Evidence for Multiple-Reason Decision Making Under Time Limits

Andreas Glöckner

Max Planck Institute for Research on Collective Goods

Tilmann Betsch

University of Erfurt

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Address Correspondence to:
Andreas Glöckner
Max Planck Institute for Research on Collective Goods
Kurt-Schumacher-Str. 10
D-53113 Bonn
Phone: +49-(0) 2 28 / 9 14 16- 51
E-mail: gloeckner@coll.mpg.de

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Abstract

It has been repeatedly shown that in decisions under time constraints, individuals predominantly use non-compensatory strategies rather than complex compensatory strategies. We argue that these findings might not be due to limitations of cognitive capacity but to limitations of information search induced by the commonly used experimental procedure mouselab (Payne et al., 1988). We tested this assumption in three experiments. In the first experiment, information was openly presented, whereas in the second experiment the standard mouselab was used under different time limits. The results indicate that individuals are able to compute weighted additive decision strategies extremely quickly if the information search is not restricted by the experimental procedure. In a third experiment, these results could be replicated using more complex decision tasks; the major alternative explanations that individuals use more complex heuristics or encode the constellation of cues only could be ruled out. In sum, the findings challenge the fundaments of bounded rationality and highlight the importance of automatic processes in decision making.

Keywords: Parallel Processing, Automatic Information Integration, One Reason Decision Making, Mouselab, Process Tracing, Time Limits

Process tracing studies in decision research have been accumulating evidence indicating that individuals often employ simple strategies that minimize the amount of information considered and mental effort invested in the decision (e.g., Payne, Bettman, & Johnson, 1988). These strategies, such as the lexicographic rule (*LEX*, Fishburn, 1974), elimination-by-aspects (*EBA*, Tversky, 1972) or the equal weight rule (*EQW*, Fishburn, 1974) minimize the cognitive effort invested in information search and integration as compared to extensional, compensatory strategies such as the weighted additive rule (*WADD*) that utility theory demands. Scholars now take it for granted that time and capacity constraints provoke strategy shifts from more complex strategies towards simple non-compensatory strategies like the LEX rule (Ariely & Zakay, 2001; Bettman, Luce, & Payne, 1998; Payne et al., 1988; Payne, Bettman, & Johnson, 1992; Rieskamp & Hoffrage, 1999). In this paper we argue that the external validity of the findings underlying this conclusion could be questioned because of methodological shortcomings. In particular it is argued that the predominantly used research methods in behavioral decision research focus on deliberate decision strategies only but are not able to capture automatic processes in decision making and in fact often hinder their application. Following the argumentation of dual-processing approaches to decision making (see below), we aim to demonstrate that automatic processes driven by the “intuitive system” (Kahneman & Frederick, 2002) enable individuals to quickly integrate multiple reasons in their decisions. We propose an alternative method and report data from three experiments which indicate that if they are unconstrained by an artificial experimental setting, the majority of individuals use automatic processes to integrate multiple-reasons in a weighted additive manner in their decisions.

Bounded Rationality and the Focus on Deliberate Decision Strategies

In line with the dual-processing framework suggested by Kahneman and Frederick (2002), we define *deliberate decision strategies* as strategies which are based on controlled cognitive operations that are rule-governed. In deliberate strategies, information is integrated in a serial manner, processing is cognitively demanding and rather slow; and individuals are aware of the underlying processes and can explicate them. Research in the tradition of the bounded rationality approach (Simon, 1955) has intensively investigated such deliberate decision strategies (cf., Frederick, 2002). The major tenet of the bounded rationality approach thereby holds that individuals employ short-cut strategies (commonly called "heuristics"[1]) because their cognitive capacities are limited. A prominent decision problem, which has been repeatedly used in this research, is the city-size decision task (Gigerenzer, Hoffrage, & Kleinbölting, 1991; Gigerenzer, Todd, & the ABC group, 1999). In this task an individual has to decide which of two cities has more inhabitants (*options*) based on conflicting pieces of evidence (*cues*). Cues vary as predictors for city-size, which means that they differ in the conditional likelihood that city A is larger than city B given a positive cue value (*cue validity*). It is assumed that the individual has no exact knowledge about the size of the cities. However, for instance, the individual knows that city A is a state capital and city B is not and that city B has a university and a major league sports team whereas city B has neither.

To make a decision, a very simple strategy would be to base the decision on only the most valid cue. If, for instance, the person presumes that the cue state capital is the most valid cue, he or she could consider only this information, ignoring the other cues and deciding that city A is larger. Such a strategy relies on one reason. The example describes the application of the Take-the-Best heuristic (*TTB*, Gigerenzer & Goldstein, 1996), which belongs to the class of LEX rules. Only if the most valid cue does not differentiate between options would the next cue be used, and so on. Such a strategy seems to be simple enough to be deliberately applied by lay people in everyday settings. Alternatively, according to an EQW strategy, cue validities could be ignored and the option with more positive cue values could be selected (i.e., city B).

Obviously, a strategy in which all the validities of all cue values are considered would be much more complicated. This could be realized by a weighted additive rule (*WADD*) in which cue values are multiplied by the validities of the respective cues and summed up. The option with the highest weighted sum is chosen. The latter strategy is aligned with the decision rule proposed by utility theory. WADD considers all relevant pieces of information, integrates cue values and cue validities for each option, and thus provides an ideal example of a compensatory strategy (i.e., a strategy in which negative values on one cue can be compensated for by positive values on other cues). It is the firm conviction of proponents of the bounded rationality approach that humans are usually not capable of applying such extensional strategies because these strategies overtax their computational capacities.

As will be pointed out in more detail later, we question this assumption and argue that individuals usually do not carry out a WADD strategy by deliberately calculating weighted sums but by relying on automatic processes.

The Mouselab - A Method for Process Tracing and Strategy Classification

One of the major challenges in behavioral decision research is to empirically identify individuals' decision strategies because the underlying cognitive processes cannot be directly observed. A multitude of methods have been developed which are used to infer decision strategies from proximal parameters like choice patterns (e.g., Bröder & Schiffer, 2003b); information search parameters (e.g., Johnson, Payne, Schkade, & Bettman, 1986; Sundstroem, 1987); decision times (e.g., Bergert & Nosofsky, 2007; Glöckner, 2006; Glöckner, in press a); confidence judgments (Glöckner & Hodges, 2006); eye movements (e.g., Russo & Dosher, 1983); self-reports and think-aloud protocols based on introspection (e.g., Montgomery & Svenson, 1983; Svenson, 1989) or combinations of them.

One of the standard tools for strategy classification is the computer-based information board called *mouselab* (Johnson et al., 1986). In the mouselab, information about options is presented in a covered information matrix. Participants have to move the mouse cursor onto boxes to uncover the outcomes of choice options. Information search is recorded and used to subsequently identify decision strategies (for an example see Figure 3).

The introduction of the mouselab was a major step. By providing an easy-to-handle tool for process tracing and strategy classification, this research method opened the door to a process view in decision research; hence, it might actually be considered a revolution (Beach & Potter, 1992). Regardless of its undisputed merits, the method entails some problems. The fundamental problem with the mouselab is that it imposes restrictions for information searching which might, in turn, influence strategy selection. Note, for instance, that in the standard mouselab, only one piece of information can be inspected at a time. This procedure promotes a serial mode of information search and hampers the possibility for quick comparisons between multiple pieces of information, as well as the detection of specific cue constellations. As such, the mouselab does not allow for differentiation between the constraints to overt search behavior imposed by the properties of the research tool and the constraints imposed by capacity limitations of the cognitive system.

In mouselab experiments, it has consistently been observed that participants change decision strategies under severe time pressure from more complex compensatory strategies to simple non-compensatory ones (i.e., strategies in which negative values on one cue cannot be compensated for by positive values on other cues) like the LEX/TTB rule (Payne et al., 1988; Rieskamp & Hoffrage, 1999; for a recent overview of time effects on decision making see Ariely & Zakay, 2001; for a related discussion of the effects of time stress see Broadbent, 1971; Zakay, 1993). However, a critical reflection on the procedure reveals that the results cannot serve as conclusive evidence for the view that a limited capacity for information integration under time pressure causes the strategy shift. The alternative explanation that time pressure simply constrains the information search operations (i.e., movements of the computer mouse) necessary to gain access to the information, cannot be ruled out.

Findings by Lohse and Johnson (1996) lend support for the latter explanation. The authors investigated the influence of different types of process tracing methods on decision behavior and identified substantial differences in choices and information search behavior between decision tasks being presented in the mouselab and the same decision tasks being presented openly so that information was instantly accessible. In the former case information had to be looked up serially using the mouse, whereas in the latter condition information search was recorded using an eye-tracking method. Lohse and Johnson found that the mouselab method significantly increased the amount of time needed to acquire information compared with the eye-tracking method. Furthermore, in the mouselab condition individuals showed a more systematic information acquisition behavior and almost one-third of the individual choices changed as a function of the manipulation of the process tracing method.

Based on the outlined methodological critique and the reported initial findings, we argue that the mouselab installs a systematic bias in resource allocation. *Pre-selectional processes* (Betsch & Haberstroh, 2005), such as screening the problem and inspecting outcomes, entail considerable costs in time and attention resources. Conversely, in many mundane decisions, both the environment and our memory system immediately provide us with a huge amount of information so that pre-selectional processes consume a minimum of resources. Assume a man approaches you on the street and begs for some change. He claims he is in dire need of the money because he wants to buy a bus ticket to his home town. You realize from his looks, his ragged clothing, the smell of alcohol on his breath and the group of people he is with that he is obviously drunk. Of course, you are aware of moral obligations, but you also feel some reservations due to your prior experience with similar situations. All these different kinds of information are available at once and form a unique impression or the "Gestalt" of the situation (cf., Koffka, 1922). The resources to be invested in an information search are small. You know everything you need to know to make a decision. We argue that individuals are able to combine these multiple pieces of evidence in a weighted additive manner rather quickly by relying on automatic processes. In contrast to many decisions in natural settings, the mouselab induces a serial search for information that hinders individuals from applying such “default strategies” (Bröder, 2003, p. 617), particularly under time pressure.

With the good intention to bring hidden processes to light, researchers force decision makers to engage in a serial consideration of information when working on the mouselab. In turn, this method induces a deliberate rule-based integration of information. These processes are slow and consume both task and mental resources. Automatic processes which could make use of a parallel consideration of information are systematically constrained in this paradigm. It is not very surprising that individuals reduce the depth of serial processing in the mouselab, especially when time and cognitive resources become scarce. At least under conditions of time pressure that do not allow for inspecting all information, the mouselab method invites the application of non-compensatory strategies (e.g., LEX/TTB). Thus, the claim that individuals would generally use this kind of strategies more often under time pressure is not warranted. Yet, we cannot rule out the possibility that the presumed increased prevalence of non-compensatory strategies under time pressure only applies to situations that resemble the mouselab.

The Neglected Role of Automatic Processes in Research on Decision Strategies

In dual processing models (Kahneman & Frederick, 2002) the discussed deliberate processes, which have been the focus of the research on choice strategies, are contrasted with automatic processes that operate without cognitive control, have a high capacity for information integration, could rely on parallel processing of information and operate rather rapidly. Individuals are not aware of the information integration processes; only the results enter awareness.

Although the importance of automatic processes has been repeatedly highlighted in other fields of psychology (Bargh & Chartrand, 1999; Bargh & Williams, 2006; Hasher & Zacks, 1984; Hintzman, 1988; Wegner, 1994; Zajonc, 1980), as well as in judgment research (Doherty & Kurz, 1996; Kahneman, Slovic, & Tversky, 1982; Kahneman & Frederick, 2002), these processes have been largely ignored in research on choice strategies (Frederick, 2002). In a long tradition of dual-processing models (e.g., Petty & Cacioppo, 1986; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977) Kahneman and Frederick (2002) suggest a two-system framework according to which decision strategies might rely on intuitive/automatic processes (system 1), as well as reflective/deliberate processes (system 2) (see also Epstein, 1990; Hogarth, 2001; Sloman, 2002; Strack & Deutsch, 2004; but see Hammond, Hamm, Grassia, & Pearson, 1987). Short-cut strategies like EQW or LEX/TTB are usually assumed to belong to the deliberate system since they draw upon controlled processes, which are cognitively demanding and rather slow, and which follow certain rules and which individuals are aware of. In contrast, decision strategies that are based on automatic processes could be considered to belong to the intuitive system.

Beyond this general framework, several models have been proposed that claim to further specify these automatic processes (e.g., Beach & Mitchell, 1996; Betsch, in press; Busemeyer & Townsend, 1993; Dougherty, Gettys, & Ogden, 1999; Frederick, 2002; Glöckner, 2006; Glöckner & Betsch, 2007; Hogarth, 2001; Lieberman, 2000; Simon, Krawczyk, & Holyoak, 2004). It is beyond the scope of this paper to discuss and compare these models. It is also beyond the scope of this paper to compare dual-processing approaches and cognitive-continuum approaches (Hammond, Hamm, Grassia, & Pearson, 1987).

For simplicity, we focused our research on one very fundamental assumption (Hammond et al., 1987): automatic processes should enable individuals to integrate information in a weighted additive manner rather quickly. This would mean that individuals apply a WADD rule without deliberately calculating weighted sums. In contrast, from bounded rationality models it would be predicted that simple deliberate strategies (i.e., heuristics) like EQW or LEX/TTB rule should enable individuals to come to choices quickly by ignoring cue information or cue validities.

Methodological Preliminaries

Notation. Decision strategies can be differentiated in process models which claim to describe the computational steps of decision making and paramorphic (or "as-if") models (Hoffman, 1960) which aim to describe the outcomes of decision strategies only. The LEX/TTB rule and the EQW rule are considered process models (Gigerenzer et al., 1999; cf., Brandstätter, Gigerenzer, & Hertwig, 2006). Some researchers imply that the WADD strategy is also a process model by assuming that the strategy can be decomposed into elementary information processes which are used as a proxy for the mental effort to carry out the strategy (Gigerenzer et al., 1999; Payne et al., 1988). Other authors understand WADD in a more paramorphic sense (e.g., Bröder & Schiffer, 2003a). In line with the latter, we use the notation WADD strategy in a paramorphic sense (Hoffman, 1960) in that we only demand that choices are in line with a weighted additive integration of cue values and cue validities. In some specific cases, we will intentionally differentiate between the possibilities by using the notation $WADD_{del}$ for a strategy that is based on a deliberate calculation of weighted sums and the notation $WADD_{auto}$ for strategies in which weighted additive information integration results from the operation of automatic processes.

Analysis of choices in diagnostic decision tasks. To avoid the aforementioned restrictions of information search by the research method, strategy classification in our experiments was primarily based on the analysis of choices. Decision tasks were systematically selected to be diagnostic for different decision strategies. Specifically, decision tasks were based on cue patterns (i.e., constellations of cue information) so that the considered strategies LEX/TTB, EQW and WADD make different predictions for substantial sub-sets of tasks. To allow for a classification of decision strategies on an individual level as compared to an analysis over all participants, decision tasks were repeatedly presented by holding constant the structural cue patterns underlying the decision tasks (cf., Bröder & Schiffer, 2003b). Note that it is obviously not possible to differentiate between the $\mathrm{WADD}_{\mathrm{del}}$ and the $\mathrm{WADD}_{\mathrm{auto}}$

strategy based on choices because choice predictions are equal; therefore, we have to consider other variables.

Analysis of decision time patterns. Besides analyzing choices, the process of information integration will be further investigated by analyzing individual decision time patterns (cf., Bergert & Nosofsky, 2007). Predictions of automatic models and heuristics concerning decision times differ considerably. For individuals who use a LEX/TTB strategy, decision times should depend on the number of cues which are necessary to differentiate between the options. Thus, people should decide faster in decision tasks in which the first cue differentiates between options as compared to decision tasks in which two or more cues have to be considered (Brandstätter, Gigerenzer, & Hertwig, 2006; Bröder & Gaissmaier, in press). Individuals who use an EQW strategy should not show any differences in decision times as long as the number of cue values is held constant and the sum of cue values differentiates between options. The same prediction holds for a WADD_{del} strategy that is based on a deliberate calculation of weighted sums (cf., Payne et al., 1988). In contrast, decision strategies which are based on automatic processes (e.g., $\text{WADD}_{\text{auto}}$) allow for deriving the prediction that decision times increase with increasing evidence that points against the favored option and that decision times decrease with increasing evidence that supports the favored option (Bergert & Nosofsky, 2007; Busemeyer & Townsend, 1993; Cartwright & Festinger, 1943; Glöckner, 2006; cf., Holyoak & Simon, 1999; for empirical evidence in favor of this claim see Festinger, 1943a, 1943b; Glöckner, in press a). Besides providing converging evidence for the choice-based strategy classification method, decision time analysis can be used to test whether individuals applied a WADD_{del} or a $\text{WADD}_{\text{auto}}$ strategy. Thus, in our experiments decision times were analyzed to further differentiate between decision strategies and to learn more about the underlying processes.

Analysis of confidence judgments. Another kind of data which depends on the applied decision strategies, and thus could be used to learn more about the processes of decision making, are subjective judgments of the confidence in choices (cf., Cartwright & Festinger, 1943; Christensen-Szalanski, 1978). According to simple LEX/TTB rules, confidence should depend on the validity of the most valid cue only (Gigerenzer, Hoffrage, & Kleinbölting, 1991); whereas WADD models would predict that the confidence is dependent on the differences in the weighted cue values for the options. We investigated confidence judgments in the last experiment. Table 1 summarizes the differential predictions of the decision strategies that were used to identify strategies in the three experiments reported in this paper.

Overview of Experiments

We conducted three experiments. In the first experiments, we were interested in whether individuals are able to quickly integrate information in a weighted additive manner if the information search is not restricted by the research method. In the second experiment, the decision tasks of Experiment 1 were presented in a mouselab format under different time limit conditions to further investigate whether strategy shifts are due to limitations of cognitive capacity or due to limitations of information search induced by the mouselab method. In the third experiment, more complex decision tasks and a manipulation of cue validities were used that allowed the further investigation of the processes of information integration.

More specifically, Experiment 1 tested whether prior findings are replicable when the research tool does not constrain the automatic processing of information. Accordingly, information was presented in an "open" matrix (no covered information) to assure that the information search was not hampered by the research method. Thus, the limitations of the information search and the limitations of computational capacity were disentangled. For all participants, time pressure was induced by instruction. Following the bounded rationality approach, it should be found that the use of simple strategies (i.e., LEX/TTB) is dominant, because cognitive capacity is insufficient for applying more complex strategies. The alternative hypothesis was that, even under time pressure, participants use complex weighted additive decision strategies, which are based on automatic processes (i.e., $WADD_{auto}$).

Decision strategies were identified by analyzing choices. Cue patterns were selected which were diagnostic for the considered decision strategies LEX/TTB, EQW and WADD. Furthermore, decision tasks were selected so that the decision time hypotheses derived from the different strategies could be tested (cf., Table 1). The number of cues needed to differentiate between the options according to a LEX/TTB strategy was manipulated in three steps along the factor CUE to test the prediction of a LEX/TTB strategy that decision time increases with an increasing number of necessary cues. Furthermore, conflicting evidence in the cue patterns was manipulated along the factors PRO_OPTION1 and PRO_OPTION2/3 to allow testing the prediction of $WADD_{auto}$ that decision time increases with increasing evidence pointing against the favored option.

Experiment 1

In the first experiment, participants were asked to take over the role of a manager of a company. In repeated decision trials, participants were instructed to select the best out of three different products. They were provided with information from three testers with different predictive validity, which provided dichotomous quality ratings (i.e., good / bad) for each product.

Method

Participants and design. Participants in the first experiment were 15 University of Heidelberg students (11 female, 4 male). The experiment lasted about 30 minutes. Participation was either compensated for by course credit or a flat fee amounting to € 4.00. Decision tasks were varied as within-participants factor, resulting in a 23 (CUE PATTERN) x 6 (VERSION) design with the further factors CUE (number of cues necessary to differentiate according to a LEX/TTB rule); PRO_OPTION1 (number of positive cue values in favor of option1); and PRO_OPTION2/3 (number of positive cue values in favor of option 2 or 3) nested within the factor cue pattern. Thus, along the factor CUE PATTERN, the structure of the decision task was varied. The factor VERSION represented six different versions of each cue pattern, in which the order of options was permutated. Table 2 shows the 23 cue patterns used in the experiment. C1 to C3 refer to cues/testers in order of validity with cue 1 being the most valid cue. O1 to O3 refer to options. Cue values are represented by the symbols “+” (positive) and “-” (negative).

The factors cue, pro_option1, and pro_option2/3 were nested within the factor cue pattern. The 23 cue patterns can be separated in three sets which correspond to the manipulation of the factors cue. In the first set (cue patterns 1 to 15; cue=1), the most valid cue has only one positive cue value which is in favor of option 1. Within set 1, the number of cues which have a positive cue value for option 1 (pro_option1) is varied from 1 to 3 (cf., main rows in Table 2). This variation is completely crossed with a variation of the number of positive cue values for options 2 and 3 (pro_option2/3) from 0 to 4 (cf., main columns in Table 2) resulting in a total of 15 stimuli for set 1. In the second set (cue patterns 16 to 21; cue=2) cue 1 has more than one positive cue value but cue 2 has only one positive cue value. In the third set (cue patterns 22 and 23; cue=3) cue 1 has all positive cue values, cue 2 has two positive cue values and the number of positive cue values of cue 3 is one or two. Individuals who use a LEX/TTB strategy should show increasing decision times from set 1 to set 3. Individuals who use a $WADD_{auto}$ strategy should show increasing decision times with increasing evidence for options 2 and 3 (pro_option2/3) and decreasing decision times with increasing evidence for option 1 (pro_option1). Individuals that use a $WADD_{del}$ rule should show equal decision times for all cue patterns.

Materials and procedure. The 23 cue patterns allowed for the classification of the decision strategies LEX/TTB, EQW and WADD, based solely on the analysis of choices. The LEX/TTB strategy predicts choices for option 1 in all 23 cue patterns, because the most valid differentiating cue (i.e., cue 1 for cue patterns 1 to 15; cue 2 for cue patterns 16 to 21; cue 3 for cue patterns 22 and 23) always points towards this option. The EQW and WADD strategies predict choices for options 2 or 3 in cue patterns 7, 10 and 13, because in these patterns both the un-weighted and the weighted sum of the cue values is higher for the options. Note that for a WADD strategy, this prediction is only valid if the sum of the subjective cue validities for cues 2 and 3 is higher than the cue validity of cue 1.

Individuals who choose option 1 in all cue patterns should be classified as LEX/TTB users, whereas individuals who mainly choose option 2 or 3 in cue patterns 7, 10 and 13 could have used EQW or WADD. The latter participants had to be further separated based on an examination of cue patterns 4, 8, 11 and 18. The EQW strategy predicts an equal distribution of choices for options 1 and 2 for these patterns because the number of cues is equal for both options, whereas WADD predicts choices for option 1 because the more valid cues speak for this option. In summary, people who choose option 1 in all cue patterns ignore less valid cues and should be classified as LEX users; individuals who choose mainly option 2 or 3 in cue patterns 7, 10 and 13 and about equally often choose option 1 and 2 in cue patterns 4, 8, 11 and 18 look at all cue values, but ignore cue validities and should be classified as EQW users; and finally, individuals who choose option 2 or 3 in cue patterns 7, 10 and 13 and mainly choose option 1 in cue patterns 4, 8, 11 and 18 take into account all the cue values, as well as their validities, and should be classified as WADD users (as argued above, the notion is used in a paramorphic sense, not implying that weighted sums are calculated in a serial manner).

A computer program written in MEL2 (Multiple Experimental Language 2) was used to run the experiment. The complete experimental instruction can be found in Appendix A. Participants were instructed to repeatedly select the vendor which provides the best-quality oranges. In each decision task a choice had to be made between three orange vendors, based on information from three testers which provided dichotomous quality ratings for each vendor (i.e., good / bad quality). Participants were further informed that the testers provide information with 80 percent (tester 1), 60 percent (tester 2) and 50 percent (tester 3) of the information being correct. Validities of the cues were presented in a frequency format in order to facilitate the understanding and processing of the information (Gigerenzer & Hoffrage, 1995). Note that there was no normative reason not to ignore the information about tester 3 since the validity of this information reaches only the level of chance, which should facilitate the application of LEX/TTB strategies. The students were instructed both to make high quality decisions and to be as fast as possible (Fazio, 1990). All nine pieces of information for each decision task were presented simultaneously in an information matrix with cues forming rows and options forming columns. Information was presented in the middle of a black screen using ASCII characters only as depicted in Appendix A. The information remained on the screen until the participants had chosen one alternative by hitting one of three adjacent keys that were marked on the keyboard (i.e., “f”, “g”, “h”). The choices and the decision times were recorded.

Eight warm-up decisions were used to familiarize participants with the procedure. These were followed by 138 relevant decision tasks, which were shown in fixed random order. Decision tasks were presented in six randomized presentation blocks, each consisting of one version of the 23 choice patterns. Two short breaks were embedded to minimize the effects of decreasing concentration. After the decision phase, participants were asked to recall the validity of the testers to ensure that participants’ cue validities were sustained over the entire course of the experiment.

Results

Classification of decision strategies. Choice proportions for option 1 in cue patterns 1 to 23 are depicted in Figure 1. On an aggregated level of analysis, choices for option 1 were most often observed, except for the critical patterns 7, 10 and 13. Thus, aggregated choices are in line with the predictions of WADD, indicating that a considerable portion of participants used this strategy. To exactly determine the size of this portion, an individual level analysis was used.

To identify participants who used a LEX/TTB strategy, choices in cue patterns 7, 10 and 13 were compared with choices in the remaining cue patterns. If a LEX/TTB strategy was applied without errors, option 1 should have always been selected. Taking into account that individuals are not able to perfectly apply decision strategies, a certain rate of error has to be considered. Because a statistically sound estimation of acceptable rates of error is methodologically problematic, an alternate method is to test whether the observed individual rate of error is the same for the different cue patterns (cf., Bröder & Schiffer, 2003b). Thus, if a LEX strategy is applied, the portion of choices for option 1 should be equal in the critical cue patterns compared to the remaining ones. This hypothesis was tested using individual χ^2-tests of independence. For each participant, it was tested whether choices for option 1, as opposed to choices for other options, were independent of cue patterns. Here cue patterns 7, 10 and 13 (*critical cue patterns*) were compared with the remaining cue patterns. Eleven participants chose option 1 significantly less often in the critical patterns than in the remaining patterns ($p < .05$). This indicates that the information of the less valid cues systematically influenced their choices, although the most valid cue discriminated between the options (cf., Table 2). Thus it can be ruled out that these participants used a LEX/TTB strategy in which information of the less valid cues would be ignored if the most valid cue already discriminates between options. Two participants made their choices in line with the predictions of a LEX/TTB strategy and were classified respectively. Two further participants distributed their choices equally among options 1, 2 and 3 over all cue patterns, which would not be predicted by any systematic decision strategy. These participants were therefore classified as using a random choice strategy (RAND).

Based on this analysis, it can be concluded that at least 11 participants did not concentrate only on the most valid cue, but instead used information from all three cues. The observed differences in the distribution of choices might be explained by EQW or WADD strategies. However, an EQW strategy further predicts that in cue patterns 4, 8, 11 and 18, an equal distribution of choices for options 1 and the other options should be observed, whereas WADD predicts choices for option 1 only. For the 11 participants still to be classified, the distribution of choices in these cue patterns was examined using χ^2-tests. Specifically, observed choices were tested against an equal distribution of choices for option 1, compared with the other options. For one person there was a precisely equal distribution; this person was accordingly classified as an EQW user. For the remaining 10 participants, choices significantly deviated from an equal distribution; these participants clearly preferred option 1 ($p < .05$). It can be concluded that they took into account the validity of the cues and used information from all three cues. Therefore these 10 participants were classified as WADD users. The results of the strategy classification are summarized in the top row of Table 3. It can be seen that about 2/3 of the participants used a WADD strategy and took into account cue values and cue validities, whereas only a few individuals used EQW or LEX/TTB strategies and ignored information. Thus, in contrast to earlier findings, simple LEX/TTB strategies have not been dominantly used under time pressure.

Decision times. The median decision time was found to be very low. Half of the decisions were made in less than 1.1 seconds (*MD* = 1.07s, *M* = 1.53s, *SD* = 1.51s, *skew* = 6.19, *kurtosis* = 65.11). Thus, it can be concluded that our time pressure instruction was obeyed by the participants. Obviously, it is not possible to integrate the available cue values and cue validities according to a deliberate WADD_{del} computation within such a short time frame. To strengthen this argument, we carried out a study in which participants were instructed to deliberately apply a WADD_{del} strategy to similar decision tasks with 2 options and 3 cues (Glöckner, 2006). The observed average decision time was 20.5 seconds (*SE* = 2.2s), which lies far above the decision times of Experiment 1.

Decision time data were log-transformed to the basis of 10 to reduce the influence of outliers and the skewness and kurtosis of the distribution (Glass & Hopkins, 1996). The transformed data points were fairly normally distributed (*MD* = 3.03, *M* = 3.09, *SD* = 0.26, *skew* = 1.05, *kurtosis* = 1.27). To analyze decision times, a 23 (cue pattern) x 6 (order) repeated measurement analysis of variance (ANOVA) was conducted, with log-transformed decision time as the dependent variable. Cue pattern and order were used as within-subject factors. Each cue pattern was presented in six different versions; these versions were presented in a random order with respect to each other. Thus, the factor ORDER ranged from 1 (first) to 6 (last) repetition of the cue pattern. A Greenhouse-Geisser correction was used because Mauchly's test turned out to be significant, indicating that the assumption of sphericity was violated (Glass & Hopkins, 1996). Note that the same correction was also used in all following analyses, if indicated by Mauchly's test (if possible, even more conservative multivariate analyses of variance were computed). The main effect for cue patterns was highly significant, $F(4.9, 68.2) = 24.04$, $p < .001$, $\eta^2 = .63$.[2] Thus, it can be concluded that decision times differ systematically between cue patterns (Figure 2), which speaks against the mere application of a $WADD_{del}$ strategy.

As expected, there was also a significant main effect for the factor order, $F(1.6, 22.8) = 7.47$, $p = .006$, $\eta^2 = .35$. Although the time needed for the decision was already very low in the first presentation of each cue pattern, decision times further decrease in later repetitions, indicating learning effects. The mean values for log-transformed decision times for the factor order starting with the first presentation (with *SE* in parentheses) were 3.17 (0.037), 3.08 (0.039), 3.08 (0.039), 3.07 (0.045), 3.05 (0.042), and 3.06 (0.041).

The effect of the factor cue on decision times was analyzed using a repeated-measurement ANOVA with cue as within-subjects factor. The main effect for cue turned out to be significant, $F(2, 28) = 4.45$, $p = .021$, $\eta^2 = .24$. However, in contrast to the predictions derived from a LEX/TTB strategy, decision times significantly decreased with the increasing number of cues needed to differentiate according to a LEX/TTB strategy ($M_1 = 3.097$, $SE = 0.006$; $M_2 = 3.070$, $SE = 0.009$; $M_3 = 3.056$, $SE = 0.016$). Thus, decision time data converge with choice data in indicating that participants did not use a LEX/TTB strategy.

The effects of the factors pro_option1 and pro_option2/3 were investigated using a 3 (pro_option1) x 5 (pro_option2/3) repeated measurement ANOVA with log-transformed decision times as the dependent variable. The analysis was run for set 1 only because there was no systematic manipulation of the factors in the remaining sets (cf., Table 2). There were highly significant main effects for pro_option1, $F(1.3, 17.9) = 31.8$, $p < .001$, $\eta^2 = .69$, and pro_option2/3, $F(2.9, 41.1) = 15.0$, $p < .001$, $\eta^2 = .52$, and a significant interaction between both factors, $F(2.2, 30.4) = 36.9$, $p < .001$, $\eta^2 = .73$. As predicted by $\text{WADD}_{\text{auto}}$, decision times decreased with an increasing number of cues favoring option 1 and decision times increased with an increasing number of cue values favoring options 2 and 3 (Figure 2). Decision times were particularly high for the critical cue patterns (7, 10, 13) accounting for the interaction effect.

Discussion

The majority of the participants (67%) took into account information from all three cues, as well as validity information. Their choices indicated weighted additive information integration within (on average) less than 1.5 seconds (*MD* = 1.07 s). Very few participants ignored information or cue validities. Obviously, participants under time pressure refrained from using simple deliberate strategies like LEX/TTB or EQW. Consequently, the major findings from mouselab studies could not be replicated when individuals had unconstrained access to relevant information. Our results suggest that individuals can capitalize on remarkable abilities for complex information integration. Considering the decision times observed in the above mentioned study in which participants were instructed to deliberately calculate weighted sums (Glöckner, 2006), it is very unlikely that individuals deliberately computed a WADD_{del} strategy, because the median decision time of less than 1.1 seconds lay far below the time necessary to calculate WADD_{del} or similar weighted additive strategies (see also Footnote 3 below). Furthermore, decision times differed significantly between cue patterns. This also speaks against the application of a WADD_{del} strategy.

We argue that these results emphasize the importance of automatic processes in decision making. As proposed by different authors (Hammond et al., 1987; Kahneman &

Frederick, 2002), individuals seem to possess the ability not only to use simple deliberate heuristics but also to apply decision strategies based on automatic processes that lead to choices according to a weighted additive information integration (i.e., $WADD_{auto}$). Even under time pressure, these automatic strategies are used by the majority of participants, whereas simple heuristics are applied by very few participants. By disentangling the limitations of information integration and information search, we were able to demonstrate that the cognitive capacity for information integration is not as limited as usually assumed by proponents of bounded rationality (Gigerenzer, 2004).

The results of Experiment 1 conflict with the well-established findings from mouselab studies showing that when there is severe time pressure, simple LEX/TTB strategies are usually employed (e.g., Payne et al., 1988). As argued above, mouselab fosters the application of LEX/TTB strategies, because information searching consumes considerable resources. We remedied this problem by using an open information display and a choice-based strategy classification method.[3] Our findings indicate that limitations of the information integration capacity is not the major reason for individuals changing towards simple strategies when subjected to time pressure. A very simple alternative explanation seems more appropriate: individuals who – because of a certain research paradigm – do not have sufficient time to look up all pieces of information concentrate on the most important information. Our results converge with several recent findings showing that people tend to use WADD strategies instead of simple heuristics if information is openly presented (Bröder, 2000; 2003; 2005; Glöckner, 2006).

The observed decision time data further strengthen our point and provide converging evidence for the choice analysis. Decision times clearly speak against the application of a LEX/TTB strategy and against the application of a $WADD_{del}$ strategy but are in line with the predictions of $WADD_{auto}$ strategies. More importantly, decision times allow for ruling out some alternative explanations. It might be argued that individuals could have used the alternative heuristic: “choose the option favored by cue 1 unless consensually outvoted by cues 2 and 3.”[4] Obviously, such a strategy would not be frugal because it takes into account all cue values and at least ordinal information about cue validities; nevertheless, it would be easy to apply. However, such a strategy could not account for the observed systematic variations of decisions times. In particular, the significant main effects of the number of positive cue values for option 1 (pro_option1) and the number of positive cue values for options 2 and 3 (pro_option2/3) could not be explained. Furthermore, for cue patterns 1 to 6, for instance, equal decision times would be expected. However, as can be seen from error bars in Figure 2, decision time data differ significantly between these cue patterns. Overall, it is very unlikely that simple heuristics can account for the differentiated findings concerning decision times.

A caveat to the first experiment is that it employs a different kind of decision problem than the one that is used in a part of the classic mouselab studies (decisions from the monetary domain, e.g., Payne et al., 1988). The reason for this was that we tried to stay close to the material that has been recently used for examining fast-and-frugal heuristics (e.g., Bröder, 2005; Gigerenzer et al., 1999; Glöckner, 2006; Newell & Shanks, 2003; Newell, Weston, & Shanks, 2003; for a discussion of advantages of such decision tasks see Gigerenzer et al., 1999). Hence, one could argue that our findings are specific to our task instead of being caused by the use of an open information matrix. To rule out such an interpretation and to further investigate our hypothesis that individuals apply $WADD_{auto}$ strategies as long as time limits allow them to inspect all pieces of information, we ran another experiment using an identical task within the standard mouselab, with hidden information.

In the experiment, time limits were manipulated on three levels. The lenient time limit condition was designed to allow for the repeated inspection of all the information. The medium time limit condition provided just enough time to look up each piece of information once. The severe time limit condition did not allow all pieces of information to be looked up, but it provided approximately the self-selected average decision time which individuals used in Experiment 1. We expected that the majority of individuals to apply a WADD strategy in the lenient and medium time limit conditions but to change towards a LEX strategy in the severe time limit condition.

In the experiment, we additionally recorded information search parameters. One reason for this was to test whether our time pressure manipulation worked in limiting information search as described above. A second reason was to investigate whether information search parameters indeed converge with a strategy classification based on choice analysis. It was expected that there could be substantial differences. For simplicity, only two important parameters of information search were analyzed: the number of information boxes opened per cue and the information search index *PATTERN* (also called SI-index; Payne et al., 1988; for a critical view see Böckenholt & Hynan, 1994; see also Footnote 6 below). The PATTERN index indicates the relative proportion of cue-based and option-based transitions between information boxes. Given the acquisition of a particular piece of information, it can be detected if the next acquisition involves the same cue but a different option (a cue-based transition) or the same option but a different cue (an option-based transition). PATTERN is calculated by subtracting the number of cue-based transitions from the number of option-based transitions and dividing this difference by the sum of cue-based and option-based transitions. Thus, the PATTERN index indicates if individuals search for information in a more cue-based or more option-based manner. The PATTERN index has a range from -1 to 1. Negative numbers indicate a more cue-based information search, and positive numbers indicate a more option-based search. Negative scores are usually interpreted as evidence for non-compensatory decision strategies like LEX, whereas positive scores are seen as evidence for compensatory decision strategies like WADD.

Experiment 2

Method

Participants and design. Fifteen students (9 female, 6 male) from the University of Heidelberg took part in the experiment. Participation in the 30-minute study was either compensated for by course credit or a flat fee of € 4.00. Decision tasks were again manipulated within subjects. Again, 23 different cue patterns in six different versions were used (see Table 2). Additionally, the time limit for the information search was manipulated within subjects. In the lenient time limit condition, 8 seconds were available for an information search, information integration and making the choice. In the medium and severe time limit conditions, 3 seconds and 1.5 seconds were provided, respectively. The six versions of each cue pattern were equally assigned to one of the time limit conditions using a random procedure. Thus, the factor version was nested within the factor time limit, resulting in a 23 (CUE PATTERN) x 3 (TIME LIMIT) x 6 (VERSION), nested within-subjects design.

Materials and procedure. The cover story, instructions and materials from Experiment 1 were used in the experiment. Again, cue information was presented in an information matrix with options in rows and cues in columns (Figure 3). In contrast to the previous study, information was hidden in boxes. Each information box opened automatically when hit by the mouse cursor. Thus, it was not necessary to engage in the motor operation of clicking on the mouse. First, participants were introduced to the task and informed about the validity of the cues, as in Experiment 1. They were familiarized with the mouselab, and they completed eight test trials. The following 138 decision tasks were presented in three blocks, each with a different time limit. Time limits were tightened over the three blocks of trials, from 8 seconds (lenient), to 3 seconds (medium), to 1.5 seconds (severe). Blocks were separated by 1 minute breaks (black screen). For each decision task, participants could move the mouse to access information. A piece of information was visible only as long as the mouse was kept on the information box. A time bar was shown at the top of the screen to inform participants of time limits. The length of the bar decreased in proportion to the elapsed time. Immediately after the decision task was presented, the time bar started counting down the available time.

Again, participants were asked to make accurate decisions and to proceed as fast as possible. Furthermore, it was required that they make their choices within the mutual time limit. Options were selected by mouse click. If the time limit had elapsed, no further information search was possible. Nevertheless, participants were forced to make a decision and were subsequently reminded to keep within time limits. Choices, decision times and information-search parameters (opened information boxes and time for opening) were recorded.[5] Decision times were measured from the onset of the decision task to the selection of the option. The mouse pointer was initially centered in the upper left corner of the screen (i.e., left of the empty matrix field, see Figure 3). Each decision task was started by clicking on a button on an introductory screen. The mouselab software was created in Visual Basic 6.0 and was run under an MS Windows 98 environment on IBM compatible computers.

Results

Classification of decision strategies by choices. The same method as in the previous experiment was used to classify strategies. Each time limit block was analyzed separately. Note that the reduced number of analyzed choices reduced the statistical power and thereby increased the probability of LEX and EQW classifications. As explained in the results section of Experiment 1, two individual χ^2-tests have to turn out to be significant in order for one participant to be classified as a WADD user. With only 1/3 of the number of observations, it becomes less likely that existing effects will be detected at a specified alpha level (i.e., the beta error increases). This means the likelihood that a WADD user is classified as a user of an EQW or LEX strategy increases substantially, which should be corrected for. Therefore, in both tests an increased alpha level of α = .10 was applied. First, it was analyzed whether the choices in cue patterns 7, 10 and 13 differed from the choices in the remaining cue patterns, using individual χ^2-tests of independence (*number of observations* = 46). Then, the choices in patterns 4, 8, 11 and 18 were tested against an equal distribution (*number of observations* = 8). It turned out that under the lenient time limit condition, the majority of participants used a

WADD strategy (Table 3). Under the medium condition, participants mainly retained their decision strategy. Three former WADD users changed to the EQW and LEX/TTB strategies. When the time limits were severe, almost all the participants changed to a LEX/TTB strategy. Thus, choice data are in line with our expectation that decision strategies only change if time pressure does not allow for inspecting all pieces of information (i.e., under severe time limit).

Decision time. Again, decision time was log-transformed to decrease the influence of outliers and to reduce deviations from normal distribution. A 23 (cue pattern) x 3 (time limit) x 2 (repeat) repeated measurement ANOVA, with log-transformed decision times as dependent variables, revealed the time limit to have a significant effect, $F(1.3, 18.4) = 457.4$, $p < .001$, $\eta^2 = .97$. This indicates that our time limit manipulation worked. With decreasing time limits, the decision time decreased. The median decision times for the lenient, medium and severe time-limit conditions in seconds were 4.28, 2.56 and 1.49 respectively. Furthermore, cue pattern was found to have a significant main effect, $F(3.1, 44.0) = 5.80$, $p < .001$, $\eta^2 = .29$. Again, for the critical patterns 7, 10 and 13, the decision times were particularly high. Similarly high decision times were found for cue patterns 4, 17, 18, 19 and 23. A considerable portion of choices (22% vs. 49%) under the medium and severe time limit conditions was made after the time limit allotted for the information search had elapsed.

Number of opened information boxes. The distribution of inspected information boxes per cue was analyzed using a 3 (cue) x 3 (time limit) multivariate analysis of variance (MANOVA), with the numbers of viewed information boxes as dependent variables. The main effect for cue was highly significant, *Pillais* $V = .84$, $F(2, 13) = 33.14$, $p < .001$, $\eta^2 = .84$, indicating that participants looked up more pieces of information for more valid cues (Table 4). There was also a significant main effect for the time limit, *Pillais* $V = .90$, $F(2, 13) = 56.54$, $p < .001$, $\eta^2 = .90$. As the time limit was decreased, the number of opened information boxes also decreased. As indicated by the information boxes index in Table 4, in the lenient time limit condition, on average, participants inspected each information box more than once;

in the medium time limit condition, on average each information box was opened once; and in the severe time limit condition, only 61 percent of the information boxes were inspected. Thus, the time limit manipulation worked as intended. The medium time limit condition offered just enough time to inspect all the information boxes once. The interaction between the factors cue and time limit was also significant, *Pillais V* = .81, $F(4, 11) = 11.59$, $p < .001$, $\eta^2 = .81$. It was found that participants focused their information search on the most valid cue even more when there were decreasing time limits.

PATTERN index. To further investigate search strategies, the information-search index *PATTERN* was computed (Payne et al., 1988).[6] A MANOVA was conducted with the different PATTERN index scores for the time limit conditions as dependent variables. There was a significant effect for time limit, *Pillais V* = .54, $F(2, 13) = 7.64$, $p = .006$, $\eta^2 = .54$. Under the first two conditions, there was a slight preference for option-based searches, whereas under the severe time-limit condition a strong preference for cue-based searches was observed (Table 4; right column). Two contrasts were computed to further pinpoint this effect. It turned out that there was no difference in the PATTERN index between the lenient and the medium time limit conditions, $F(1, 14) = .16$, $p = .70$, $\eta^2 = .01$. However, there was a significant difference of the severe time limit condition compared to the medium and lenient time limit conditions, $F(1, 14) = 16.32$, $p < .01$, $\eta^2 = .54$. Thus, in line with our expectation, the information search only changed when decision time was too short to investigate all pieces of information.

For each person and each time limit block, it was further analyzed whether the information search – as indicated by the PATTERN index – aligned with the results of the choice-based strategy classification reported above. In 73 percent of the cases ($N = 45$; note that each comparison was computed for three time limit condition per person resulting in a total of 45 observations), both parameters were consistent. In 8 cases (18%), participant searches were more cue based but they still used a WADD strategy; in 3 cases (7%)

participants used option-based searches but decided in line with a LEX/TTB strategy; and in 1 case (2%) a cue-based information search was used but the decisions were in line with an EQW strategy. In line with our expectation, the direction of the information search and the direction of the information integration diverged for a considerable portion of participants. Note, however, that over 70 percent of the classifications still corresponded.

Discussion

The experiment examined whether changes in decision strategies in mouselab experiments under time pressure (e.g. Payne et al., 1988) are due to limitations in the information search instead of limitations in the cognitive capacity, as is generally assumed. It was found that when allotted sufficient time to inspect all the information (i.e., under the lenient and medium time limit condition), participants showed choices in line with WADD strategies. Under the severe time limit of 1.5 seconds, it was no longer possible to inspect all the information boxes. Participants inspected only the most important information – particularly the information of the most valid cue – and decided on the basis of this information, using a LEX/TTB strategy. Thus, the results indicate that it was not the limitation of the cognitive capacity for information integration but rather the limitation of the information search that induced the increased use of LEX/TTB strategies.

The results also show that there is a considerable intra-individual stability in strategy use under the lenient and medium time limit conditions. This aligns with findings by Bröder (2005); furthermore, it speaks for the reliability of the strategy classification method based on choices.

A comparison of search-based strategy analysis and choice-based strategy classification shows convergences as well as differences (cf., Bröder, 2003). In line with strategy classification, the analysis of the PATTERN index indicates that a strategy shift occurs only under the severe time limit condition. However, from the PATTERN index it was not possible to detect the clear dominance of WADD strategies under the other conditions.

For a considerable portion of participants, a divergence between the direction of the information search and the conceptual direction of information integration was observed.

Note that the mouselab builds on the assumption that overt search-movements map onto hidden cognitive processes (and vice versa). For instance, from the ratio of cue-based and option-based transitions in the information search, conclusions are drawn about whether participants actually use cognitive strategies that imply cue-based (e.g., LEX/TTB) or option-based (e.g., EQW) information integration. Although persuasive on first glance, this reasoning might be misleading. The type of information search and information integration could differ considerably because information can be temporarily stored in memory before being processed further (Bröder, 2003). In other words, overt information searches and internal processes of integration and evaluation might be dissociated (Billings & Marcus, 1983; Maule, 1994; but see Bröder, 2003). The results of Experiment 2 indicate that this dissociation occurs for a considerable portion of participants in decision tasks of medium-level complexity.

By now we have demonstrated in two experiments that choices and decision time patterns are in line with our hypothesis that individuals are able to quickly integrate multiple pieces of evidence in a weighted additive manner. There is conclusive evidence that the majority of individuals takes into account available pieces of information and considers them according to their validity. Thus, our results cannot be explained by fast-and-frugal heuristics (Gigerenzer et al., 1999) that ignore either cue values or cue validities. The applied decision strategies are obviously not frugal but exhaustive in their use of available information.

Nevertheless, the findings could still be challenged in two ways. First, it might be questioned whether the results generalize to more complex decision tasks. More importantly, there could still be some doubt that the results could be explained by alternative models. One possible hypothesis is that individuals encode the array of information as a constellation. This constellation could be compared with different prototypes (Juslin, Olsson, & Olsson, 2003;

Olsson, Enkvist, & Juslin, 2006), or mere perceptual pattern recognition processes could be used to quickly reach a decision. This alternative explanation was investigated in the third experiment.

To test the alternative explanation, the constellation of cue information was held constant and the validity of only one cue was manipulated without changing the constellation (i.e., without changing the order of cues in the cue hierarchy). If decisions are made based solely on the conceptual constellation of cue information, this manipulation should not influence decisions. Furthermore, the presentation order of cues in the information-matrix was randomized to prevent mere perceptual pattern recognition processes.

To allow for deriving a high proportion of diagnostic decisions, more complex decision tasks with six cues and two options were used. Confidence judgments were measured to further investigate decision processes (cf., Table 1). According to a LEX/TTB strategy, confidence judgments should depend on the validity of the differentiating cue only. According to a $WADD_{auto}$ strategy, confidence judgments should depend on the difference between the weighted sums of cue values and cue validities for the available options.

Experiment 3

Method

Participants and design. Sixty-three students (55 female, 8 male) from the University of Erfurt took part in the experiment. The 20-minute experiment was part of a one-hour experimental battery of unrelated experiments. Students received € 6.00 for their participation in the battery. Decision tasks were again manipulated within-participants resulting in a 6 (CUE PATTERN) x 4 (CUE VALIDITY) x 3 (REPETITION) design.

Materials and procedure. As in the previous experiments, participants made decisions between oranges based on the predictions of different testers. Decision tasks with six cues and two options were used. Six cue patterns were used (CUE PATTERN; Table 5). In cue patterns 1, 2 and 6, an equal number of cues had positive cue values for both options. In cue patterns 3, 4 and 5, the most valid cue made a prediction contrary to at least two other cues. Cue patterns were repeated three times with randomized orders of options and cues (REPETITION). Again, individuals were provided with explicit information about the probability of correct predictions made by each tester. This probability was varied for the most valid cue from .80 to .95 in steps of .05 (CUE VALIDITY). The accuracy probabilities were constant for the remaining cues 2 to 6 at levels of .75, .70, .65, .60, and .55.

Independent of the cue validity manipulation, the LEX/TTB strategy predicts choices for option 1 in all six cue patterns, because the most valid cue always points towards this option. Similarly, the EQW strategy predicts all choices for options 2 in cue patterns 3, 4 and 5 and a random selection of options in the remaining cue patterns. Also, independent of the manipulation of the validity of cue 1, the WADD strategy predicts choices for option A in cue patterns 1, 2 and 6.

In cue patterns 3, 4 and 5 an *ignorant WADD* strategy which is based on a simple weighted sum of the cue values (i.e., 1 / -1) and the provided accuracy probabilities of cues (e.g., .55 for cue 6) would make predictions for option B only. Note that such a strategy could easily be misleading because it does not take into account that cues with a probability of .50 are not informative at all and should be ignored (cf., Experiment 1). It would be more appropriate that participants transform provided probabilities into cue weights so that information about cues with a probability of .50 gets a weight of 0. Individuals who use an ignorant WADD strategy would select option B in cue patterns 3, 4 and 5 independent of the cue validity manipulation. Individuals who take into account the problem and correct their decision weights should show decreasing choices for option B with increasing validity of cue 1.

The cue validity manipulation should only influence choices if participants use decision strategies that are based on processes that integrate information in a weighted additive manner; no influence of the cue validity manipulation on choices would be predicted if individuals base their decision simply on the constellation of cues. Thus, the manipulation of cue validities was used for testing the alternative explanation raised above.

The central instructions were essentially the same as in the previous experiments. The cover story was shortened in that participants were only instructed to make decisions about oranges based on the predictions of testers. An additional instruction was included to assure that the probabilistic information about the accuracy of the predictions of cues was well understood (see Appendix B). Another instruction was included that informed individuals about the fact that confidence judgments were measures after each trial and that different oranges and testers would be presented in each new trial. Information was presented in an open matrix format and individuals were instructed to make a high quality decision and to proceed as quickly as possible. Participants selected options via mouse click (Figure 4). After each decision, individuals were asked to indicate the confidence in their decision on a continuous horizontal scroll-bar based on the instruction “Please indicate how certain you are of your decision!” Only the extreme values of the scroll-bar were labeled (i.e., *very uncertain* and *very certain*). The scroll-bar was presented below the information matrix which remained visible until the judgment was made. After that, a screen was shown on which participants were instructed to click on the continue button to work on the next decision. This screen was also used to hold the initial mouse position approximately constant (i.e., in the middle of the screen).

After one learning trial, individuals were presented with 72 decision tasks which consisted of different versions of the six cue patterns presented in Table 5. Each cue pattern was realized for all four cue validity conditions and each of the resulting decision tasks was repeated three times. Decision tasks were presented in individually randomized order. The order of the options and the order of the cues in each decision were also individually randomized for each trial.

Results and Interpretation

Aggregated choice analysis. Proportions of choices for option B in the six cue patterns and the four cue validity conditions are depicted in Figure 5. There were very few decisions for option B in cue patterns 1, 2 and 6, but there was a considerable proportion of choices for option B in cue patterns 3, 4 and 5, with choice proportions for option B decreasing with increasing validity of cue 1. To test whether choices differ significantly between the six cue patterns, a χ^2- test against an equal distribution of choices for option B for the six cue patterns was conducted which turned out to be highly significant, χ (5; N = 789) = 1176.6, $p < .001$. Thus, against the predictions of a LEX/TTB strategy aggregated choices differ significantly between cue patterns indicating that not only the most valid cue was taken into account. To test whether choices differ between levels of cue validity for cue 1, a χ^2- test against an equal distribution of choices for option B in the four cue validity conditions was conducted. The test turned out to be highly significant, χ (3; N = 789) = 86.5, $p < .001$. Thus, against the predictions of the EQW strategy choices are influenced by the cue validity manipulation, indicating that cue information was considered according to its validity. Finally, a test was made to determine whether the manipulation of cue validities had differential effects on choices for option B in different cue patterns using a χ^2- test of independence between cue validity and cue pattern. The test also turned out to be highly significant, χ (15; N = 789) = 35.6, $p = .002$, indicating an interaction effect of cue pattern and cue validity on choices for option B. In line with the predictions of a WADD strategy (but not with the predictions of an ignorant WADD strategy) in cue patterns 3, 4 and 5, choices for option B decreased with increasing cue validity whereas the cue validity manipulation did not influence choices in the remaining cue patterns. Most importantly, the significant effects of the cue validity manipulation and the interaction effect rule out the hypothesis that individuals simply react to constellations of cues because the constellation of cues was held constant and only cue validities of the most valid cue were manipulated.

Individual strategy classification. To investigate decision strategies more closely, individual choice patterns were analyzed relying on the methodology introduced in the previous experiments. For each individual, two χ^2- tests were conducted to test against the predictions of the LEX/TTB and the EQW strategies. The first tested whether the proportion of choices for option A or B were the same in the cue patterns 1, 2 and 6 as compared to the cue patterns 3, 4 and 5 using a χ^2- test of independence. A significant difference would indicate that individuals took into account also less valid cues and did not use a LEX/TTB strategy. A second χ^2- test was carried out to test whether the choices for option A and B were equally distributed in cue patterns 1, 2 and 6. A significant deviation from the equal distribution would indicate that individuals took into account the validity of cues and did not use an EQW strategy. A significance level of α = .05 was applied in both tests. Individuals for whom no significant differences were detected were classified as users of LEX/TTB or EQW. The results of the strategy classification are shown in Table 3 (last row). As already indicated by the aggregated choice data, for the large majority of individuals choice patterns could be best explained by a WADD strategy. However, as in the previous experiments there was also a minority of LEX/TTB users.

Decision times. The median of decision times was 3.71 seconds indicating that individuals obeyed the time pressure instruction (*SD* = 4.29, *skew* = 8.26, *kurtosis* = 127.7). Note that the increase in decision times compared to the previous experiments is likely to be due to the fact that six rather than three cues were provided and that the presentation order of cues was randomized, which was not the case in Experiments 1 and 2. For the further analyses, decision times were again log-transformed to reduce the influence of outliers and to account for deviations from normal distribution. A 6 (cue pattern) x 4 (cue validity) x 3 (repetition) repeated measurement MANOVA with log-transformed decision times as dependent variables was conducted to investigate decision times. The main effects for cue pattern turned out to be significant, *Pillais V* = .81, $F(5, 58) = 48.1$, $p < .001$, $\eta^2 = .81$. The highest decision times were observed for cue pattern 5 and the lowest decision times were found for cue patterns 1 and 2 (Figure 6; *SE* ranged from 0.014 to 0.027). Thus, the finding that decision times are particularly long in decisions with conflicting cue information (i.e., cue patterns 3, 4 and 5) could be replicated. There was also a significant main effect for cue validity, *Pillais V* = .43, $F(3, 60) = 14.9$, $p < .001$, $\eta^2 = .43$. Decision times decreased with increasing validity of cue 1 (see Figure 6). And there was a significant main effect for repetition indicating learning effects, *Pillais V* = .71, $F(2, 61) = 75.4$, $p < .001$, $\eta^2 = .71$. The means of the log-transformed decision times for the three repetitions (with *SE* in parentheses) were 3.68 (0.016), 3.59 (0.012), and 3.54 (0.012). There was also a significant interaction between cue validity and cue pattern, *Pillais V* = .39, $F(15, 48) = 2.0$, $p = .03$, $\eta^2 = .39$.

To explore whether decision times differ between LEX/TTB users and WADD users, the MANOVA was rerun with the decision strategy resulting from the strategy classification as an additional factor. There was no main effect of strategy on decision time, $F(1, 61) = 0.36$, $p = .55$, $\eta^2 = .01$. The two-way interactions between decision strategy and cue validity turned out to be significant, *Pillais V* = .14, $F(3, 59) = 3.14$, $p < .05$, $\eta^2 = .14$; and the three-way interaction between decision strategy, cue validity and cue pattern also turned out to be significant, *Pillais V* = .47, $F(15, 47) = 2.82$, $p < .01$, $\eta^2 = .47$. The non-significant main effect indicates that participants were able to integrate all pieces of evidence according to a WADD rule in approximately the same time that (other) participants needed to apply a simple LEX/TTB rule. However, the substantial interactions indicate that the application of the different decision strategies lead to different patterns of decision time (cf., Table 1).

Confidence judgments. Confidence ratings were measured on a horizontal scroll-bar, which contained text labels for the extremes (see methods section) but did not contain value labels. The ratings on the scroll-bar were internally recorded on a scale ranging from -100 to 100. Confidence judgments were analyzed using a 6 (cue pattern) x 4 (cue validity) x 3 (repetition) repeated measurement MANOVA. The main effect for cue pattern turned out to be significant, *Pillais V* = .67, $F(5, 58) = 23.9$, $p < .001$, $\eta^2 = .67$. High confidence was observed in cue patterns 1, 2 and 6 and lower confidence ratings were observed in cue patterns 3, 4 and 5 (Figure 7; *SE* ranged from 3.2 to 6.0). There was also a significant main effect for cue validity, *Pillais V* = .46, $F(3, 60) = 17.0$, $p < .001$, $\eta^2 = .46$. Confidence increased with increasing validity of cue 1 (see Figure 7). There was a significant interaction between cue validity and cue pattern, *Pillais V* = .49, $F(15, 48) = 3.1$, $p = .001$, $\eta^2 = .49$. The cue validity manipulation led to a general increase in confidence except for cue pattern 5, in which a decrease was observed. This differential effect fits nicely with the predictions of a WADD strategy because only in this cue patterns is an increase in cue validity for cue 1 likely to lead to a decrease in the difference between options.

To more specifically test the hypothesis that confidence judgments increase with increasing differences between the weighted cue values of options, correlations between difference scores and confidence judgments were computed. Difference scores were computed by $D = \left| \sum c_i^{O_1} w_i^{O_1} - \sum c_i^{O_2} w_i^{O_2} \right|$ in which $c_i^{O_1}$ and $c_i^{O_2}$ are cue values of cue *i* for options 1 and 2 (i.e., -1 or 1). $w_i^{O_1}$ and $w_i^{O_2}$ are decision weights for options 1 and 2. Decision weights were calculated in three different ways. First, according to an ignorant WADD strategy, accuracy probabilities (e.g., .75 for cue 2) were directly used as decision weights ($w_{cue} = p_{cue}$); second, difference scores were calculated by correcting for the fact that information of cues which have an accuracy probability of .50 only are uninformative using $w_{cue} = p_{cue} - .50$; third, based on the empirical observation that an option that is recommended by one cue with an accuracy probability of .85 is approximately equally attractive to an option which is recommended by two cues with a probability of .75 and .70 (i.e., choice proportions for option A and B are almost equal in cue pattern 3 with a cue validity of .85 for cue 1; see Figure 6), a correction of $w_{cue} = p_{cue} - .60$ was used because this correction leads to equal weighted cue values for both options in this specific decision task. Thus, three correlations were calculated between confidence judgments and difference scores based on ignorant WADD, theoretically corrected WADD and empirically corrected WADD. There was a significantly negative correlation for difference scores based on ignorant WADD, $r = -.51$, $t(70) = -5.01$, $p < .001$ (two-tailed), but significantly positive correlations for theoretically corrected difference scores, $r = .35$, $t(70) = 3.16$, $p = .002$ (two-tailed), and empirically corrected difference scores, $r = .66$, $t(70) = 7.37$, $p < .001$ (two-tailed). The negative correlation between confidence ratings and ignorant WADD scores is in line with findings concerning choices that indicate that individuals did not use decision weights in such a way. For the corrected difference scores substantial positive correlations between confidence judgments and difference scores were found which support the hypothesis derived from WADD strategies that the difference of the weighted cue values between options influences confidence judgments. Thus, the findings lend further support for our general hypothesis that individuals integrate information in a weighted additive manner. If cue validities or cue values would be ignored, no correlation would be expected.

Discussion

In the third experiment, the general findings of the previous experiments could be replicated and strengthened by additional evidence. Also, in this experiment the large majority of individuals took into account cue values and cue validities. Choices and confidence judgments indicate that the information was integrated in a weighted additive way. The low overall decision times as well as the systematic variations of decision time indicate that individuals thereby relied on automatic processes (i.e., $WADD_{auto}$). It could be shown that individuals are sensitive to minor manipulations of cue validities which do not change the general constellation of cue values. This clearly speaks against the idea that cue information is merely encoded as a constellation and compared with prototypes. Individuals integrate information in a weighted additive manner that is sensitive to minor changes in cue validities. Note that this observation also clearly rules out alternative fast-and-frugal heuristics that are all based on ignorance or only ordinal considerations of cue validities (as the one discussed as an alternative explanation for the findings in Experiment 1).

The analysis of confidence judgments lends additional support for the fact that cue values are integrated in a weighted additive manner; in particular, the substantial correlation between confidence judgments and difference scores clearly rules out that cue values or cue validities are ignored in the decision. Our findings furthermore indicated that individuals do not use cue probabilities as decision weights in an ignorant way. They correct for the fact that cues with a probability of .50 have no informative value. However, it should be noted that we cannot rule out that individuals would use an ignorant WADD strategy if probabilities are less clearly explained in the instructions (cf., Experiment 1).

General Discussion

In process tracing studies, it has been repeatedly shown that individuals employ simple strategies that minimize the amount of considered information and the mental effort invested in the decision. Although the question of strategy selection is still unsolved (for recent approaches see Rieskamp & Otto, 2006; Glöckner & Betsch, 2007; Lee & Cummins, 2004; Newell, 2005), it is often assumed that time and capacity constraints provoke strategy shifts towards a LEX/TTB rule (e.g., Bettman, Luce, & Payne, 1998; Rieskamp & Hoffrage, 1999). Moreover, simulations and experimental results converge in showing that LEX/TTB rules can lead to quite accurate decisions, especially under time pressure (e.g., Payne et al., 1988). Taken together, these findings strongly corroborate the cornerstone assumptions of the bounded rationality approach that have been directing and inspiring psychological decision research over the last decades. One of these assumptions holds that humans commonly lack the cognitive resources to apply extensional, compensatory strategies such as the WADD rule, particularly under time pressure. Based on recent dual processing models, we hypothesized that this assumption does not hold if decision strategies are considered that make use of automatic processes for information integration. We further argued that the prominent mouselab method hinders the application of such strategies and is not able to detect them.

Herbert Simon (1955) himself claimed that the boundaries he described pertain to the deliberative side of the cognitive system: "My first empirical proposition is that there is a complete lack of evidence that, in actual choice situations of any complexity, these [EU] computations can be, or are in fact, performed… but we cannot, of course, rule out the possibility that the *unconscious is a better decision-maker than the conscious*" (p. 104, italics added). Unfortunately, the research method regularly used in studying strategy application, the mouselab, hinders both the operation and the observation of automatic processes. It forces decision makers to engage in a step-by-step consideration of information. The units of observation are the steps represented by the movements of a computer mouse. The underlying assumption of this method is that the overt information search behavior mimics hidden cognitive processes. We doubt that this assumption is justified. Moreover, we have claimed that urging individuals to uncover information one piece at a time binds task resources such that decision makers in the mouselab cannot unfold their processing potential since they have to waste most of their time and effort on the information search. Under time constraints, they are not able to collect as much information as they could process and therefore they might work below their computational capacity. If this reasoning is true, the conclusions drawn from mouselab studies would have to be reconsidered. Accordingly, the prevalence of shortcut strategies under mouselab conditions might not provide evidence of limitations in the cognitive apparatus but simply show limitations in information search (i.e., uncovering hidden information in a matrix). Hence, we suspected that the predominance of LEX/TTB strategies found in the majority of the mouselab studies under time pressure were caused by the experimental procedure.

We tested this assumption in three experiments using choice-based strategy classification with open information presentation, as well as a standard mouselab under different time pressure conditions. The results indicate that individuals are able to apply WADD rules within an astoundingly narrow time period if the information search is not restricted by artificial conditions. Most importantly, we could replicate prior findings (e.g., those from Payne et al., 1988) in Experiment 2 when we employed the standard mouselab. In such an environment, participants searched for information in accordance with the LEX/TTB rule when time limits were too tight to inspect all pieces of information. In a third experiment, we investigated the cognitive processes that allowed individuals to quickly integrate information according to a WADD rule. Specifically, we have shown that choices are sensitive to small changes in cue validities even if the constellation of cues does not change. This rules out the alternative explanation that individuals only encode constellations of information and compare them to prototypes. Taken together, the studies provide strong evidence for our claim that the predominance of simple, non-compensatory strategies documented in the mouselab studies was caused by the experimental method and not by limitations of the cognitive system. Testing the potentials of the human mind in the mouselab is like testing the power of a Ferrari's engine in a parking lot. Obviously, one would not expect the Ferrari to unfold its powers in such a constrained environment. Rather, we should run it on a speedway before making a verdict about its performance.

Our results indicate that individuals are capable of performing decision strategies involving complex information integration in an astoundingly short time period. Thus, the assumption that limitations of the cognitive capacity for information integration cause the application of simple serial strategies – as proposed by proponents of the bounded rationality approach – has to be revised. As anticipated by Herbert Simon, there seems to be another possibility for relieving humans from the burden of endless, complex mathematical computations. Evolution may have equipped humans with very powerful cognitive tools that capitalize on the automatic integration of information (Glöckner, in press b). It has been shown that even sticklebacks select mating partners by a weighted consideration of multiple pieces of evidence (Künzler & Bakker, 2001) and that monkeys react to stimuli by considering probabilities and values in a weighted additive way (cf., Glimcher, Dorris, & Bayer, 2005). Thus, from an evolutionary perspective it seems rather unlikely that only humans lack the cognitive capacity for such operations.

According to our experiments, automatic strategies are likely to be used if a quick purview of information is possible. However, Glöckner and Hodges (2006) also found evidence for automatic strategies in experiments in which information had to be retrieved from memory. However, further research will be needed to investigate the application of automatic strategies under different context conditions including monetary multi-attributive decisions, which have often been used in classic mouselab studies.

Cognitive Processes Underlying the WADD$_{auto}$ Strategy

Based on our data it is not possible to conclusively differentiate between the automatic processing models proposed by different authors (e.g., Beach & Mitchell, 1996; Busemeyer & Townsend, 1993; Dougherty et al., 1999). Nevertheless, only such models that predict choices based on weighted additive information integration and systematic differences in decision times and confidence judgments can account for our findings.

This is particularly the case for parallel constraint satisfaction (PCS) network models (Betsch, 2005; Thagard & Millgram, 1995; Simon, Krawczyk, & Holyoak, 2004; Glöckner, Betsch, & Schindler, 2006; Glöckner, 2006; Glöckner, in press a; Glöckner, in press b; Glöckner & Betsch, 2007). PCS models postulate that information is not integrated according to deliberate integration rules but that the constellation of information is weighed as a whole. Conceptually, mental representations are formed based on available information (i.e., cue values and cue validities) and automatic processes operate towards maximizing coherence within the mental representation. These processes lead to an automatic restructuring of the decision task so that a consistent interpretation (“Gestalt”) emerges in which one option clearly dominates the others (cf., Montgomery, 1989; Svenson, 1992). Glöckner (2006) used an a priori simulation approach to show that PCS network models predict choices that approximate weighted additive information integration. Furthermore, PCS models predict an increase in decision times when there is an increase in the evidence supporting the not-favored options and when there is a decrease in the evidence supporting the favored option. Corresponding main effects on decision time were observed in Experiment 1.

Another comprehensive model that could account for the findings reported in this paper is the decision field theory (Busemeyer & Townsend, 1993). According to this theory, evidence for the available options is accumulated in a random-walk process until the specific threshold for the decision is reached. Information is thereby integrated in an additive manner so that the model could account for our findings concerning choices. Furthermore, in line with our decision-time data decision field theory predicts that an increase in conflicting information will lead to an increase in decision time because more information has to be integrated to reach the threshold.

However, results from other studies (Glöckner, Betsch, & Schindler, 2006; Holyoak & Simon, 1999; Simon, Krawczyk, & Holyoak, 2004; Simon, 2004; cf., Russo, Medvec, & Melloy, 1996; Russo, Meloy, & Medvec, 1998) indicate that parallel constraint satisfaction models might be empirically more appropriate. The studies show that decision making is not carried out in a *unidirectional* manner, by reasoning from cues to choices only. Cue information itself is substantially influenced within the decision process by *bidirectional* reasoning processes (Holyoak & Simon, 1999; for a related discussion of bidirectional processes in perception see Goldstone, Steyvers, Spencer-Smith, & Kersten, 2000). Simon (2004) summarized his empirical findings concerning PCS models as follows: (a) with the emergence of the decision task, the mental representation of the task shifts towards a state of internal consistency (*coherence shifts*): the information that supports the emerging decisions is accepted, and the information that supports the alternative is devalued or ignored; (b) people are not aware of these coherence shifts, and the ensuing decision is “experienced as rationally warranted by the inherent values of the variables, rather than be an inflated perception imposed by the cognitive system" (p. 545); (c) these coherence shifts, which are caused by consistency maximizing processes, "play an operative role in the decision process" (p. 546). As outlined in more detail by Simon, Snow and Read (2004), coherence shifts cannot be explained by decision field theory (or other theories like information integration theory, Anderson, 1981; 1996) that assume a pure unidirectional reasoning from cue information to choices. In contrast, such bidirectional processes are the core operations underlying PCS models (Simon, 2004).

How Properties of Decision Tasks Influence Decision Behavior

The often used research paradigm mouselab seems to influence strategy selection by restricting the information search. Certainly, numerous decision situations can be identified in which information is looked up serially. This can, for instance, be observed in first-year law students who check legal cases in a serial manner by looking up relevant aspects piece by piece following an implicit check list. If they are put under time pressure, they will probably try to speed up and if time pressure increases further they will restrict decision making to the most important information (cf., Payne et al., 1988). It could be expected that customers who aim to buy a product without any prior knowledge about it might behave in a similar way. For these situations, findings from mouselab studies are likely to be valid. However, generalizations about results based on this specific research paradigm should be made with caution. Our data indicate that it is not possible to generalize about the finding that time pressure necessarily leads to the application of simple non-compensatory strategies such as LEX/TTB to decision situations in which information is instantly available. It could be expected that in many decision tasks a huge amount of information is instantly available and taken into account in the decision. This is, for instance, the case if expert decision makers like experienced judges are confronted with complex legal cases. Interestingly, legal institutions like the German code of criminal procedure requires judges not only to take into account all formal evidence of the case according to its validity but also to consider cognitions formed on the basis of the holistic impression of the trial (Glöckner, in press b; Schoreit, 2003).

Taking a somewhat broader perspective it can be argued that the properties of the decision task influence decision-making processes (cf., Payne et al., 1992). According to our data, it is thereby important to differentiate decision tasks in which information is instantly available and decision tasks in which this is not the case. In situations in which no information is instantly available (e.g., because no information is presented and no prior knowledge is available), information has to be looked up in a serial manner. If there is doubt that all information can be inspected (e.g., because of time pressure) it is reasonable to assume that decision makers start with the most important information (cf., Experiment 2; Payne et al., 1988). Similarly, in situations in which expected gains from the information search are estimated to be lower than its costs, only the most important information is inspected (cf., Beach & Mitchell, 1978; Newell & Shanks, 2003). Also, if a person has learned from repeated feedback that the environmental structure is so that only one cue is needed to make good decisions (e.g., because the validity of the other cues taken together is smaller than the validity of this cue or because all cues are highly correlated), the person will ignore less valid cues and apply a LEX/TTB strategy (Rieskamp & Otto, 2006). It is important, however, to note that these strategy shifts are not caused by limitations of cognitive capacity but contingent upon properties of the decision task and the environment.

It is also not unlikely that the selection of decision strategies is influenced by whether decision tasks are based on multiple attributes (e.g., choices between cars based on the attributes price, color, and mileage) or multiple cues (e.g., city-size decision tasks). Attributes are assumed to be independent, whereas cues are usually highly correlated (Glöckner, 2006). The former kind of decision tasks were often used in the classic mouselab studies (e.g., Payne et al., 1988), whereas the latter have been investigated in more recent research inspired by the adaptive toolbox model (Gigerenzer et al., 1999; cf., Bröder, 2003; Bröder & Schiffer, 2003a). It could be expected that decision tasks based on highly correlated cues lead to an increased use of simplifying strategies (e.g., LEX/TTB) because further cues do provide little additional information. However, our data indicate that even in the latter situations WADD strategies are most often applied.

Furthermore, the format of information presentation might play an important role in strategy selection. Bröder and Schiffer (2003a) could, for instance, show that a textual presentation of information increased the use of LEX/TTB strategies as compared to decision tasks in which the information is provided as a picture. In line with recent research (e.g., Bröder, 2005), we used a very simple symbolic presentation format (i.e., +/-) to present dichotomous information, whereas Payne et al. (1988) used numbers to present information with multiple levels. It is not unlikely that this could also influence strategy selection. Remember, however, that such influences would not challenge the internal validity of our findings because we held these factors constant between Experiments 1 and 2.

Further research using different methods will be necessary in order to explore and disentangle the effects of the research method and other context variables. From our point of view, it is suboptimal that some of the methods that are often used to identify decision strategies (i.e., the mouselab; think aloud protocols) seem unsuitable for identifying an important class of decision strategies, namely, strategies that capitalize on automatic processing of information. Relying more strongly on eye-tracking methods and methods like analyzing individual choices with considerations of decision times and confidence judgments could be fruitful research approaches to improve our understanding of these obviously important decision strategies.

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Footnotes

1. Note that in research on human judgments, the term “heuristics” refers to strategies that are based on automatic processes (cf., Kahneman & Frederick, 2002)

2. The effect-size measures reported in this paper are all partial η^2-values. Therefore, values do not add up to 1.

3. Taking a methodological critical perspective, it must be discussed whether the choice-based strategy classification method used in Experiment 1 is sufficiently valid. One point of criticism is that focusing on three major decision strategies is a somewhat simplistic perspective considering the wide spectrum of heuristics proposed (for an overview see Payne et al., 1988). Note, however, that because of the simplicity of the material used in our experiments (i.e., dichotomous cues), the choice predictions of other strategies converge with the predictions of the considered strategies. For instance, elimination by aspects (Tversky, 1972) and lexicographic semi-order (Tversky, 1969) strategies converge with LEX. The majority of confirming dimensions strategy (Russo & Dosher, 1983), the strategy of good features (Alba & Marmorstein, 1987) and other (unweighted) tallying heuristics predict the same choices as those arrived at with an EQW strategy. Thus, the results can be understood in a broader sense, as a classification into three broad classes of strategies: lexicographic elimination strategies, equal weighting strategies and weighted additive strategies. Furthermore, it might be criticized that the overall high number of significance tests caused by computing two tests for each individual led to an overestimation in the share of WADD users due to the accumulation of alpha errors (Glass & Hopkins, 1996). Considering that predictions were made a priori and that tests were run on separate data points, we take the position that such a correction would not be appropriate. Furthermore, the results concerning the portions of decision strategies converge with the results from studies in which different classification methods were used (Glöckner, 2006) as well as decision time results reported in this paper. Thus, we argue that it can be assumed that the method is sufficiently valid.

4. We thank Peter Ayton for the suggestion of this alternative heuristic.

5. For pragmatic reasons, information-search data were recorded only for the first 20 inspected information boxes per decision task.

6. Note that transitions in which the acquisition involves both another cue and another option are not considered in the index and that the PATTERN index for each participant was computed using the total number of cue-based and option-based transitions for the 46 decision trials in each time limit condition. It has been argued that the former could lead to biased strategy classification results if the number of options and the number of cues (or dimensions) in the mouselab matrix differ (Böckenholt & Hynan, 1994). This was not the case in our experiment. Nevertheless, we additionally calculated the unstandarized *SM** index that also takes into account all other transitions (Böckenholt & Hynan, 1994). As expected, this did not change our results substantially ($SM*_{lenient\ TP}$ = .06, $SM*_{medium\ TP}$ = .07, $SM*_{sever\ TP}$ = -.30).

Table 1

Predictions of Decision Strategies

	Decision Strategies			
	LEX/TTB	EQW	$WADD_{del}$	$WADD_{auto}$
Choices				
1. Less valid cues are ignored[1,2,3]	Yes	No	No	No
2. Cue validities are ignored[1,2,3]	No	Yes	No	No
3. Weighted additive information integration[1,2,3]	No	No	Yes	Yes
Decision Times				
1. Time dependent on the necessary cues to differentiate with a LEX strategy[1]	Yes	No	No	No
2. Time equal for all cue patterns[1,3]	No	Yes	Yes	No
3. Time decreases with increasing differences between the options[1,3]	No	No	No	Yes
Confidence Judgments				
1. Confidence dependent on the validity of the differentiating cue with LEX[3]	Yes	No	No	No
2. Confidence increases with increasing differences between the options[3]	No	No	Yes	Yes

Note. Hypotheses are stated in the left column. Exponents indicate the experiment(s) in which the hypothesis was tested. The predictions of the decision strategies are presented in the right columns with the values yes / no indicating that the respective hypothesis should hold / not hold if the strategy is applied.

Table 2

Cue Patterns Experiment 1 and 2

Cue Patterns Set 1 (CUE=1)

		Positive O2 and O3														
Positive O1		0			1			2			3			4		
		Pattern 1			Pattern 4			Pattern 7			Pattern 10			Pattern 13		
		O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3
1	C1	+	-	-	+	-	-	+	-	-	+	-	-	+	-	-
	C2	-	-	-	-	+	-	-	+	-	-	+	+	-	+	+
	C3	-	-	-	-	-	-	-	+	-	-	+	-	-	+	+
		Pattern 2			Pattern 5			Pattern 8			Pattern 11			Pattern 14		
		O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3
	C1	+	-	-	+	-	-	+	-	-	+	-	-	+	-	-
2	C2	+	-	-	+	+	-	+	+	-	+	+	+	+	+	+
	C3	-	-	-	-	-	-	-	+	-	-	+	-	-	+	+
		Pattern 3			Pattern 6			Pattern 9			Pattern 12			Pattern 15		
		O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3
	C1	+	-	-	+	-	-	+	-	-	+	-	-	+	-	-
3	C2	+	-	-	+	+	-	+	+	-	+	+	+	+	+	+
	C3	+	-	-	+	-	-	+	+	-	+	+	-	+	+	+

Cue Patterns Set 2 (CUE=2)

	Pattern 16			Pattern 17			Pattern 18			Pattern 19			Pattern 20			Pattern 21		
	O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3	O1	O2	O3
C1	+	+	-	+	+	+	+	+	-	+	+	+	+	+	-	+	+	+
C2	+	-	-	+	-	-	+	-	-	+	-	-	+	-	-	+	-	-
C3	-	-	-	-	-	-	-	+	-	-	+	+	+	+	-	+	-	-

Cue Patterns Set 3 (CUE=3)

	Pattern 22			Pattern 23		
	O1	O2	O3	O1	O2	O3
C1	+	+	+	+	+	+
C2	+	+	-	+	+	-
C3	+	-	-	+	-	+

Note. The 23 cue patterns used in Experiment 1 and 2 are depicted in a matrix format. C1 to C3 represent cues 1 to 3, with cue 1 being the most valid cue and cue 3 being the least valid cue. O1 to O3 represent options. Cue patterns are categorized in three sets for which the number of cues increases, which would be necessary to differentiate between options according to a LEX/TTB strategy. Set 1 consists of cue patterns 1 to 15, set 2 consists of cue patterns 16 to 21 and set 3 consists of cue patterns 22 and 23. Within set 1, the number of positive cue values for option 1 is varied from 1 to 3 (cf., main rows). This variation is fully crossed with a variation of the number of positive cue values for options 2 and 3 (0 to 4; cf., main columns).

Table 3

Results of Choice-Based Strategy Classification

	Decision Strategies			
	LEX/TTB	EQW	WADD	RAND
	Experiment 1			
Time Pressure	2 (13%)	1 (7%)	10 (67%)	2 (13%)
	Experiment 2			
Lenient Time Limit	4 (27%)	1 (7%)	10 (67%)	0
Medium Time Limit	5 (33%)	3 (20%)	7 (46%)	0
Severe Time Limit	14 (93%)	0	1 (7%)	0
	Experiment 3			
Time Pressure in Complex Decision Tasks	13 (21%)	0	50 (79%)	0

Table 4

Information-Search Parameters Experiment 2

	Information-Search Parameters					
	Information Box Index				PATTERN	
	Cue 1	Cue 2	Cue 3	*M*	*M*	*SE*
Lenient Time Limit	1.51	1.49	1.01	1.34	.05	.10
Medium Time Limit	1.31	1.16	0.60	1.02	.08	.11
Severe Time Limit	1.16	.49	0.16	0.61	-.42	.09

Note. The Information Box Index is a measure for the number of information boxes opened, divided by the number of available information boxes. A value of 1 indicates that the number of opened information boxes was equal to the number of available information boxes, whereas lower values indicate that fewer boxes were opened than available. The PATTERN index indicates whether information searches were predominantly cue-based (negative values) or option-based (positive values).

Table 5

Cue Patterns Experiment 3

	Cue Pattern											
	1		2		3		4		5		6	
	O1	O2	O1	O2	O1	O2	O1	O2	O1	O2	O1	O2
Cue 1(*p* = .80 to .95)	+	-	+	-	+	-	+	-	+	-	+	-
Cue 2 (*p* = .75)	-	+	-	-	-	+	-	-	-	+	+	-
Cue 3 (*p* = .70)	-	-	-	-	-	+	-	-	-	+	-	-
Cue 4 (*p* = .65)	-	-	-	-	-	-	-	-	-	+	-	-
Cue 5 (*p* = .60)	-	-	-	-	-	-	-	+	-	+	-	+
Cue 6 (*p* = .55)	-	-	-	+	-	-	-	+	-	+	-	+

Note. The six cue patterns used in Experiment 3 are depicted in a matrix format. Cues are shown in the left column. The percentage of correct predictions *p* of each cue is given in parentheses. O1 and O2 represent options.

Figure 1

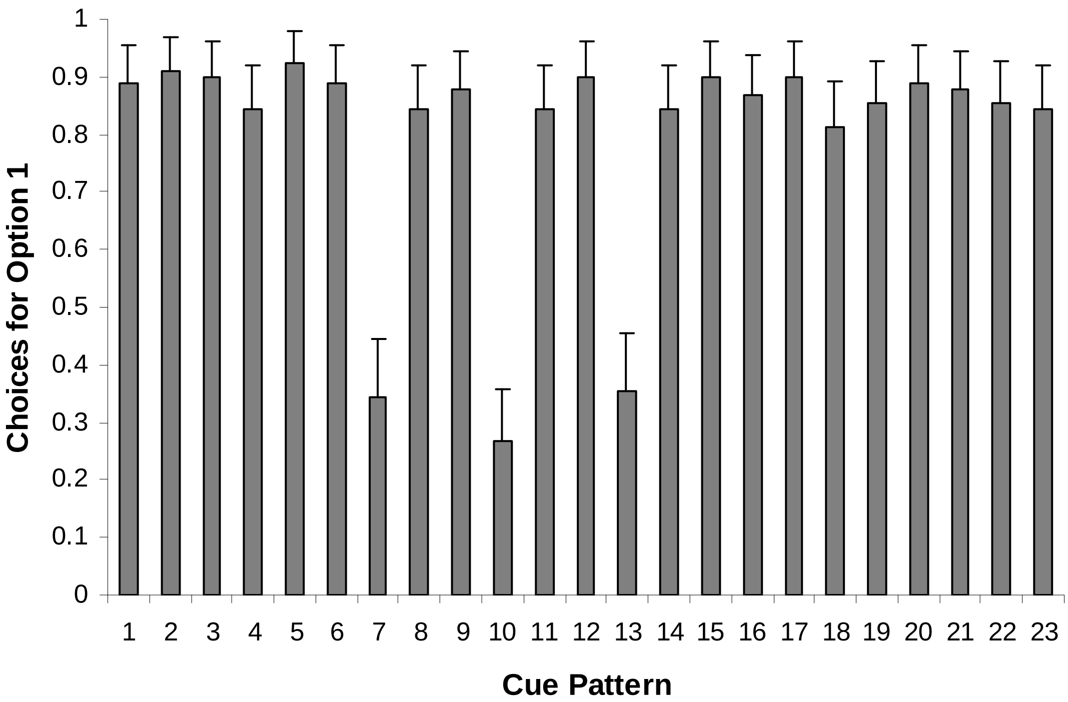

Figure 1. Percentage of choices for option 1 in Experiment 1. Error bars indicate 95 percent confidence intervals.

Figure 2

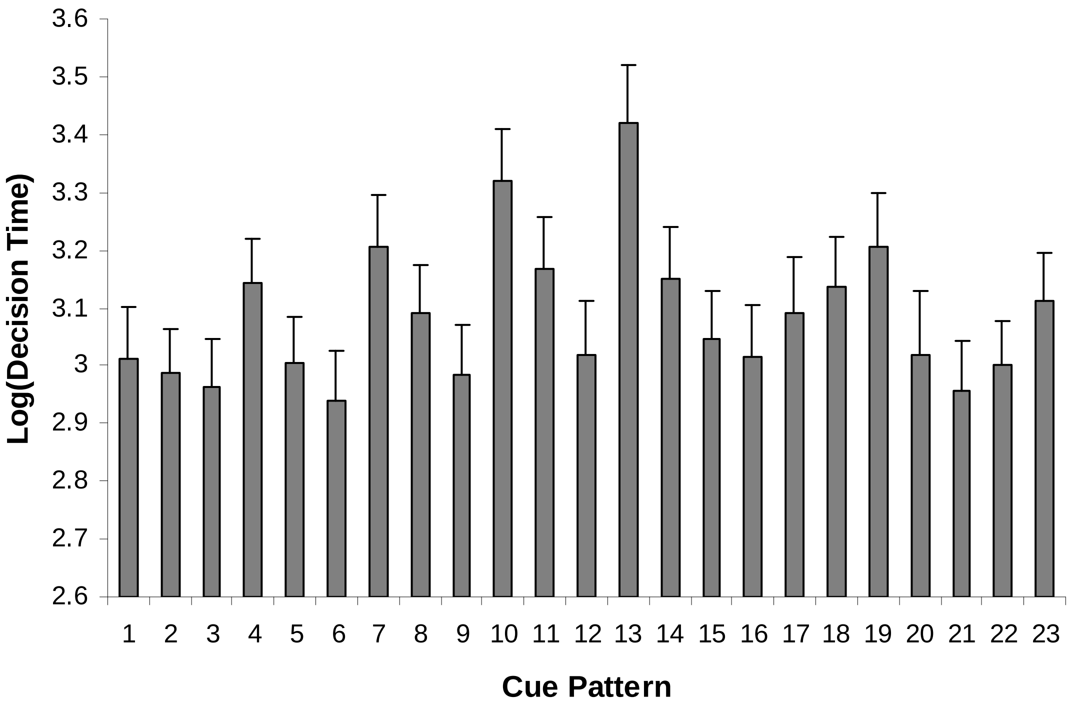

Figure 2. Log-transformed decision times in Experiment 1. Error bars indicate 95 percent confidence intervals.

Figure 3

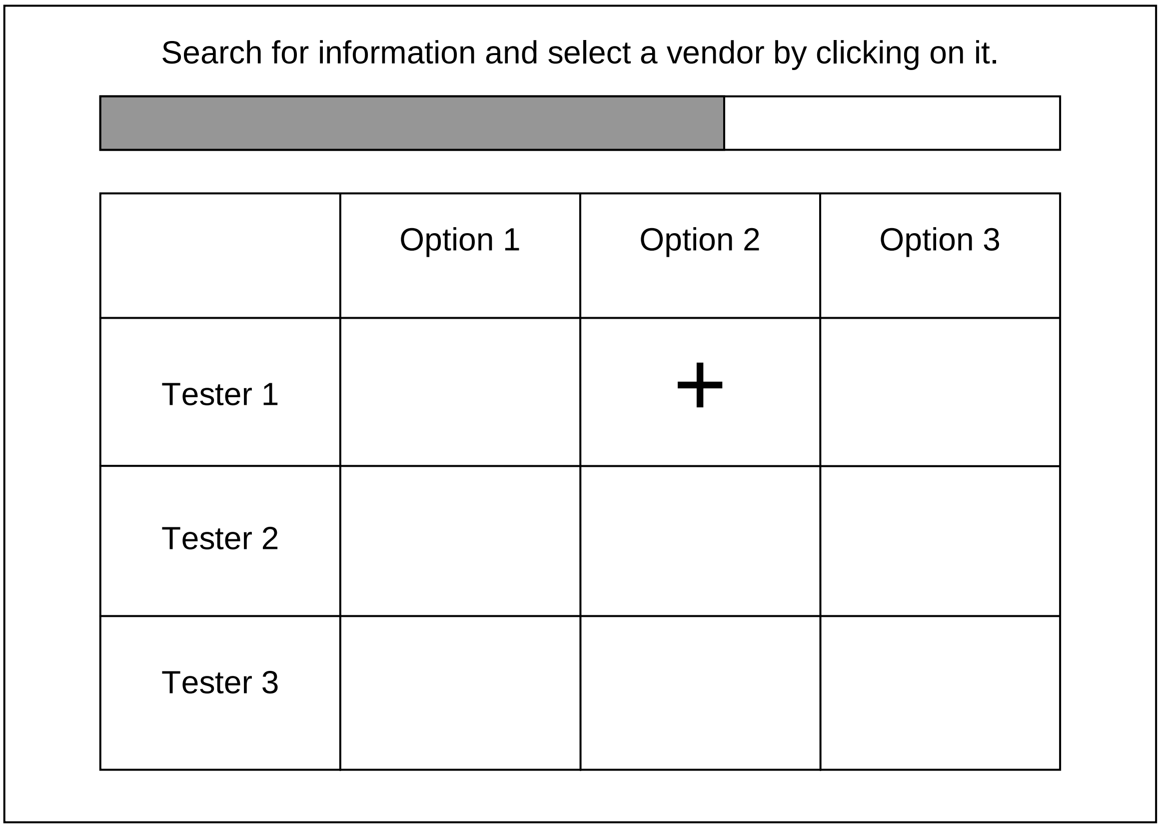

Figure 3. Mouselab presentation used in Experiment 2.

Figure 4

	Oranges A Choose	Oranges B Choose
Tester 1 (90% correct)	+	-
Tester 2 (60% correct)	-	-
Tester 3 (70% correct)	-	+
Tester 4 (75% correct)	-	+
Tester 5 (65% correct)	-	-
Tester 6 (55% correct)	-	-

Figure 4. Presentation format of decision tasks used in Experiment 3.

Figure 5

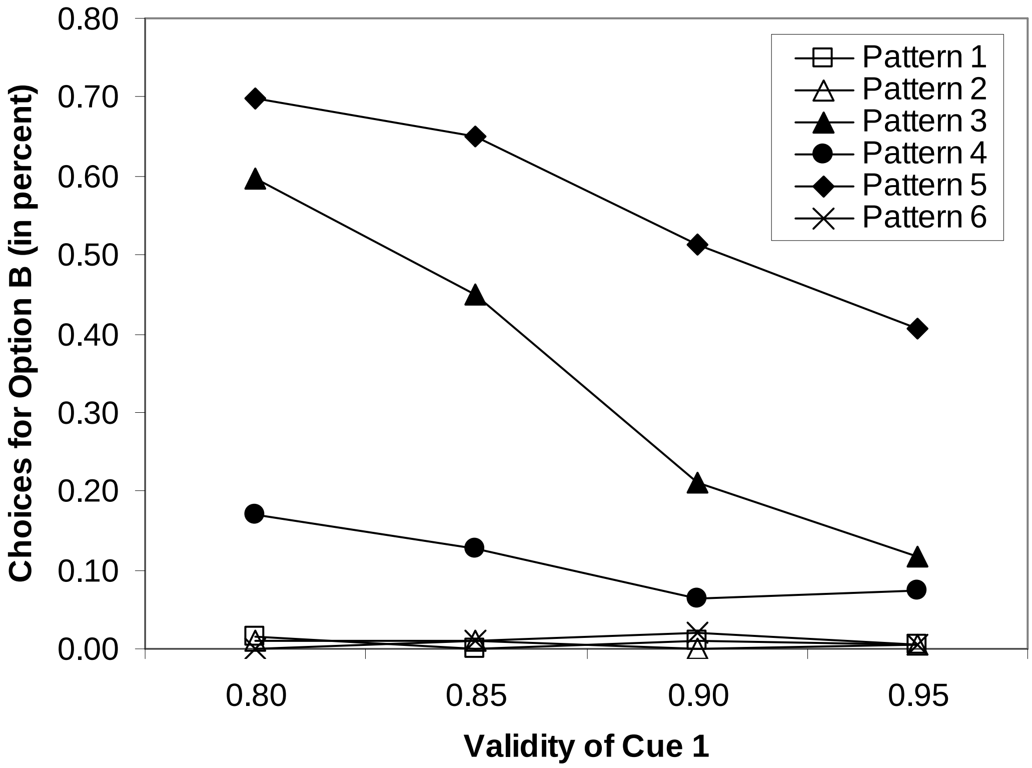

Figure 5. Percentage of choices for option 2 in Experiment 3.

Figure 6

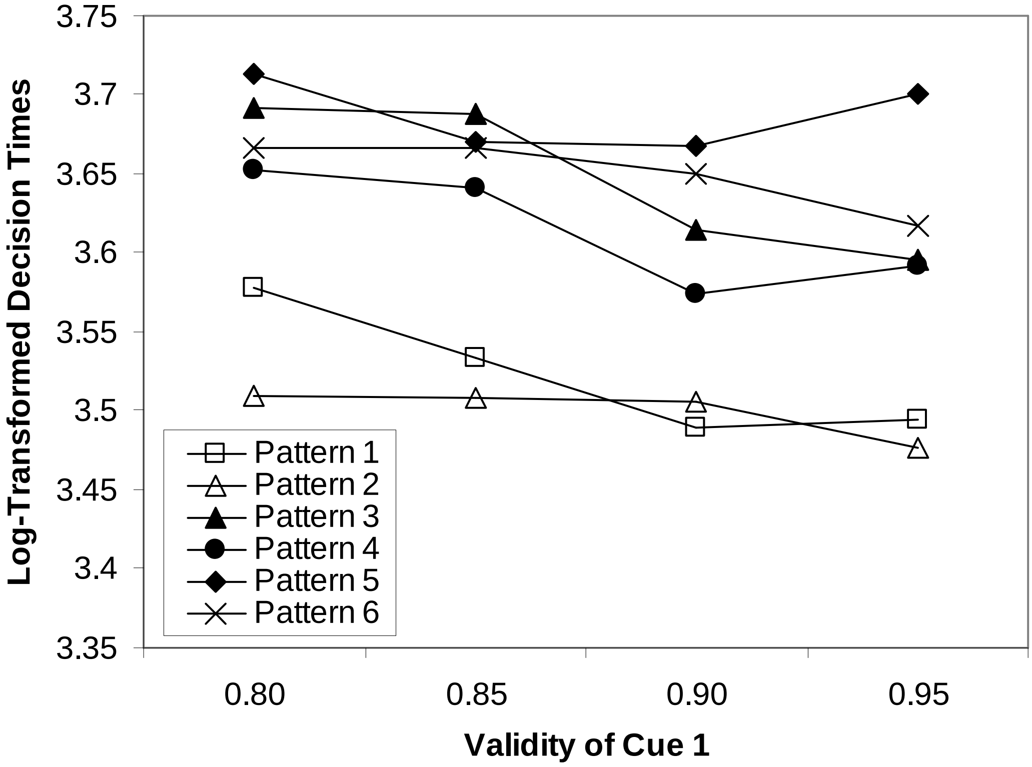

Figure 6. Log-transformed decision times in Experiment 3.

Figure 7

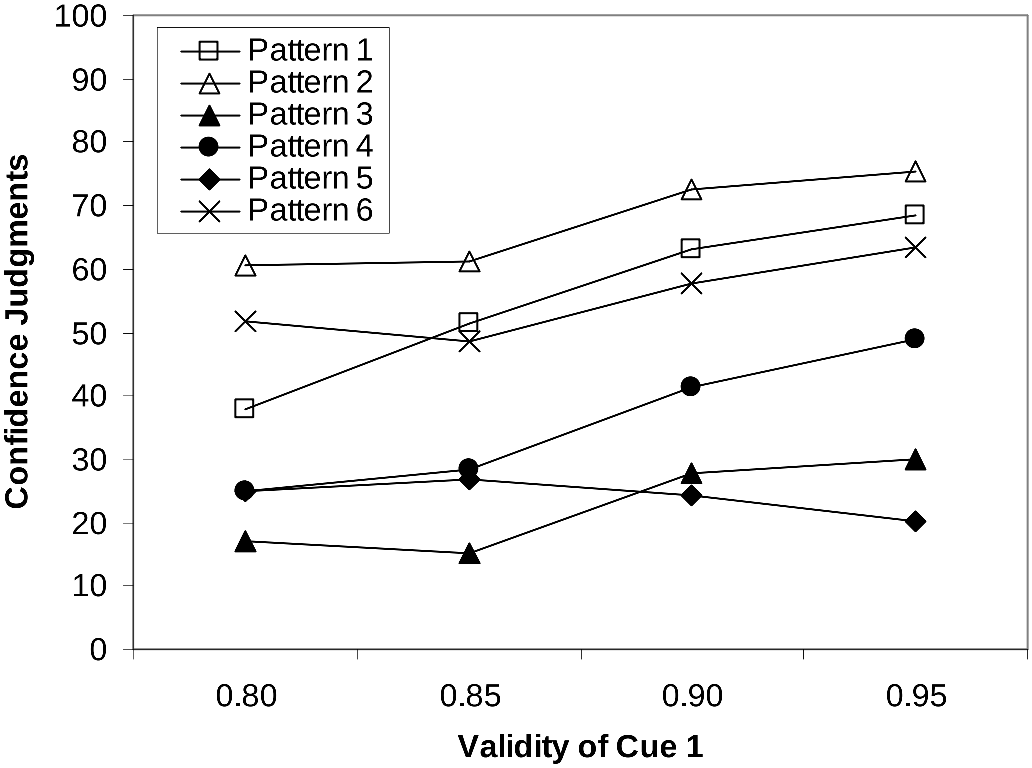

Figure 7. Confidence judgments in Experiment 3 with high values indicating a high level of confidence.

Appendix A: Instructions used in Experiment 1

Please imagine you are the head of a company which produces orange juice. You get offers from different orange vendors and you have to decide from which vendor to select. You have three testers A, B and C who check the oranges of each vendor for their quality. They give you information about each vendor: “+” meaning the oranges of the vendor are of good quality, “-” meaning the oranges of the vendor are of bad quality. [pagebreak] You know from experience that the testers give differently reliable information: The information of tester A is in 8 out of 10 cases correct; the information of tester B is in 6 out of 10 cases correct; and the predictions of tester C are in 5 out of 10 cases correct. [pagebreak] In the study you will be repeatedly presented with offers from three different vendors and the information of the testers A, B and C in the following format:

	Orange Vendors		
	1	2	3
A	+	+	-
B	-	+	-
C	+	-	+

Your task is to select the vendor with the best-quality oranges. Please try to make good decisions and to proceed as quickly as possible. [pagebreak] Three keys are marked on the keyboard which you should use to select the vendors. Please lay three fingers of one hand on the three keys to avoid unnecessary errors. Hit the left key to select vendor 1, hit the middle key to select vendor 2, hit the right key to select vendor 3.

Appendix B: Additional Instructions used in Experiment 3

Explanations for the Information on Testers' Reliability

The values for the reliability of the prediction of the testers range from 50 percent to 100 percent. Fifty percent correct predictions mean that 5 of 10 predictions of the tester are wrong. Because there are only two possible predictions (good / bad), this equates to random probability. This means that the information of testers with 50 percent correct predictions can be ignored because they provide no information about the quality of oranges. In contrast, the information of a tester with 100 percent correct predictions is always correct. The testers in the study will have different reliability values that are between 50 and 100 percent.