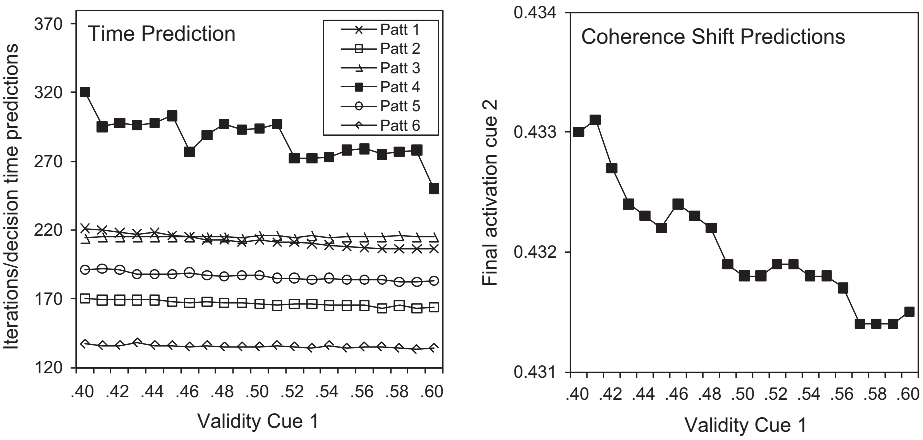

Figure 3. Decision time predictions for cue patterns 1–6 (left) and coherence shift predictions for cue 2 (right) for cue pattern 4. Decision time is estimated by the number of iterations to find a stable solution in the network. Coherence shifts are estimated by the final activation of cue 2.

a stable solution of the network. The average numbers of iterations for cue patterns are shown in Table 1 (middle). The PCS model predicts high decision times for cue pattern 4, medium decision times for cue patterns 1, 2, 3, and 5, and low decision times for cue pattern 6. The effect of the cue validity manipulation is presented in Figure 3 (left).

Confidence

Confidence predictions were derived from the absolute difference of the final activation of the options (Glöckner, 2010). Hence, predictions were calculated as relative activation advantage of one option over the other (Table 1, bottom). Confidence predictions correlated with $r = -.98$ with decision time predictions.

Cue Validity

As mentioned above, one of the core properties of PCS networks is that the validity of the cues is changed within the decision process (coherence shifts, Holyoak & Simon, 1999). In PCS networks, the resulting posterior cue validity is conceptualized as activation of nodes (whereas prior cue validities are represented by links). The final activations of the node representing cue 2 were analyzed. The manipulations of the cue pattern and the cue validity of cue 1 both influenced the final activation of cue 2 which is exemplarily shown for cue pattern 4 (Figure 3, right).

Discussion

Overall, the results converge with the predictions derived from theoretical considerations and earlier simulations of PCS networks (Glöckner, 2001, 2006, 2010; Holyoak & Simon, 1999). First, and most important, by applying PCS mechanisms, individuals should arrive at choices that take into account all pieces of information according to their a priori cue validity (approximating a kind of WADD strategy), and they should arrive at these choices rather quickly. Second, decision time should increase and confidence should decrease as inconsistency in the decision situation increases. In other words, if the cues that speak for one option are almost as strong as cues that speak for the other, then decision times should be longer, whereas decision times should be faster if all cues speak for one option and no dominance structuring is necessary (and vice versa for confidence). Finally, the PCS model predicts that subjective cue validities change during the decision process to form a consistent representation (and result in different posterior cue validities). The last prediction has been extensively tested and is supported by ample evidence (e.g., DeKay et al., 2009; Holyoak & Simon, 1999; Russo et al., 2008). The first three predictions will be tested in the following experiments using inferences from memory and different time-pressure conditions.

Methodological Preliminaries

To allow for strategy classification, predictions concerning choices and decision times for each cue pattern were derived and are summarized in Table 3. For TTB, EQW, and WADD, decision times were derived from the number of computational steps necessary to come to the decision (for details, see Glöckner, 2010) as it has been common practice in many previous studies (e.g., Bröder & Gaissmaier, 2007; Lohse & Johnson, 1996). Note that for pattern 4, choice predictions of WADD and PCS depend on individuals' cue validities. If the most valid cue is considered to be far more valid than the remaining ones, A would be chosen, otherwise B. In the maximum-likelihood strategy classification reported below we started with the distinct prediction that B should be chosen in pattern 4 and A in the remaining patterns. As mentioned above, for the decision time predictions and confidence predictions of PCS we use the average prediction derived from the simulation, to avoid giving PCS the advantage of free parameters. Average predictions were calculated by averaging predictions for each cue pattern over all cue validity variations for cue 1 used in the above reported simulation.

It should be noted that in the current paper we assume the classic implementation of WADD calculations following

Table 3. Predictions of TTB, EQW, WADD, and PCS for choices and decision times

	Predictions for choices					
	Pattern 1	Pattern 2	Pattern 3	Pattern 4	Pattern 5	Pattern 6
TTB	A	A	A	A	A	A
EQW	A:B	A:B	A:B	B	A	A
WADD	A	A	A	A/B	A	A
PCS	A	A	A	A/B	A	A
	Predictions for decision times (contrast weights)					
TTB	−1	−1	5	−1	−1	−1
EQW	0	0	0	0	0	0
WADD	0	0	0	0	0	0
PCS	0.5	−1.5	0.5	3.5	−0.5	−2.5

Note. Patterns 1–6 refer to the respective cue patterns in Table 1. In the upper part of the table, predictions for choices are shown. A and B stand for the predicted option. "A:B" indicates no predicted difference between the selection of A or B. "A/B" represents the choice of A or B depends on high or low differences between cue validities of the most and the less valid cues. The lower part of the table shows predictions of decision times expressed in contrast weights. Differences in values should only be compared within a decision strategy (within one line of the table) because they represent relative weights comparing different cue patterns for one strategy.

Payne et al. (1988). Other processes which approximate weighted compensatory strategies and lead to decision time predictions similar to those of PCS are decision field theory (DFT) (Busemeyer & Johnson, 2004; Busemeyer & Townsend, 1993), multiattribute decision field theory (MDFT) (cf. Diederich, 2003), as well as the paramorphic generalized rational model (gRAT) by Bergert and Nosofsky (2007). In line with PCS the latter models essentially assume that decision time increases with increasing evidence-difference between the options which has been supported by previous empirical data (e.g., Bergert & Nosofsky, 2007; Birnbaum & Jou, 1990; Diederich, 2003; Glöckner, 2001; Hilbig & Pohl, 2009). It would be beyond the scope of this paper to test PCS against these models. Decision time findings in line with PCS would therefore also support DFT, MDFT, and gRAT. PCS (as well as DFT and MDFT) can be understood as process implementations of gRAT.

Three experiments were conducted to explore decision strategies in memory-based probabilistic inferences and to test the predictions of the PCS model. In Experiment 1, implicit time pressure was induced by instructing participants to respond as quickly as possible, whereas in Experiments 2 and 3, explicit time limits were applied using a visible timer that counted down participants' remaining available response time. Based on findings for memory-based decisions (Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b), in Experiment 1, TTB would be expected to be the dominating decision strategy. In contrast, findings of Glöckner and Betsch (2008c) indicate that fast weighted compensatory strategies that are partially based on automatic, intuitive processes (i.e., PCS or other automatic models that implement weighted compensatory information integration) could dominate. Thus, in the first experiment we tested the hypothesis that even under time pressure, fast weighted compensatory strategies are predominantly applied in memory-based decisions with cues that have natural validity. We furthermore expected to find a substantial proportion of PCS users who show choices, decision times, and confidence to be in line with the predictions of the model.

Experiment 1

Method

Participants and Design

Participants of the first experiment were 20 University of Oregon undergraduate students (15 female) between the ages of 18 and 24. The experiment lasted about 45 min and the participants partially fulfilled a course requirement in exchange for their participation. Decision tasks were manipulated within subjects using a 6 (Cue pattern) × 4 (Version) design, with "version" representing different specific city comparisons (i.e., only the city label was changed) that realized the above introduced cue patterns (Table 1).

Materials and Procedure

Participants had to decide which of two cities had more inhabitants based on probability cues. Information was provided as to whether a city was a state capital, whether it had a university, and whether it had a major league sports team. In order to make the decisions memory-based, participants learned information about 12 unfamiliar German cities[8] in a preliminary learning phase and then later had to decide

[8] The cities used in the experiment were Wiesbaden, Mannheim, Rostock, Dortmund, Schwerin, Hannover, Potsdam, Kassel, Leverkusen, Freiburg, Magdeburg, and Dresden. Three of 36 cue values were altered from the real values to fit our design.

Table 4. Results of strategy classification

	Decision strategies				
	TTB	EQW	PCS	WADD	RAND
Experiment 1 (instruction)	2 (10%)	7 (35%)	8 (40%)	3 (15%)	0 (0%)
Experiment 2 (time limit 3 s)	9 (33%)	5 (19%)	8 (30%)	4 (15%)	1 (4%)
Experiment 3					
Condition 1 (time limit 12 s)	5 (25%)	6 (30%)	4 (20%)	4 (20%)	1 (5%)
Condition 2 (time limit 6 s)	4 (20%)	8 (40%)	5 (25%)	2 (10%)	1 (5%)
Condition 3 (time limit 3 s)	4 (20%)	3 (15%)	7 (35%)	5 (25%)	1 (5%)

Note. Due to rounding, the sum of percentages in a row may slightly differ from 100.

which of the two cities was larger when the information was no longer present. The decision tasks always consisted of two options (i.e., cities) and three cues (i.e., information about the presence of state capital, university, and major league sports team). Each of the six cue patterns presented in Table 1 was realized by four different combinations of cities resulting in a total of 24 decision tasks. The experiment was completely computer-directed.

Participants were informed that they would learn information about real existing German cities and afterward they would be asked to recall the information. They were further informed that the three students with the best performance on this task would additionally earn \$20, \$10, and \$5. The learning phase of the study consisted of repeated learning trials in four parts. It started with 10-s presentations of each of the cities with all three cue values at once. Then in the second part, single cue values were presented for 6 s in random order (e.g., "Kassel – has a university"). In the third part of the learning phase, participants had to answer questions about single cue values in random order (e.g., "Does Kassel have a university?") and were provided with feedback. In the fourth part of the learning phase, for each city, participants were asked to recall all three cue values at once. Again, direct feedback was provided on the correctness of the answers. This whole learning procedure was repeated three times. In the third repetition, presentation of single cue values (part 2) was omitted to decrease the overall duration of the study. The resulting learning phase lasted about 25 min. Hence, we used a fixed number of learning trials in contrast to a fixed learning criterion.

In the subsequent decision phase, participants were asked to decide which of two cities had more inhabitants and were told that correct choices would be rewarded with bonus points that would increase their likelihood of winning the money for best performance. Students were instructed to make accurate decisions and to respond as quickly as possible. No information on the validity of the cues was provided and participants had to construct subjective cue validities from existing knowledge. The 24 decision tasks were presented in random order. Two additional decision tasks were used for warm-up purposes. Only the names of the two cities were presented, and participants had to select one of them with a mouse click. After each decision task participants were asked to indicate how confident they were that their choice was correct on a scale from -100 (*very unconfident*) to +100 (*very confident*) using a horizontal scrollbar. Choices, decision times, and confidence judgments were recorded as dependent variables.

Participants were asked in a posttest to recall cue values for all cities. Prior knowledge about the German cities was also measured at this time by asking participants to choose one of three options: (a) I have never heard of this city before, (b) only the name of the city was familiar to me, or (c) I knew more than just the name of the city before the study. Cue validities were explicitly measured by indicating how important the cues were for their decision on a scale from -100 (*very unimportant*) to +100 (*very important*) using a horizontal scrollbar. Note, that, in the terminology of the classic lens model (Brunswik, 1955), we thereby measure *cue validity* not as judgment of the objective relation between distal criterion an cues (i.e., left side of the lens) but as participants' estimation of their personal weighting of these cues (i.e., right side of the lens).

Results

Learning Phase and Prior Knowledge

Inspection of the results of the posttest revealed that on average 89% of the cue values were recalled correctly. Thus, it can be concluded that the learning phase was successful. There were no considerable differences in recall performance between cities (all $p > 81\%$). Participants had almost no prior knowledge about the German cities. Overall, 23% of the ratings indicated that a city name was known; only 2% indicated that more than the name was known.

Strategy Classification

Strategy classification was done in two steps, the first analyzing choices, the second analyzing decision time. Table 4 reports the final results after both steps. Individuals' decision strategies were first analyzed using a maximum-likelihood method (Bröder & Schiffer, 2003a).[9] Specifically, we computed the likelihood of each choice vector given each decision strategy and a constant error rate. To conduct the analysis for the strategies TTB and WADD/PCS, the (ordinal) position of the cues was calculated from individuals' explicit cue validity ratings.[10] To test the robustness of this procedure we conducted Monte-Carlo simulations, varying error parameters for explicit cue validities, and strategy application. The simulations revealed that the classification method is robust but shows a slight tendency to overestimate TTB usage.[11] We nevertheless used the method because the bias works against our hypothesis.

The maximum-likelihood analysis revealed choices in line with TTB for two participants, with WADD/PCS (assuming choices for B in pattern 4) for six participants, and with EQW for nine participants. For three participants, their choices suggested an equal likelihood of using TTB and WADD/PCS. Note, however, that TTB and EQW choices can always be produced by applying the more complex strategies of WADD/PCS with specific weights (i.e., non-compensatory weights or equal weights; see Lee & Cummins, 2004). We used decision times to further investigate which strategy was actually used by participants who showed choices in line with TTB and EQW for which WADD/PCS could also account (Bergert & Nosofsky, 2007; Glöckner, 2010). For each individual, we correlated average decision times for the six cue patterns with the predictions of the models (i.e., TTB and PCS) and tested these correlations for significance (cf. Glöckner, 2010).

To account for deviations from normal distribution and to reduce the influence of outliers, decision times were log-transformed. The log-mean of decision times was 5.2 seconds (*skew* = 0.41 and *kurt* = −0.16). Furthermore, decision times were re-sorted according to individuals' cue hierarchies measured in the posttest, so that, for instance, in cue pattern 1, the best cue always spoke against the second best cue (irrespective of whether the best cue for a particular individual was state capital or university). Individuals' mean decision times for the six cue patterns were correlated with the time predictions of TTB and PCS (Table 3). We tested the correlations against the null hypotheses that individuals used EQW and WADD ($H_{0(a)}$: $\rho = 0$) or TTB ($H_{0(b)}$: $\rho_{TTB} = \rho_{PCS}$). The alternative hypothesis in both cases was that PCS was used. For the tests we used an increased alpha level of $\alpha = .20$ which allowed us to detect medium to large effects ($\rho = .4$) with a power of .57 for $n = 6$ observations using a one-tailed test (Faul & Erdfelder, 1992). Participants who showed choices in line with EQW or WADD and for which $H_{0(a)}$ could be rejected were classified as PCS users; participants who showed choices in line with TTB and for which $H_{0(b)}$ could be rejected were classified as PCS users. In the rare cases in which the likelihood of the observed choice vector was equal for TTB and WADD (and PCS), participants were classified according to the highest absolute decision time correlation.

In line with our hypothesis, the majority of participants used weighted compensatory strategies (Table 4, first row). Eight participants (40%) seemed to use PCS and three participants (15%) used WADD. Seven participants (35%) used an EQW heuristic. In contrast to earlier findings (Bröder & Gaissmaier, 2007) only two participants used the non-compensatory TTB strategy.[12] A sensitivity analysis shows that the core results concerning mainly compensatory strategy use also hold if the alpha level in the decision time test is reduced to $\alpha = .05$, although then the number of TTB users increases from 2 to 4.

Decision times of the different strategy users were in line with the predictions derived for the strategies (Figure 4). There was an almost perfect correlation, $r = .97$ ($p < .001$), between the average decision time of PCS users

[9] According to the maximum-likelihood method the likelihood L_k of an observed choice vector given the application of a decision strategy k and a constant error rate ε_k is calculated by:

$$L_k = p(n_{jk}|k, \varepsilon_k) = \prod_{j=1}^{J} \binom{n_j}{n_{jk}} (1 - \varepsilon_k)^{n_{jk}} \varepsilon_k^{(n_j - n_{jk})}.$$

The six cue patterns are used as categories J ($J = 6$). The number of decisions in each category is denoted n_j. In Experiment 1 *all* $n_j = 4$, in the other experiments *all* $n_j = 8$. The number of observed choices in line with the prediction of the decision strategy k is indicated by n_{jk}. The error rate ε_k for strategy k is estimated by:

$$\hat{\varepsilon}_k = \left[\sum_{j=1}^{J} \left(n_j - n_{jk}\right)\right] \div \left[\sum_{j=1}^{J} n_j\right].$$

For WADD and PCS in cue pattern 4, option B was used as prediction. For EQW in cue patterns 1–3, random choice between A and B was implemented by using an error rate of .5. For individuals' error rates above .5 no likelihoods were computed. We also included a random choice strategy in the analysis to avoid chance-based misclassifications.

[10] People showed clear cue hierarchies in their explicit cue validity ratings which are also reflected in clear preferences for cities with the more valid positive cue as compared to cities with the less valid cue in cue patterns 1–3.

[11] For instance for an error rate of 30% for strategy application and cue hierarchy detection, the strategy classification was biased in favor of TTB by approximately 12%, disfavoring WADD/PCS, and EQW by 7% and 5%, respectively.

[12] It has been argued that TTB might also be applied in combination with the recognition heuristic (Gigerenzer & Goldstein, 1996). Thus, an individual might first use the cue "Do I know the city?" and then apply TTB with the remaining cues (e.g., state capital). Thus, we reran the analysis adding the recognition cue to TTB only. The predictions of the other strategies were left unchanged. The classification results remained stable except that one former EQW user was then classified as a TTB user.

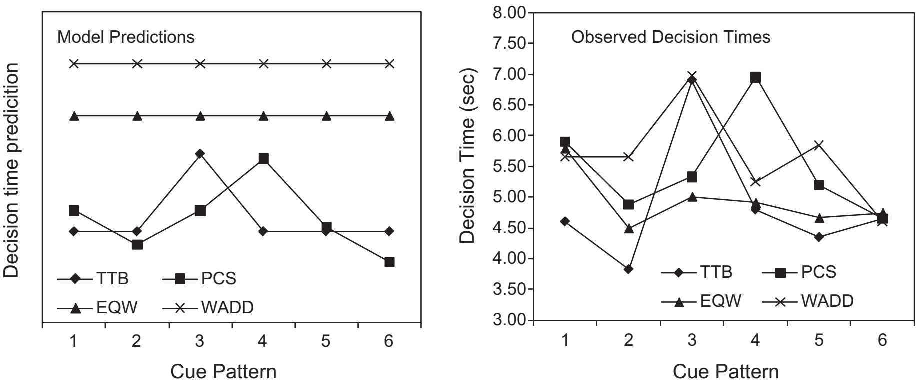

Figure 4. Model predictions for decision times (left) and decision times (log-means) in Experiment 1 (right) by cue patterns and individuals' decision strategies. The intercept and the scaling of the prediction curves are not determined by the models.

and the predicted decision times. For the TTB user, this correlation was also very high, $r = .91$ ($p < .001$). This provides converging evidence for the strategy classification. Keep in mind, however, that for PCS users, the correlation was also used in the classification procedure, which might inflate the correspondence between these two measures in this condition.

Confidence Judgments

The mean observed confidence judgments for cue patterns 1 to 6 (with the *SE* in parentheses) were 38.7 (6.9), 36.9 (7.0), 31.6 (6.5), 34.1 (7.0), 46.5 (7.3), and 44.5 (6.1). The confidence judgments generally show the inverse patterns of decision times. Mean confidence judgments for PCS users correlated almost perfectly with PCS confidence predictions presented in Table 1 ($r = .90$, $p < .001$). In line with our expectations, for PCS users confidence increases with decreasing inconsistency.

Discussion

In the first experiment, we investigated strategies in memory-based decisions. The results show that the majority of participants used weighted compensatory strategies (PCS and WADD) rather quickly and only a minority used TTB. These results conflict with Bröder and colleagues' (Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b) conclusion that TTB dominates in memory-based probabilistic inferences. Their findings apparently do not generalize to situations in which familiar cues with natural cue validities and binary values are used.

Our data also challenge the assumption that people either have to ignore cue values or cue validities because of limited cognitive capacity. The results indicate that people are able to use both sources of information in at least reasonably complex decision situations – even in memory-based decisions in a weighted compensatory way. Because of low individual decision times, it is unlikely that information was integrated using solely deliberate computations. Further support for this idea also comes from the fact that decision times for PCS and WADD users were only slightly higher than decision times for TTB and EQW users. In line with our second hypothesis, the intuitive PCS model accounted well for the behavior (choices and decision times) of a substantial proportion of the participants. On an aggregated level, decision times and confidence judgments provide converging evidence for the PCS model although decision time results can also be explained by other models (see above).

Decision time data also rule out the alternative explanation that individuals were already constructing knowledge about city sizes in the learning phase. Had this been the case, no systematic differences in decision times among cue patterns should be observed. The highly systematic variations of decision times in line with the PCS predictions make it also very unlikely that participants classified as PCS users relied on exemplars (Juslin & Persson, 2002). Furthermore, the highly systematic differences in confidence ratings in line with the predictions of PCS cannot easily be explained by classic evidence accumulation models such as DFT and MDFT.

Two methodological differences to Bröder and Schiffer (2003b) should be noted which might partially account for our somewhat different findings: We used pairwise comparisons of options based on three instead of four cues and a learning phase with a fixed number of trials instead of a fixed performance that had to be reached. We cannot rule out that the lower complexity (cf. Sundstroem, 1989) and participants (assumed) higher homogeneity in motivation in the test phase might have additionally reduced TTB usage.

In a second experiment, we tested whether the results of Experiment 1 would also be found under severe explicit time limits of 3 s, which is well below the minimum average decision times observed in Experiment 1 (see Figure 4). According to findings for outcome-based decisions (Payne et al., 1988), extreme time limits lead to increased use of simplifying non-compensatory strategies. Thus, we might expect to see greater use of TTB. However, because PCS is based on automatic processes, it could also be expected that PCS would still be the predominantly used strategy, as was found for decisions made from readily available information (Glöckner & Betsch, 2008c). Thus, from a theoretical as well as from an empirical perspective, no clear predictions favoring either TTB or PCS could be derived. We decided to start with the preliminary assumption that time limits would lead to a similar distribution of decision strategies as in Experiment 1.

Experiment 2

Method

Participants and Design

Twenty-seven undergraduate students of the University of Oregon (16 female) between the ages of 18 and 25 years took part in the experiment. They were recruited and rewarded using the same procedure as in Experiment 1. Decision tasks were manipulated within subjects using a 6 (Cue pattern) × 4 (Version) × 2 (Order of options) design. The "order of options" factor was added such that all city comparisons in Experiment 1 were presented twice with the order of cities being reversed to increase power in the analysis.

Materials and Procedure

Essentially the same materials and procedure as in Experiment 1 were used. The only major change in the decision phase was that a dynamic down-counting time bar was added to the computer screen to provide an explicit time limit of 3 s. The length of the bar decreased proportionally to the elapsed decision time and changed color from green to red after 2.5 s. If a participant did not make a decision in time, a choice was no longer possible and the participant was instructed to decide faster the next time. Participants were instructed to make accurate decisions within the time limits. No confidence judgments were collected in this study.

Results

Learning Success and Manipulation Check

The posttest showed that 84% of the answers in the posttest for knowledge about the cities were correct. Thus, the learning procedure was again successful and there were no substantial differences in recall performance between cities. Again there was almost no prior knowledge concerning the cities (4%), and only 24% of the city names were known to participants. Inspection of decision times revealed that 98.5% of the choices were made in time, thus the individuals followed the instructions to answer within the time limit. The log-mean of decision time was 1.7 s (*skew* = −0.03 and *kurt* = −0.6). Thus, the explicit time limit forced people to decide on average 3.5 s faster than under the implicit time pressure present in Experiment 1.

Strategy Classification

Choices and log-transformed decision times were analyzed using the same method as in the previous experiment.

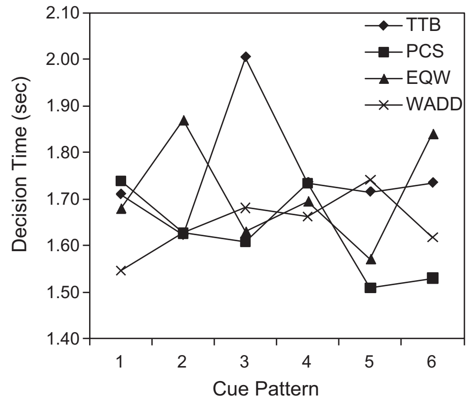

Figure 5. Decision times (log-means) under severe time-pressure of 3 s (Experiment 2) by cue patterns for the different decision strategies. The decision time predictions of the strategies are shown in the left graph of Figure 4.

We used the same stepwise procedure in which choices were analyzed first and decision times were analyzed afterward. In the maximum-likelihood method 10 participants showed choices in line with TTB, five in line with WADD/PCS, and eight in line with EQW. One person showed random choices. For three participants likelihoods for TTB and WADD/PCS were equal.

The overall results of the strategy classification are shown in Table 4 (second row). Nine participants used TTB. Eight participants still appeared to be using PCS. Five participants used EQW; four participants used WADD. In sum, although the proportion of TTB users was higher as in Experiment 1, compensatory strategies still predominated under severe time pressure and decision times of only 1.7 s.

To investigate the influence of the explicit time pressure on strategy classification, we compared the results of Experiments 1 and 2. The chi-square test of independence between strategy classification (TTB, EQW, PCS, and WADD) and experiment (i.e., either Experiment 1 or Experiment 2) was not significant, χ^2 (N = 46, df = 3) = 4.22, p = .24, although the manipulation of time pressure did have a sizable influence on decision times. Thus, it was not possible to reject the initial hypothesis that decision strategy selection remains stable under severe time limits. Note, however, that the power of the analysis was rather low.

Aggregated decision times were analyzed for the different strategy users (Figure 5). Mean decision times for PCS users were again in line with the predictions of the model, r = .71, p < .05. The same was true for TTB users, r = .94, p < .001.

Discussion

Strategy selection under severe explicit time limits did not differ significantly from strategy selection under implicit time pressure (i.e., "respond as quickly as possible").

The results of Experiment 2 indicate a trend for TTB to be used more often under severe time limits, a finding that is in line with the predictions and previous findings of Payne et al. (1988). However, even under severe time limits, and in an average decision time of 1.7 s, almost two-thirds of the participants made decisions reflecting use of compensatory strategies (PCS, WADD, and EQW). These participants' patterns of response suggested that they were activating all pieces of information from memory and integrating them. The decision times make it very unlikely that individuals could have applied deliberate sequential processes to carry out these calculations and to make the decisions, suggesting instead that intuitive decision strategies that rely on automatic processes might have been used. Furthermore, decision times of the participants classified as PCS users were once again highly correlated with the decision time predictions derived from the simulations. Taken together, the findings lend support to the PCS model and other models that assume fast complex compensatory information integration (e.g., DFT and MDFT).

We aimed to investigate the effects of time limit more closely. Thus, we ran a third experiment using a between-subjects design manipulating the level of time pressure. We once again used the severe time limit condition which replicated Experiment 2, and included two additional conditions as comparisons: one in which decision time was also highly limited but somewhat less stringently than in Experiment 2 and, in fact, close to the actual mean amount of time that subjects took in Study 1, and another in which subjects had an explicit time limit, but one that gave them almost double the amount of time the average participant took in Study 1 under implicit time limits.

Experiment 3

Method

Participants and Design

Sixty undergraduate students at the University of Oregon, who were recruited and rewarded as in Experiments 1 and 2, took part in the experiment. Participants were randomly assigned to one of the three conditions: a lenient (12 s), medium (6 s), or severe (3 s) time limit. Again, decision tasks were manipulated within subjects using a 6 (Cue pattern) × 4 (Version) × 2 (Order of options) design.

Materials and Procedure

Materials and procedure were essentially the same as in Experiment 2. The speed of the down-counting time bar was varied for the between-subjects time limit manipulation.

Results

The learning phase was again successful (87% correct answers). Prior knowledge about the cities was very similar to that in Experiments 1 and 2 (5% prior knowledge, 24% names known, and 71% unknown). Again, the individuals' choice vectors and decision times were analyzed for strategy classification, using the same method as in the previous experiments. The results are presented in Table 4 (third, fourth, and fifth row). Once again, we found a high proportion of users of compensatory strategies under severe time limits, replicating Experiment 2. Yet in each of the three time limit conditions, compensatory strategies prevailed. There was no significant change in decision strategies (i.e., TTB, EQW, WADD, and PCS) with increasing time pressure, $\chi^2(N = 60, df = 6) = 4.54$, $p = .60$.

There was a substantial proportion of PCS users (overall 27%) which was similar to that observed in Experiment 2 (26%), but at a rate less than that observed when only implicit time pressure was present (Experiment 1: 40%). This might be partially due to the fact that explicit time limits blur the effects on decision times. Thus, the proportion of PCS users is likely to be underestimated in the lenient and medium time limit conditions and there is a high likelihood that PCS users might not be detected (and instead erroneously classified as WADD users). Note that even in the low time-pressure condition, observed decision times of 2.6 s made it very unlikely that a WADD strategy was deliberately applied (cf. Lohse & Johnson, 1996).

Inspection of mean decision times revealed that all three time limit conditions led to generally low decision times. The log-means of decision times for the three conditions were 1.70 s, 2.39 s, and 2.61 s.[13] More than 99% of the choices were completed in time. Mean decision times of the strategy users were again correlated with the predictions of the respective strategies. The correlations of PCS and TTB users for the time limit conditions were respectively, $r_{PCS} = .74/r_{TTB} = .88$ (lenient), $r_{PCS} = .50/r_{TTB} = .67$ (medium), and $r_{PCS} = .91/r_{TTB} = .35$ (severe). Decision time results are presented in Figure 6.

Discussion

The results replicate and extend the findings of the previous experiments. In all three time limit conditions, compensatory strategies predominated. A considerable proportion of participants showed decisions and decision times in line with the predictions of PCS. Consistent with the theoretical consideration about properties of intuitive processes (Hammond et al., 1987) and in line with recent findings in decisions from given information (Glöckner & Betsch, 2008c) the time limit manipulation did not have a significant effect on decision strategies. Many individuals seem to use intuitive decision strategies that allow for weighted compensatory information integration from the beginning

[13] Due to a programming error, six decision times for the first and six other decision times for the second occurrence of each version of each decision task were not recorded, resulting in 36 instead of 48 recorded decision times.

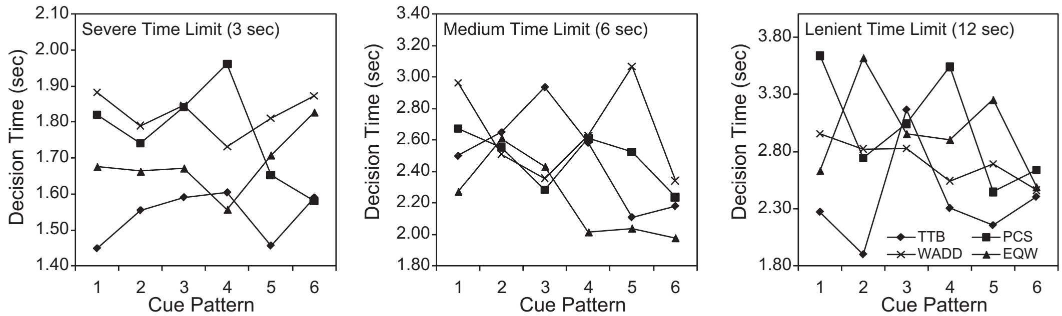

Figure 6. Decision times (log-means) in decisions under different time-pressure conditions (Experiment 3). The decision time predictions of the different strategies are shown in the left graph of Figure 4.

(cf. WADD as default strategy, Bröder, 2003). Participants seem to be able to use these strategies even under severe time limits; but they also apply them under lenient time limits in order to decide quickly. In the latter case the available time is only partially used.

General Discussion

In this paper we investigated decision strategies in memory-based decisions using the city-size task. Specifically, we tested whether compensatory strategies such as the PCS model or the non-compensatory TTB heuristic could better account for memory-based decision behavior under different time-pressure conditions. We first derived choice, decision time, and confidence predictions by conducting simulations for PCS. We ran three experiments to test these predictions at an aggregated level and to test strategy usage at an individual level. In line with earlier findings, we observed high interindividual heterogeneity in strategy usage. Under all conditions, we found a substantial proportion of TTB users (overall 22%) who showed choices and decision times very much in line with the predictions of the strategy. However, in contrast to earlier findings, the majority of individuals appeared to apply compensatory strategies in our studies. Overall, 30% of the participants' decision times and choices were best explained by the PCS model. An additional 17% showed WADD choices with response times that make it very unlikely that weighted sums were deliberately calculated. Finally, 27% of the participants appeared to use an EQW strategy.

It was found that time pressure had no significant effect on strategy choice, although, when comparing the results of Experiment 1 with the remaining experiments, there was a trend toward increased use of simple non-compensatory strategies such as TTB when explicit time limits were applied. However, even with severe time limits and decision times as low as 1.7 s, the majority of participants used compensatory strategies. It is very unlikely that in such a short time the necessary pieces of information are deliberately retrieved from memory and serially integrated. This indicates that intuitive strategies might have been used which are not bound by cognitive capacity constraints. It is, however, up to further research to investigate whether the results generalize to memory-based decision in more complex environments. It might particularly be of interest whether the results can be replicated in environments with more than two options for which an increased usage of non-compensatory strategies has been observed in previous studies investigating inferences from givens (Payne, 1976).

In line with the predictions by Hammond et al. (1987), and as derived from our simulation, intuitive-automatic decision strategies seem to integrate information in a weighted compensatory way. The almost perfect correlations between decision time and (in Experiment 1) confidence predictions of the PCS model and the observed data indicate that the PCS model is a good candidate to explain these processes. Thus, the findings add to the growing body of evidence supporting PCS approaches in decision making (e.g., Holyoak & Simon, 1999).

It has been recently argued that – similar to the strategy selection problem in multi-strategy models (Glöckner et al., in press) – single strategy models such as PCS could eventually fall prey to a problem of parameter selection (Marewski, in press). In the worst case, different sets of parameters would lead to opposite predictions so that the model loses any predictive power (but see also Glöckner & Betsch, in press). In our recent research including the current work we therefore tried to avoid the problem by using similar parameters in all of them. We generally found that the applied parameters can account well for a wide variety of behaviors in rather different tasks (Glöckner et al., in press; Glöckner & Bröder, in press) and even for findings that have been classically explained by adaptive strategy selection (Glöckner & Hilbig, 2010).

Note that for pragmatic reasons in the current studies, the PCS model was used without taking into account individual differences in the magnitude of cue validities. Furthermore, the power for detecting differences in decision times in strategy classification was rather low and the strategy classification favored TTB. Finally, wrong explications of cue validities by participants are likely to have produced further misclassifications in favor of EQW. Thus, the proportion of PCS users is likely to be considerably underestimated in the reported studies.

Additional investigations should be conducted to test the PCS model against other comprehensive decision models such as DFT, MDFT, image theory (Beach & Mitchell, 1996), and prototype or exemplar models (Dougherty, Gettys, & Ogden, 1999). Our findings indicate that a model for memory-based decision making should be able to account for fast weighted compensatory information integration and systematic differences in decision times. As mentioned above, this is particularly the case for DFT and MDFT which are both also indirectly supported by our decision time data. Further investigations that aim to differentiate between models could focus on confidence, because in contrast to PCS, classic versions of DFT and MDFT cannot account for the systematic confidence differences observed in Experiment 1. As another starting point for further investigations comparing DFT and PCS, a recent eye-tracking study on risky choices has shown that attention is not distributed proportional to the probability of outcomes – as one might expect based on DFT – but that it is mostly directed to the most attractive outcome of the favored gamble as predicted by PCS (Glöckner & Herbold, in press). It is due to further research whether these findings generalize to memory-based probabilistic inferences. More generally, and as we have argued elsewhere (Glöckner & Witteman, 2010), evidence accumulation models, exemplar models, and PCS models do not exclude each other but might describe complementary automatic-intuitive processes that can all be applied to make quick compensatory decisions.

The application of TTB to memory-based decisions in the city-size task has been explicitly hypothesized (Gigerenzer & Todd, 1999). However, our results show that the findings by Bröder and colleagues (Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b) in favor of a dominant TTB use in memory-based decision do not generalize to decision tasks in which cues have natural cue validities which are easy to access and have binary cue values. In line with our expectations, this allowed individuals to apply intuitive decision strategies which quickly integrate information and seem to be less prone to time pressure induced capacity constraints.

Intuitive strategies like PCS rely on the possibility for a quick activation of information in memory. A comparison of our findings with Bröder and colleagues' results indicates that the accessibility of information might be an important moderating factor for strategy selection in memory-based decisions. Frugal strategies that rely on one cue only seem to be used more often if the retrieval of information is more effortful because cue values and cue validities are not so easy to access. In our studies, we did not induce cue validities by instruction or by lengthy cue validity learning phases, but we used individuals' own cue hierarchies which they had learned in the real world. In such situations the prevalence rate of TTB was surprisingly low.

Based on the reported results and other findings in decisions from given information (e.g., Ayal & Hochman, 2009; Bröder, 2000; Bröder, 2003; Glöckner & Betsch, 2008a, 2008c; Glöckner & Bröder, in press; Hilbig, 2008, in press; Hilbig, Erdfelder, & Pohl, 2010; Hilbig & Pohl, 2008; Hochman, Ayal, & Glöckner, in press; Newell et al., 2003), the sometimes claimed ubiquity of simple fast and frugal heuristics (e.g., Gigerenzer, 2004) seems to be overestimated. By focusing on the "simplifying approach" to decision making, in a parallel fashion, alternative decision strategies which are based on complex automatic information integration processes may have been underestimated. The reported results speak for the importance of intuitive strategies that integrate many pieces of information quickly using automatic processes. As suggested many years ago (e.g., Wertheimer, 1938), automatic processes that may have evolved from processes of perception seem to play a particularly important role in human cognition. The PCS model integrates such processes in a decision strategy and was supported by the data.

Acknowledgments

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Andreas Glöckner

Max Planck Institute for Research on Collective Goods
Kurt Schumacher Str. 10
D-53113 Bonn
Germany
Tel. +49 0 228/91416 857
E-mail gloeckner@coll.mpg.de