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Cognitive Processes Underlying Heuristic Decision Making

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Sebastian Dummel

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Dean: Prof. Dr. Birgit Spinath
Advisors: Dr. Jan Rummel, Prof. Dr. Joachim Funke

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S.D.G.

gratia autem Dei sum id quod sum (1 Corinthians 15:10)

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List of scientific publications of the publication-based dissertation

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Article 1

Dummel, S., Rummel, J., & Voss, A. (2016). Additional information is not ignored: New evidence for information integration and inhibition in take-the-best decisions. *Acta Psychologica, 163*, 167–184. doi: 10.1016/j.actpsy.2015.12.001

Article 2

Dummel, S., & Rummel, J. (2015). Take-the-best and the influence of decision-inconsistent attributes on decision confidence and choices in memory-based decisions. *Memory,* advanced online publication. doi: 10.1080/09658211.2015.1117642

Article 3

Dummel, S., & Rummel, J. (2016). Effects of Ego-Depletion on Choice Behavior in a Multi-Attribute Decision Task. *Journal of Cognitive Psychology*. doi: 10.1080/20445911.2015.1135929

1 Introduction and background

Our life is full of choices—choices that differ, among others, in the amount of information on which they are based. For instance, when facing a choice between two options that differ on several decision-relevant attributes, one could rely on the most relevant attribute only to make the decision, or one could integrate information from several attributes and base the choice on that combined information. When a decision maker bases her choice on the most relevant attribute only, however, what does this mean with regard to the amount of information this decision maker had processed prior to making the decision: did she process information about the most relevant attribute only and ignored additional information, or did she consider additional pieces of information as well but let her choice nonetheless be guided by only the most relevant attribute? Understanding the cognitive processes underlying those choices that are based primarily on the most relevant attribute is the main subject of this thesis, in particular, the question of whether or not for these choices additional information is ignored, and if additional information is not ignored, how is this information being processed? Furthermore, the work presented here seeks to get a better understanding of the conditions under which decision makers may become more likely to base their choice on only one piece of information. Before presenting the empirical studies conducted to tackle these questions, I will give a brief overview of the field of decision making relevant to the present work.

1.1 The study of multi-attribute decision making

Facing a choice between two options that differ on several decision-relevant attributes constitutes a typical instance of a multi-attribute decision task, which is the kind of task the work presented in this thesis deals with. In a multi-attribute decision task, decision makers have to choose between two (or more) choice options (e.g., unit funds) the one that scores higher on a certain criterion (e.g., the more profitable fund). The choice options are described by several attributes or cues (e.g., expert recommendations) each of which is predictive of the decision criterion, also known as cue validity. The cues typically differ in their validities, whereby validity is commonly defined as the frequency with which a cue points to the correct option given that the cue discriminates between the options (Gigerenzer & Goldstein, 1996). To illustrate, Figure 1 depicts an example trial of the decision task used in article 3. Decision makers of this task were to choose the more profitable of two unit funds and they were shown the recommendations of six financial experts who varied in their validities[1]. The cues were arranged in descending order of their validities. In this task, cue information

[1] This kind of multi-attribute decision task is often also called *probabilistic inference task*, because the cues (e.g., the expert recommendations) are probabilistically related to an objective decision criterion (e.g., profitability), rendering it possible, therefore, to probabilistically infer a 'correct' solution on the basis of the cue information. The decision criterion in a multi-attribute decision task can also be a subjective one, such as the likeability of one of two or more options (e.g. consumer products). This kind of multi-attribute decision task is referred to as *preferential choice task* (e.g., Payne, Bettman, & Johnson, 1988). Similar processes have been suggested to underlie both types of multi-attribute decision tasks, but because probabilistic inference tasks allow a researcher

was completely shown to participants during decision making on an information board (*open information board*). However, there are also variants of multi-attribute decision tasks (which were also employed in the present work) where cue information is initially hidden and decision makers need to uncover information about single cues sequentially (*closed information board*); or tasks, where decision makers have to retrieve cue information from memory.

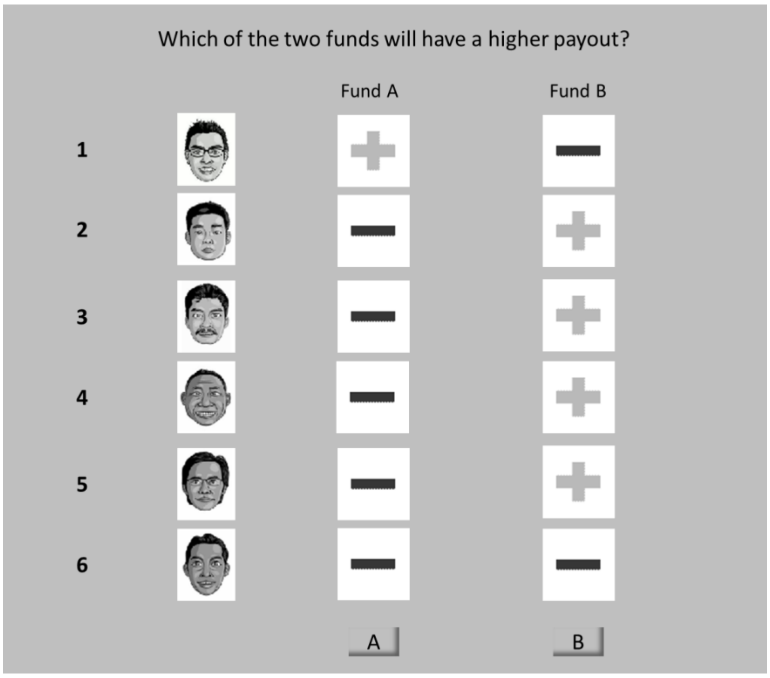

Figure 1. Example trial of the multi-attribute decision task of article 3.

The example in Figure 1 shows a decision situation where information about different cues is in conflict: the most valid cue points to the first option (Fund A) whereas several less valid cues point to the second option (Fund B). Decision-making researchers have shown an ongoing interest in studying how people tackle such decision situations (Gigerenzer, Todd, & The ABC Research Group, 1999; Payne, Bettman, & Johnson, 1988), and there is now a relatively large body of evidence showing that decision makers—when facing such a situation—differ in the amount of information on which they base their decisions: Some decision makers consistently make their choices in line with the most valid cue (which would be indicated by the choice of Fund A in the example), whereas others are found to base their choices consistently on the combination of several cues (which would be indicated by the choice of Fund B in the example). Different frameworks of decision making exist that provide theoretically different explanations for these inter-individual differences in choice behavior (Gigerenzer & Gaissmaier, 2011; Lee & Cummins, 2004). Yet although these frameworks differ on a

to define a correct solution for any decision problem a priori, the tasks used in the studies presented here were all of this kind.

theoretical level, they share a common assumption, namely that decision makers who consistently base their choices on the most valid cue ignored information about less valid cues. I will next present two frameworks that share this assumption.

1.2 Two frameworks, one assumption: Ignoring information

1.2.1 The multiple-strategy framework

The multiple-strategy framework (MSF) proposed by Gerd Gigerenzer and colleagues (Gigerenzer et al., 1999) assumes that decision makers have a repertoire of qualitatively different decision strategies. When facing a choice between options, a decision maker is supposed to select among the set of strategies the one that fits best to the situation at hand. The framework by Gigerenzer and colleagues was particularly inspired by Herbert Simon's notion of bounded rationality (Simon, 1955)—the view that inferences about the world often have to be made "with limited time, knowledge, and computational power" (Todd & Gigerenzer, 2000, p. 728). Taking into account the boundedness of rationality, Gigerenzer and colleagues proposed and specified several decision heuristics, one of which is the take-the-best heuristic (TTB). TTB consists of three cognitive building blocks: a search rule, a stopping rule, and a decision rule. The search rule specifies how cues are searched, namely in descending order of their validities. The stopping rule specifies when cue search is terminated: once a cue discriminates between options. The decision rule specifies which option to choose: the option pointed to by the discriminating cue. To illustrate, consider the example in Figure 1. A decision maker following TTB would start comparing the options on the most valid cue (search rule). As this cue discriminates already between the options, the search would terminate here (stopping rule) and the option with the positive cue value (Fund A) would be chosen (decision rule). Due to its stopping rule, TTB requires the processing of only part of the information whereas the rest is ignored. Although TTB takes into account only part of the information, simulation studies as well as analyses of data from real-world domains demonstrated that the predictive power of TTB (i.e., the extent to which it makes correct choice predictions) is close to, and sometimes even higher than, the predictive power of decision strategies that take into account all information available (Czerlinski, Gigerenzer, & Goldstein, 1999). A strategy of this latter kind is the weighted additive rule (WADD; Payne et al., 1988). According to WADD, all cues of a decision option are considered and weighted by their validity. For each decision option the weighted cues are summed up and the option with the higher weighted evidence is chosen. Provided that the weighted sum of the less valid cues in Figure 1 is higher than the validity of the most valid cue, a decision maker following WADD would choose Fund B. Because WADD allows for the possibility that a highly valid cue can be compensated for by a combination of less valid cues, WADD is also called a compensatory strategy. TTB, in contrast, is a non-compensatory strategy. Another compensatory strategy to be considered here is the equal weight strategy (EQW). Like WADD, EQW takes into account all cues; but instead of being weighted by their validities, the cues are all weighted equally. Hence, following an EQW strategy, a decision maker confronted with the decision options in Figure 1 would count the number of positive cue values for each option and would choose the option with the higher sum (Fund B). For sake of simplicity, I will concentrate on TTB and WADD in the following sections.

TTB well captures the notion of bounded rationality; WADD, in contrast, is more in line with classical models of rationality—models that imply that human knowledge and capacities are unbounded. The MSF supposes strategy selection to be adaptive, meaning that the selection of a strategy depends on the structure of the environment (Gigerenzer & Gaissmaier, 2011); when the fit between the strategy and the environmental structure is high, the MSF calls this strategy *ecologically rational* (thus, rationality in this framework is context-dependent). The mechanism by which decision makers select a certain strategy, however, is still not fully understood, though some research suggests that reinforcement learning (Rieskamp & Otto, 2006) or effort-accuracy trade-offs (Payne et al., 1988) might play a role. That said, although the mechanism of how strategies are selected is still not clear, quite a lot has been learned about the conditions under which the adoption of certain strategies, like TTB, becomes more likely. A full review of these studies is beyond the scope of this introduction, but a few findings relevant to the present work will be mentioned. In line with the idea of bounded rationality, decision makers were found to behave more in line with a TTB strategy when decision time was constraint (Glöckner & Betsch, 2008a; Rieskamp & Hoffrage, 2008); when cues were redundant (Dieckmann & Rieskamp, 2007); when cue dispersion was high (Bröder, 2000); when information costs were high (Newell & Shanks, 2003); or when cue information had to be retrieved from memory rather than being completely shown to participants during decision making (Bröder & Schiffer, 2003).

In decision research, a common way of identifying the decision strategy a decision maker most likely used to make her decisions is to analyze the decision maker's actual choices (Bergert & Nosofsky, 2007; Bröder & Schiffer, 2003a; Bröder, 2003). To illustrate, consider the example in Figure 1, which is a pair of options for which TTB and WADD make opposing choice predictions (provided that the summed evidence of the less valid cues outweigh the most valid cue). Confronting decision makers with several such pairs in a decision task, one can eventually compare a decision maker's actual choice pattern with the choice pattern predicted by a specific strategy. Arndt Bröder (Bröder, 2003) developed a choice-based strategy-classification method that follows this rationale and that is widely used in decision research. In a nutshell, the classification method estimates for each decision strategy under consideration (e.g., TTB, WADD, or EQW) the fit between the choice pattern predicted by that strategy and a decision maker's observed choice pattern, and the strategy with the best fit is considered the strategy that the decision maker used.

In sum, the MSF accounts for inter-individual differences in decision makers' choice behavior by supposing that decision makers use different decision strategies to come up with their decisions. The identification of individual decision strategies can be accomplished, for example, by the choice-based strategy-classification method by Bröder (2003). In this regard, then, decision makers who consistently make choices in line with the best discriminating cue are supposed to use a TTB strategy to make their choices, implying also that these decision makers ignored information (as indicated by the TTB-stopping-rule). I will henceforth refer to these decision makers as *TTB-consistent choosers* (TTB-CC). Decision makers who consistently make choices in line with WADD (or EQW) are supposed to use a WADD (or EQW) strategy, implying also that these decision makers processed cue information completely. I will refer to these decision makers as WADD- or EQW-consistent choosers (WADD-CC and EQW-CC, respectively).

1.2.2 The evidence accumulation model by Lee and Cummins (2004)

Whereas the MSF assumes that different strategies or mechanisms underlie the choices of TTB-CCs and WADD-CCs, another framework of decision making suggests there to be a single mechanism only. This framework subsumes the class of evidence accumulation models, sometimes also called sequential sampling models (Busemeyer & Townsend, 1993; Lee & Cummins, 2004; Voss, Nagler, & Lerche, 2013). In general, evidence accumulation models (EAMs) assume that decision makers who face a choice between decision options, sequentially sample evidence about these options (i.e., the cue values) and automatically integrate this information. Once the accumulated evidence in favor of an option passes a decision maker's decision threshold, the sampling process terminates and the option favored by the evidence is chosen. Lee and Cummins (2004) proposed a specific instance of an evidence accumulation model that provided a single account for the choice behavior of both TTB-CCs and WADD-CCs. A simplified graphical depiction of this model is shown on the left side of Figure 2, where the decision situation of Figure 1 is exemplified (i.e., the situation where the most valid cue points to option A, whereas the remaining cues point to option B). The Lee and Cummins (L&C) model assumes a step-wise cue search, starting with the most valid cue and continuing along the validity hierarchy (i.e., along the x-axis in Figure 2), as it is suggested by the TTB-search rule. Note that for each step in Figure 2, the cumulative evidence is depicted on the y-axis. That is, at each step, the evidence provided by the cue (which is determined by the cue's validity) becomes automatically integrated into the preceding evidence value. The region above the midline constitutes evidence in favor of the TTB-option (i.e., the option pointed to by the best cue), whereas the region below the midline constitutes evidence in favor of the WADD-option. According to the L&C model, TTB-CCs and WADD-CCs differ only in their decision thresholds, with TTB-CCs having lower thresholds than WADD-CCs. Specifically, the decision threshold of TTB-CCs (represented by the dashed line) is supposed to be that low, that the discovery of the most valid cue would be sufficient to terminate the sampling process (in analogy to the TTB-stopping-rule). The decision threshold of WADD-CCs (represented by the dotted line), in contrast, is assumed to be that high that it guarantees the sampling of all cues, which in case of the example of Figure 1 means that the cumulative evidence crosses the midline, that is, the evidence points to the WADD-option. Note that in Figure 1, the decision threshold supposed for WADD-CCs is still not passed even after each cue had been considered; but as there are no more cues available and the up-to-that-point accumulated evidence is in favor of the WADD-option, the decision maker would finally choose this option. To summarize, according to the L&C model, decision makers who base their choices on a single cue (TTB-CCs) are assumed to do so because they stopped information sampling at the discovery of this cue—as the accumulated evidence provided by this cue already passed their low decision thresholds. Decision makers who base their choices on a combination of several cues (WADD-CCs), in contrast, are assumed to do so because they sampled information about all cues and integrated this information in a WADD-like manner.[2]

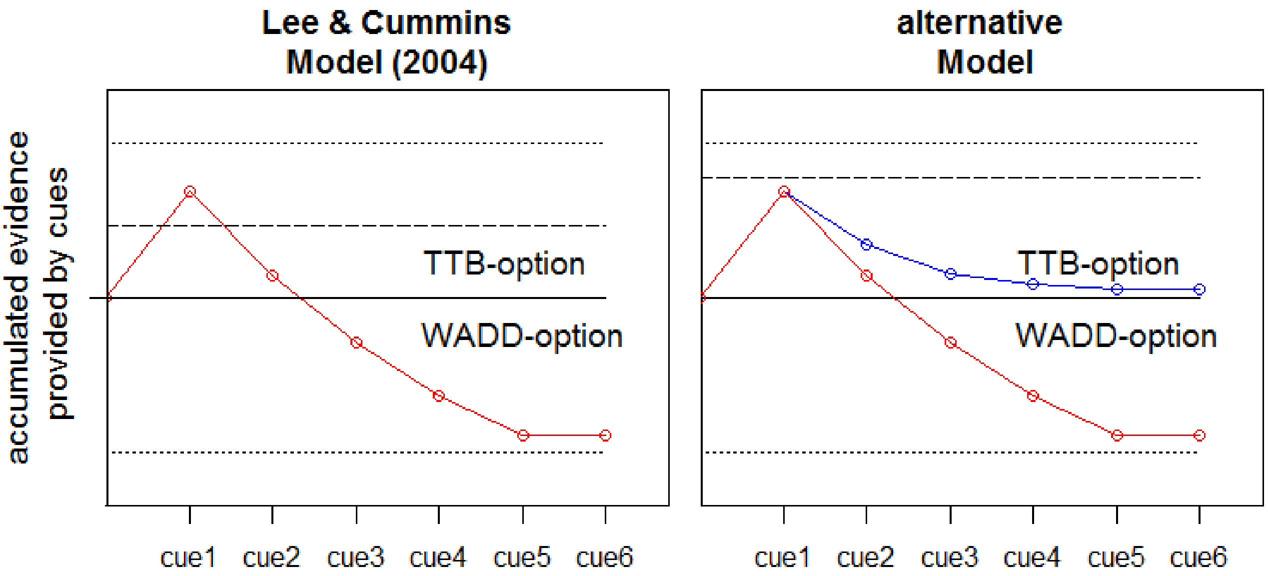

Figure 2. Left Panel: Graphical depiction of the evidence accumulation process as suggested by Lee and Cummins (2004). Right Panel: Graphical depiction of two possible evidence accumulation processes that differ in the way information is combined (compensatory weighting is shown by the red line, non-compensatory weighting is shown by the blue line)

The EAM framework faces a similar problem as the MSF when it comes to the question of how decision makers set or adjust their decision thresholds—a question that has not been answered satisfactorily yet (e.g., Newell, 2005). However, consistent with the assumption that TTB-CCs have lower decision thresholds than WADD-CCs, Newell and Lee (2011) found that TTB-CCs acquired less cue information in a decision task with a closed information board than WADD-CCs (see also

[2] One might probably wonder what the difference is between a WADD strategy and some kind of EAM strategy. Generally, the WADD strategy is considered a deliberate decision strategy (Payne et al., 1988) where decision makers are supposed to consciously integrate the cue information (i.e., multiplying the cues by their validities and summing them up). The assumption underlying EAMs, in contrast, is that information integration occurs automatically.

Söllner & Bröder, 2015)[3]. In tasks with closed information boards, it is possible to directly draw conclusions about the amount of information a decision maker processed prior to making a decision. This is not the case, however, for tasks with open information boards or memory-based tasks, where the process of cue sampling cannot be directly observed and where the classification into TTB-CCs and WADD-CCs often relies on choice outcomes alone. One of the questions addressed in this thesis therefore asks whether decision makers, classified as TTB-CCs on the basis of their choices, can really be said to have ignored information in a task with open information boards (article 1) or in a memory-based task (article 2), as it is implied by both the MSF and the L&C model. The assumption that TTB-CCs may probably not ignore additional information raises the question of how such a choice behavior could be explained. In the next section I will outline two possible models that could account for such a choice behavior.

1.3 Take-the-best without ignoring information

1.3.1 An evidence accumulation model alternative to the Lee and Cummins model

When a decision maker bases her choice on the best discriminating cue, she may have done so because she only processed information about this cue, as suggested by the MSF (Gigerenzer & Gaissmaier, 2011) and the L&C model (Lee & Cummins, 2004). Yet it could also be that this decision maker processed cue information completely and nevertheless let her choice be guided by only the best discriminating cue, because this cue is considered strong enough to outweigh the joint evidence of the less valid cues. Such a decision behavior may well fit with the evidence accumulation framework, but the specific model accounting for this behavior would be different from the L&C model in important respects. Specifically, the alternative model would assume that TTB-CCs have decision thresholds *higher* than the evidence provided by a single cue, so that additional cues would not be ignored but processed as well. The additional cues would be integrated in a non-compensatory manner, which means that the TTB-relevant best discriminating cue would never be outweighed by the joint evidence provided by the additional cues; thus, the best discriminating cue would consistently drive the decision maker's choice. A graphical depiction of such a decision behavior is shown on the right side of Figure 2 (blue line). Note that in this model, the decision threshold for TTB-CCs (dashed line) is not passed by even the most valid cue, which is why information sampling continues. However, as the cumulative evidence does not cross the midline, TTB-CCs finally choose the TTB-option. The decision threshold of WADD-CCs (dotted line) is likewise not passed by the most valid cue; but as WADD-CCs combine the cues in a compensatory manner, they end up choosing the WADD-option (as it is implied by the original L&C model, which is represented by the red line in Figure 2). Thus, the difference between TTB-CCs and WADD-CCs may not necessarily be the height

[3] Note, however, that this finding also fits with the MSF and the assumption that people use different strategies. Indeed, most research on multi-attribute decision making can be considered and interpreted within both frameworks, and it is not until recently that attempts have been made to empirically contrast the different frameworks (e.g., Söllner & Bröder, 2015).

of their thresholds (though there could still be some differences), but the way in which they combine the cues.

The L&C model does not take into account that decision makers may differ in the way they combine cue information (i.e., compensatory vs. non-compensatory). Rather, the L&C model is based on the premise that decision makers have quite accurate knowledge about the cue validities of a decision environment, and that they all combine the cues in the same way. When the cues of an environment are compensatory, the L&C model therefore predicts that decision makers would necessarily make choices in line with WADD when cues had been processed completely (as indicated by the red line in Figure 2). The assumption of equal and accurate validity knowledge across decision makers becomes somewhat doubtable, however, when decision makers have to learn the validities of a decision environment themselves, as was the case in the studies conducted to test the L&C model (Lee & Cummins, Newell & Lee, 2011). Specifically, previous research demonstrated that people have large difficulties learning cue validities (e.g., Bergert & Nosofsky, 2007; Newell & Shanks, 2003), which generally may call into question the assumption of accurate validity knowledge, but which may suggest that decision makers differ in the way they perceive the cue validities of an environment (compensatory vs. non-compensatory). Based on this assumption, the studies of article 1 (open information board) and 2 (memory-based) of this thesis test whether TTB-CCs would not ignore information about additional cues, but that they would process these cues and integrate them in a non-compensatory manner. Furthermore, in article 1, cue validities have to be learned by participants, which additionally allows for testing whether TTB-CCs and WADD-CCs differ in the ways they perceive the cue validities (as indicated by the alternative model in Figure 2).

Because the choices of TTB-CCs alone cannot tell whether or not additional information had been processed by these decision makers, decision times and decision confidence will additionally be assessed. The analyses of decision times and decision confidence have proven successfully in previous studies interested in the processes underlying decision making (e.g., Bergert & Nosofsky, 2007; Bröder & Gaissmaier, 2007; Glöckner & Betsch, 2008). In brief, according to EAMs, decision time and decision confidence is a function of a decision maker's threshold as well as of the consistency of the processed cue information. If TTB-CCs ignore information (i.e., low threshold) the consistency between the TTB-relevant best discriminating cue and additional information should not affect decision times nor confidence. However, if additional information is not ignored by TTB-CCs (higher threshold), EAMs predict slower decision times and lower decision confidence when additional cue information is inconsistent with the best cue rather than consistent.

1.3.2 A connectionist account

The alternative EAM outlined previously constitutes a formal model that could account for the decision behavior of decision makers who process cues completely and nevertheless make choices in line with TTB. Another formal model that could account for such a behavior is of the class of connectionist network models, the Parallel Constraint Satisfaction model (PCS) by Glöckner and Betsch (2008a; 2008b). The PCS model assumes that cue information is processed holistically and in parallel in a PCS network where the options and the associated cues are represented as nodes, and the nodes are interlinked. Being faced with a choice between options, the network aims at striving for coherence by maximizing the difference between the options, and the lower the overall coherence of the cue information is, the longer it takes the network to settle on a stable solution. Originally, the PCS algorithm was specified in such a way that cues were combined in a compensatory manner, so that the complete processing of cues would result in choices consistent with WADD (as it is also implied by the L&C model). Recently, however, Glöckner and colleagues (Glöckner, Hilbig, & Jekel, 2014) specified a second version of the PCS model that allowed for a non-compensatory combination of cues as well; this model specification predicts the same choices as TTB even when cues had been processed completely. Thus, similar to the EAM account outlined in the previous section, the recent PCS model supposes TTB-CCs to process cues completely and to combine them in a non-compensatory manner.

PCS is a model predominantly concerned with the processes of information integration and several findings reported by Glöckner and colleagues provide support for the assumption that decision makers integrate information in a PCS-manner (e.g., Glöckner & Betsch, 2008a, 2012; Glöckner et al., 2014). To date, however, the model does not specify how information is searched or when information search is terminated. Indeed, the holistic-processing assumption might imply that cue information is always processed completely. Taking into account the processes of information search and the point at which information search terminates, however, may be of critical importance when studying decision making, as I will argue in the next section.

1.4 Adaptive flexibility of information search

An attractive feature of EAMs, in comparison to PCS, is that they are more specific with regard to how and how much information is processed in a decision situation before a choice is made. Specifically, according to EAMs, the extent of information search is a function of a decision maker's decision threshold and, theoretically, decision thresholds may vary along a continuum. Thus, the amount of information a decision maker processes prior to making a decision is allowed to vary within the EAM framework. Although the specific mechanism by which decision makers set their decision thresholds is still not understood (e.g., Newell, 2005), findings from within the EAM literature show that decision makers can flexibly adjust their decision thresholds to situational demands, such as time pressure or need for accuracy (Voss, Rothermund, & Voss, 2004). This evidence for adaptive flexibility may be of particular interest when considering again the decision behavior of TTB-CCs who, as supposed in section 1.3.1, combine cue information in a non-compensatory manner. As can be seen in Figure 2 (right side), regardless of where along the y-axis the decision threshold of those decision makers falls, they would consistently choose the option favored by the most valid cue. Thus, without having to change their choice behavior, which is determined by the most valid cue, TTB-CCs have quite a large latitude in the extent of their information search behavior, ranging from minimal (only one cue is considered) to exhaustive (cues are processed completely). A second goal of the work presented here was therefore to examine how flexible TTB-CCs are in adjusting their decision thresholds. Information search behavior was considered under the two conditions typically considered in EAM research: time pressure and need for accuracy. It was further examined, how the availability of cue information (open and closed information boards) would affect the decision behavior of TTB-CCs.

In multi-attribute decision research, adaptive decision making has typically been considered in terms of adaptive strategy selection, which is incorporated in the MSF (Gigerenzer & Gaissmaier, 2011; see also Payne et al., 1988). That is, depending on the situation (e.g., time pressure, need for accuracy, high information costs, etc.), decision makers are supposed to either select a TTB strategy or a WADD strategy (or any other strategy). As each strategy is defined by both, the extent of information search (minimal for TTB, exhaustive for WADD) and the choice behavior (see section 1.1), this view suggests that situational factors would generally affect individuals' information search behavior *and* their choice behavior simultaneously. Put differently, a change in information search due to situational factors (e.g., from minimal to extensive) is expected to also lead to a change in choice behavior (e.g., from TTB to WADD)[4]. There is some support for that view on adaptive decision making. For instance, studying the effects of time pressure on decision making, researchers found that under high time pressure, information search tended to be minimal and choices were more in line with TTB, whereas under low time pressure, information search became more extensive and choices were more in line with WADD (Glöckner & Betsch, 2008a; Rieskamp & Hoffrage, 1999; Rieskamp & Hoffrage, 2008). This finding suggests that information search behavior and choice behavior vary together. The particular question addressed in this thesis, however, was whether individual decision makers (especially TTB-CCs) might adaptively adjust their information search behavior but without necessarily changing their choice behavior[5].

[4] As can be seen in Figure 2 (left side), this assumption is also consistent with the L&C model. That is, when decision thresholds are higher than the evidence provided by the best cue, information search will be exhaustive and choices will be as predicted by WADD, but when decision thresholds fall below the evidence provided by the best cue, information search will be minimal and choices will be as predicted by TTB.

[5] The findings of the cited studies, that a change in the extent of information search due to time pressure also led to a change in choice behavior, implies that decision makers of these studies perceived the cues as compensatory; because only then it seems plausible that the processing of complete cue information results in WADD-consistent choices, whereas the processing of only part of the information results in TTB-consistent choices (see also Figure 2, left side). Indeed, in the cited studies, participants may most likely have perceived the cues as compensatory, because the cue validities were instructed and the validity values pointed to a compensatory environment. The assumption that decision makers may adjust their information search behavior without changing their choice behavior, however, is of particular interest for those decision makers who perceive cues as non-compensatory because they would end up making choices in line with TTB regardless of whether they only considered the best discriminating cue or whether they processed cues completely.

Because EAMs are more specific than PCS with regard to decision makers' information search behavior, I will predominantly focus on EAMs in the present work. But EAMs are not only specific about information search behavior; these models also make specific assumptions about *how* information is processed by decision makers. In the next section, I will discuss this latter issue in more detail and also present an additional assumption about the supposed processes underlying decision making.

1.5 Automatic information integration and deliberate processes

EAMs are quite specific with regard to the question of how information is being processed by decision makers in a multi-attribute decision task. It is supposed that information that is encountered in the course of information search becomes automatically integrated, and a decision option is finally chosen by a decision maker because the accumulated, combined evidence favored that option. Crucially, however, for TTB-CCs who perceive cues as non-compensatory, the combined evidence will always be in favor of the option pointed to by the best discriminating cue (cf. Figure 2, right side). The best discriminating cue might thus be said to have some rule-like properties and, in the spirit of the MSF, TTB-CCs might be said to follow some kind of TTB-decision-rule ('go with the best cue')—though without necessarily following a TTB-stopping-rule[6]. Therefore, another question addressed in this work was whether, in addition to automatic integration processes (as postulated by EAMs), more deliberate and rule-driven processes (as suggested by the MSF) might also be at work when TTB-CCs make their decisions. The presence of such rule-like and deliberate processes might probably become most apparent when the rule is disconfirmed, that is, when information from the best discriminating cue, which consistently drives the choices of TTB-CCs, is in conflict with information from another cue, say the cue that directly follows the best cue in the validity hierarchy (i.e., the next-best cue). In these cases, TTB-CCs may be assumed to experience a cognitive conflict which they might want to reduce by inhibiting the conflicting information.

Inhibition has received quite some attention in research on selective attention (see Tipper, 2001; for a review), and a prominent task where inhibition has been studied, among others, is the color-naming Stroop task (e.g., Marí-Beffa, Estévez, & Danziger, 2000). I will briefly outline the rationale that underlies the empirical investigation of inhibition in the Stroop task, because this

[6] Note, however, that I do not want to suggest here that the MSF could be adjusted in any possible way so as to account for any possible decision pattern; this would make this framework arbitrary and meaningless. However, an often neglected feature of the MSF is that it has at its basic units the cognitive building blocks, that is, the rules for search-, stopping- and choice behavior (Gigerenzer & Gaissmaier, 2011). Decision strategies are only specific (and fix) configurations of specific building blocks; in this regard, the study of decision strategies generally reveals insights into whether the assumptions about the postulated configurations of building blocks are valid or not. This approach, however, may somehow obscure the view on the cognitive building blocks themselves, which, in my view, are the concepts most closely related to the cognitive processes postulated to underlie decision making. Therefore, the notion of a TTB-decision-rule may well capture the regular pattern of TTB-CCs' choices, and it reflects and acknowledges the idea of the most basic units postulated within the MSF (i.e., cognitive building blocks) without sticking to postulated superordinate units (i.e., the strategies).

rationale also applies to the present work. Participants' task in a color-naming Stroop task is to name the color of a written word and the written words—their meanings—typically also denote colors. A general finding is that participants require more time to name the color of a word, when the meaning of the word is inconsistent with the color of the word (e.g., *BLUE*) as compared to when the meaning and the color of a word are consistent (e.g., *BLUE*). More interesting with regard to the present work, however, is the following finding. On inconsistent trials, participants have been found to need more time to name the color of a word (e.g., *BLUE*), when on the *preceding* trial the *meaning* of the word denoted that very color (e.g., *RED*) as compared to when it denoted another color (*YELLOW*). A common explanation for this type of *negative priming* effect (Tipper, 2001) is that participants, in order to successfully name the color of the word, inhibit the meaning of the word. According to this view, the slower responding to a word on trial *n* is due to the inhibition of that word (its meaning) on trial *n*-1.

In the present work, a similar rationale will be applied to a multi-attribute decision task in order to examine whether inhibitory processes might be at work when TTB-CCs make their decisions. It should be noted that inhibition might only play a role for TTB-CCs but not necessarily for WADD-CCs. As noted above, TTB-CCs may want to inhibit information in particular when this information is in conflict with the best discriminating cue—for this cue has rule-like features for TTB-CCs. WADD-CCs, in contrast, do not consistently choose the decision option favored by the best discriminating cue, which is why this cue does not have the same rule-like properties for WADD-CCs as it has for TTB-CCs. Thus, WADD-CCs may not necessarily experience a cognitive conflict when cue information is inconsistent, and they therefore might also not necessarily want to inhibit conflicting information.

2 The Present work within current strands of multi-attribute decision making

2.1 Information integration, inhibition, and adaptive flexibility—Article 1

Dummel, S., Rummel, J., & Voss, A. (2016). Additional information is not ignored: New evidence for information integration and inhibition in take-the-best decisions. *Acta Psychologica, 163*, 167–184. doi: 10.1016/j.actpsy.2015.12.001

In this article, we addressed several of the questions raised in the previous sections. The first goal was to find evidence that TTB-CCs would not ignore information when this information is fully shown. In a recent study, Glöckner et al., (2014) found initial support for this assumption. The researchers showed that the decision times and confidence ratings of TTB-CCs were affected by the overall coherence of openly displayed cue information, suggesting therefore that TTB-CCs processed cue information completely. However, the processing of complete cue information in this research may have been driven by some methodological factors (for a full discussion of these factors, see the original article). Most importantly, in the decision task used by Glöckner and colleagues, the arrangement of the cues (i.e., the position of the cues on the open information board) changed trialwise. Thus, participants searching for the best cue to make their decisions (TTB) may have processed additional cues inadvertently. We carefully controlled for this and other critical factors in our experiments, thereby providing a more stringent test of the assumption that TTB-CCs would not ignore openly displayed information. Moreover, whereas previous research on multi-attribute decision making exclusively focused on automatic integration processes, we sought to find evidence for more deliberate, inhibitory processes underlying the choices of TTB-CCs. A second goal of article 1 was to examine the adaptive flexibility of TTB-CCs' information search behavior, or in terms of EAMs, their decision thresholds. To that end, we studied the decision behavior of TTB-CCs under varying conditions (open vs. closed information boards; time pressure vs. need for accuracy). Thus, rather than suggesting that TTB-CCs would generally process cue information completely, the work presented here aimed at getting a better understanding of the conditions under which TTB-CCs actually may become more likely to ignore information. Recent research by Söllner and colleagues (Söllner, Bröder, Glöckner, & Betsch, 2014; Söllner, & Bröder, 2015) showed that TTB-CCs do not consistently ignore information in tasks with closed information boards, but the adaptive flexibility of TTB-CCs information search behavior (and thus the extent to which they ignore information) has not been examined.

To tackle each of the questions just mentioned, we ran four experiments. We used the same decision task in all experiments: Participants were shown a series of pairs of bugs and had to choose the more poisonous of the two bugs. The bugs were described by four binary cues: body, antennae, legs, and fangs. The cues differed in their validities (i.e., the extent to which they predicted poisonousness) and participants of all experiments had to learn the validities in an initial feedback learning phase. Subsequent to the validity learning phase, participants of all experiments entered the test phase[7]. With the exception of Experiment 3, the test phase of the experiments consisted of two parts. In the first part, an open information board was used (all Experiments). To examine whether participants would ignore information in this task, we manipulated the consistency between the best discriminating cue and the supposedly TTB-irrelevant next-best cue. The next-best cue was either consistent or inconsistent with the best discriminating cue (in Experiment 3 we also used pairs for which the next-best cue was neutral, that is, non-discriminating). We also manipulated the validity rank of the best discriminating cue, that is, whether it was the 1st rank, the 2nd rank or the 3rd rank cue. The main dependent variable was decision times; in Experiments 1b and 3 we further assessed decision confidence (in Experiment 1b by having participants bet on some of their decisions; in Experiment 3 by directly asking for confidence ratings).

In the second part of the test phase (Experiments 1a, 1b, and 2), participants performed the bug decision task once again—this time with a closed information board. The main dependent variable

[7] From the perspective of participants, the validity learning and the test phase differed mainly in that choice feedback was given only in the former—in order to enable validity learning—but not in the latter.

here was the amount of cues participants acquired before making a decision. Participants of Experiment 2 performed this task twice, once with an instructional focus on decision speed and once with a focus on accuracy. Table 1 gives an overview of the test phases we used in the different experiments together with the respective main dependent variables. In each test phase, participants were also shown pairs for which TTB and WADD make opposing choice predictions. We used the choice-based strategy-classification method by Bröder (2003) to classify participants into TTB-CCs or WADD-CCs, respectively[8]. At the end of each experiment, participants were further asked to rate the predictive usefulness of each of the four cues. This enabled us to examine whether TTB-CCs and WADD-CCs differed in the way they perceived the cues (non-compensatory vs. compensatory).

Table 1

Overview of the Test Phases of Experiments 1–3 and the Respective Dependent Variables

	Test phases of the experiments		
Experiment	First part (open information board)	Second part (closed information board)	
1a	*Decision times*	*Amount of acquired information (AAI)*	
1b	*Decision times and bets*	*AAI*	
		Manipulation of instructional focus	
		Decision speed	Accuracy
2	*Decision times*	*AAI*	*AAI*
3	*Decision times and confindence ratings*	-	-

Finally, in Experiment 3 we tested our hypothesis that TTB-CCs would inhibit information from a cue (here the next-best cue), when this cue information was inconsistent with the best discriminating cue. To this end, we modified the bug decision task with open information board in the following way. Participants were again shown pairs of bugs for which we manipulated the consistency between the best discriminating cue and the next-best cue (consistent, neutral, or inconsistent). Some

[8] We also considered the EQW-strategy for the individual classification; but there were only few participants classified as EQW-CCs at all and these participants might possibly have been misclassified. For these reasons, I will concentrate on TTB-CCs and WADD-CCs in this overview.

of the decision trials, however, were followed by a trial on which only a single cue value (i.e., a single feature of a bug) was shown to participants and their task was then to quickly indicate whether this cue value was indicative of poisonousness or not. Our manipulation was whether the single cue value depicted on these trials was part of an inconsistent, consistent, or neutral next-best cue on the preceding decision trial. The assumption was that a participant's response to a single cue value should be slowed, when this cue value had previously been inhibited (i.e., part of an inconsistent next-best cue) as compared when it had not been inhibited (i.e., part of a consistent or neutral next-best cue).

In the following I will first summarize and discuss the results related to the question of whether TTB-CCs ignore information fully shown to them (Experiments 1–3) and whether TTB-CCs would inhibit conflicting information (Experiment 3). The results of all experiments showed that TTB-CCs were sensitive to the consistency manipulation in the task with open information board, suggesting therefore that TTB-CCs did not ignore information. TTB-CCs made slower decisions, bet less on their decisions, and were less confident with their decisions, when the next-best cue was inconsistent with the best discriminating cue as compared to when the cues were consistent. The consistency manipulation also strongly affected the decision behavior of WADD-CCs. TTB-CCs' decision times were further strongly affected by the validity rank of the best discriminating. Decision times increased with the validity rank of the best cue decreasing. The validity rank had no, or only a weak effect, on WADD-CCs' decision times.

These findings were generally in line with the predictions made by the EAM account outlined in section 1.3.1, which assumes that TTB-CCs combine cues in a non-compensatory manner, whereas WADD-CCs combine cues in a compensatory manner[9]. The assumption that TTB-CCs and WADD-CCs differed in the way they perceived the cues received some support from participants' predictive utility ratings of the four cues. In all but one experiment, the utility ratings showed a larger dispersion for TTB-CCs than for WADD-CCs (a high dispersion is indicative of non-compensation). The predictions made by the EAM account, however, were only partially supported by the decision time results of Experiment 3. The EAM account predicted an increase in decision times with a decrease in information consistency. In comparison to a neutral next-best cue, however, it was only an inconsistent next-best cue that affected TTB-CCs' decisions by slowing them, but a consistent next-best cue did not additionally speed the decisions. The slowdown in TTB-CCs' decisions was as predicted by EAMs, but it was also in line with our additional assumption that TTB-CCs might inhibit conflicting cue information. In Experiment 3 we found first evidence for the supposed inhibitory processes: On those trials of the decision task on which participants were to respond to only a single cue value, TTB-CCs were slower in doing so, when this cue value had been inconsistent with the best discriminating cue on the preceding trial (assumed inhibition) as compared to when it had been neutral

[9] That is, when cues are perceived as non-compensatory, they are perceived as being largely different from each other with regard to their validities. In this case, the validity rank of the best discriminating cue may exert quite a strong effect on decision times, as was observed for TTB-CCs.

or consistent (no inhibition assumed). A similar pattern of inhibition did not emerge for WADD-CCs though, which was in line with our assumption that WAD-CCs may have perceived an inconsistent next-best cue as less conflicting than did TTB-CCs (see section 1.5 for a full explanation). Before further discussing some theoretical implications that we also discussed in the article, I will summarize the results from the experiments related to the adaptive flexibility question. For these findings, it is important to note that the strategy-classification procedure, which was applied for each test phase, revealed high consistency in individual classifications across test phase.

Results from Experiments 1a and 1b showed that, when cues had to be acquired sequentially (closed information board), TTB-CCs became more likely to ignore information. Overall, TTB-CCs acquired less cues before making a decision than did WADD-CCs. The finding that TTB-CCs did not ignore information when it was easily available (open information board), but that the same TTB-CCs became more likely to ignore information when cue availability decreased (closed information board), supported the assumption of TTB-CCs' adaptive flexibility in information search behavior (or, in terms of EAMs, TTB-CCs' adaptive adjustment of decision thresholds). The results of Experiment 2 complemented these findings. When task instructions emphasized decision speed, both TTB-CCs and WADD-CCs acquired less cues before making a decision as compared to when task instructions stressed accuracy. Contrary to previous research, however, we found no evidence for individual strategy shifts under time pressure (i.e., a shift from WADD to TTB)[10]. That is, although TTB-CCs and WADD-CCs adaptively adjusted the extent of information search in response to the different instructions, they did not change their choice behavior (from WADD-CCs to TTB-CCs). These findings suggest that adaptive decision making does not necessarily have to emerge as adaptive strategy selection (e.g., Gigerenzer & Gaissmaier, 2011; Payne et al., 1988), but it can emerge more subtle on the level of individual information search behavior.

In the article, we discussed two explanations for the discrepancy between our and previous findings. In previous research on adaptive decision making (Glöckner & Betsch, 2008a; Rieskamp & Hoffrage, 2008), time pressure was induced by imposing an explicit time limit on participants' information search. Thus, participants could probably only sample a small amount of cues, which may have decreased the likelihood that a highly valid cue could have been compensated for by less valid cues. This should then have fostered a choice behavior in line with TTB. In our experiment, in contrast, time pressure was stressed only in the instructions, but there was no external time constraint. Participants who perceived cues as compensatory (WADD-CCs) might therefore have sampled at least as many cues as necessary to figure out whether a highly valid cue could have been outweighed by less valid cues (see also Dieckmann & Rieskamp, 2007). Another explanation we discussed, for why we found no signs of strategy shifts in our experiments, suggests that decision makers may have

[10] For TTB-CCs a strategy shift to WADD under accuracy instruction was not expected, because we supposed TTB-CCs to perceive cues as non-compensatory. For these decision makers, therefore, a complete processing of cues would have led to the same choices as the processing of only the most valid cue.

adopted and routinized a certain decision strategy already during the initial validity learning phase, and they may have stick to this strategy throughout the experiment. There is some evidence for routine effects in multi-attribute decision making, showing that decision makers tend to stick to that strategy they initially learned in an experiment (Bröder & Schiffer, 2006). Importantly, however, even though we found no strategy shifts in our experiment, the finding that TTB-CCs and WADD-CCs were sensitive to the different instructions support the assumption of adaptive flexibility.

Results from the task with closed information board further showed that TTB-CCs generally acquired fewer cues than did WADD-CCs. This finding is consistent with the model by Lee and Cummins (2004), which assumes that TTB-CCs have lower decision thresholds than WADD-CCs (see section 1.2.1). As we argued in the article, however, the L&C model cannot account for the results from the task with open information board, where TTB-CCs apparently did not ignore information. We suggest that the L&C model could be reconciled with these findings by allowing for individual differences in the way decision makers combine cues (compensatory vs. non-compensatory).

In the article, we considered EAMs as an overarching framework for our research, because EAMs make specific predictions about various aspects of decision behavior, such as decision times, decision confidence, and information search. EAMs are also quite specific with regard to the processes that are supposed to underlie decision making. In our experiments we found quite some support for the predictions made by EAMs. However, regarding the assumptions about the processes supposed to underlie decision making, our findings also point to a possible limitation of EAMs. Specifically, EAMs suggest that decision behavior can be accounted for by a single mechanism—the accumulation and automatic integration of information. Based on our findings, we consider it quite likely that information-integration processes may have underlain the decision behavior of participants in general (i.e., TTB-CCs and WADD-CCs). However, the inhibition findings from Experiment 3 suggest that additional, more deliberate processes might also have operated during decision making and, critically, that TTB-CCs and WADD-CCs differed in the extent to which they engaged in these processes. The assumption of a single mechanism may therefore be too constraint to capture the variability in decision makers' decision pattern.

We also discussed a potential objection to that conclusion. The idea that information is inhibited during decision making may fit with the single-mechanism model PCS, which supposes that decision makers strive for coherence when making their decisions and coherence could be achieved by means of inhibition. Yet although PCS may provide an explanation for inhibitory processes as mechanisms underlying decision making, the model suggests that all decision makers should engage in inhibition. This, however, was not the case in our experiment; WADD-CCs showed no signs of inhibition. PCS provides no explanation for why some decision makers should be more inclined to strive for coherence (TTB-CCs) than others (WADD-CCs). This difference, in our view, could have been due to TTB-CCs' stronger reliance on a deliberate decision rule, which might have been fostered by TTB-CCs' highly regular choice behavior (see section 1.5). However, irrespective of why TTB-CCs and WADD-CCs may have differed in the extent of inhibition, the critical point for single-process models is that we found a difference between decision makers. We suggest therefore that the processes underlying decision making might probably be more complex than assumed by single-process models.

2.2 TTB-irrelevant information in memory-based decisions—Article 2

Dummel, S., & Rummel, J. (2015). Take-the-best and the influence of decision-inconsistent attributes on decision confidence and choices in memory-based decisions. *Memory,* advanced online publication. doi: 10.1080/09658211.2015.1117642

Tasks with open information boards have sometimes been considered unfair tests for the TTB strategy [11] (Gigerenzer et al., 1999; Newell & Shanks, 2003). Indeed, TTB has originally been postulated for memory-based decision making because, so the argument goes, the strategy requires a decision maker to retrieve only part of the information and thus reduces retrieval efforts (Gigerenzer & Goldstein, 1996). In one study, Bröder and Schiffer (2003b) found that the proportion of TTB-CCs was higher in a condition where participants had to retrieve cue information from memory compared with a condition where cue information was fully shown to participants on screen during decision making. This finding was in line with the assumption that TTB might reduce retrieval efforts and might thus be preferred for memory-based decisions. However, the assumption underlying TTB, that memory retrieval happens sequentially and that TTB-irrelevant information is ignored (i.e., not retrieved) has been challenged by recent research. For instance, using a memory-based decision task, Khader, Pachur, and Jost, (2013) found that TTB-CCs took longer to make a choice between two options the more cue information they had previously learned about these options. The increase in decision times with the number of option-associated cues has been suggested to result from an automatic retrieval of complete cue information. As we argued in the article, however, from the finding that TTB-CCs' decision times increased proportionally to the number of option-associated cues, it remained unclear to what extent TTB-CCs deliberately processed and integrated TTB-irrelevant cues. We addressed this issue in the study of article 2 by using the same manipulation of information consistency as we also used in article 1 (Dummel, Rummel, & Voss, 2016).

Participants first had to learn the cue patterns of nine options. Similar to previous memory-based studies (e.g., Bröder and Schiffer, 2003b), we used a murder cover story whereby the nine

[11] This criticism may deserve some clarification. There have indeed been some studies using open information boards where only few people were found to make choices in line with TTB at all. That is, in these studies the majority of participants were classified as WADD-CCs. The results from our as well as other studies (Bergert & Nosofsky, 2007; Dummel et al. 2016; Lee & Cummins, 2004), however, show that even with open information boards a considerable proportion of participants make choices in line with TTB. Thus, open information boards may not necessarily be unfair tests for TTB. Another reading of the criticism, however, could be that open information boards are unfair tests for the ignorance assumption implied by TTB. Although this interpretation of the criticism was probably not what the critics originally had in mind, the findings from article 1 (Dummel et al., 2016) lend support to this reading. That is, when cue information is openly displayed even TTB-CCs do not ignore this information.

options were the nine murder suspects. Each suspect was described by four binary cues which participants were asked to learn; the cues referred to the suspects' items of clothing and cars. After this learning phase, participants received information about the validity hierarchy of the four cues and then performed the decision task. Here, participants repeatedly had to choose the more suspicious suspect out of two possible suspects. Participants were further asked to indicate their decision confidence, which was our main dependent variable. The pairs participants were shown in the decision task varied on (1) the validity rank of the best discriminating cue (1st, 2nd, or 3rd rank) and (2) the consistency of the TTB-irrelevant next-best cue (whether it was consistent or inconsistent with the best cue, or neutral/non-discriminating). Participants were further shown pairs for which TTB and WADD made opposing choice predictions and we used the choice-based strategy classification by Bröder (2003) to classify them accordingly. Hypotheses regarding TTB-CCs' confidence ratings were derived from TTB and EAMs/PCS. They both predict an effect of the validity rank manipulation on decision confidence, such that confidence should decrease with the validity rank of the best discriminating cue increasing. According to TTB, decision confidence should remain unaffected by the consistency manipulation as TTB-irrelevant information is supposed to be ignored. However, if TTB-CCs retrieve TTB-irrelevant information, EAMs/PCS further predict that confidence should decrease with information consistency decreasing. In addition to analyzing decision confidence, we also considered the extent of participants' strategy-inconsistent choices, as EAMs predict a higher proportion of strategy-inconsistent choices when information is inconsistent rather than consistent.

The results showed that the validity rank of the best discriminating cue affected TTB-CCs' decision confidence just as predicted by both TTB and EAMs/PCS. Of greater importance, however, TTB-CCs were also affected by the consistency of the next-best cue, suggesting therefore that TTB-CCs retrieved supposedly TTB-irrelevant information. In line with the predictions made by EAMs/PCS, TTB-CCs were less confident in their decisions and made more strategy-inconsistent decisions, when the next-best cue was inconsistent with the best discriminating cue as compared to when it was consistent or neutral. Compared with when the next-best cue was neutral, however, a consistent next-best cue did not additionally increase TTB-CCs' decision confidence, as had been predicted by EAMs/PCS. Taken together, the findings showed that, contrary to the TTB-stopping-rule, TTB-CCs did not ignore cue information. The results were mostly in line with the predictions made by EAMs/PCS, which might suggest that TTB-irrelevant had somehow become integrated.

In the article, we discussed a possible methodological explanation for why the consistent information, compared with the neutral information, did additionally increase TTB-CCs' decision confidence. The pairs with a neutral next-best cue differed on only one cue, whereas the pairs with a consistent or inconsistent cue differed on two cues. The higher number of dissimilar cues and the memory-based comparison of these cues might thus have led to a general increase in participants' uncertainty (which may have worked against the consistency effect). As we also argued in the article, however, this methodological constraint should not have undermined the general finding that TTB-CCs retrieved TTB-irrelevant information, because if this information had not been retrieved, the consistency manipulation would have had no effect whatsoever. Furthermore, the difference in confidence ratings between consistent and inconsistent pairs could not have been attributed to the suggested methodological factor, because these pairs had an identical number of dissimilar cues (two). We conclude therefore that TTB-CCs did not only retrieve TTB-irrelevant information, but they also appeared to have integrated this information somehow.

We also discussed a possible objection to our conclusion that TTB-CCs retrieved additional, TTB-irrelevant information when making their decisions. One could argue, for example, that additional cues had probably only been retrieved for the post-decisional confidence ratings. However, the finding that TTB-CCs made more strategy-inconsistent decisions when cue information was inconsistent rather than consistent speaks against this assumption and suggests that TTB-CCs had retrieved TTB-irrelevant information prior to making their decisions.

Another point we discussed in the article referred to the level of analyses we considered. We examined TTB-CCs as a group of decision makers and found that, on average, TTB-CCs did not ignore TTB-irrelevant information. This hence allows for the possibility that some TTB-CCs may have behaved completely in line with TTB and ignored information. The point we wanted to make with our research, however, was not to suggest that TTB-CCs would generally not ignore information; but the finding that at least some TTB-CCs appeared to have not behaved in line with TTB requires one to rethink the processes supposed to underlie decision making. Of course, whether the processes underlying TTB-CCs actually match the processes assumed by EAMs/PCS is another question and awaits further research. As for example argued in article 1, even when the decision behavior of participants is mostly in line with the predictions made by specific models such as EAMs/PCS, this does not necessarily mean that the processes underlying the decision behavior also conforms to the model processes (see also the General Discussion section).

2.3 Ego-depletion and TTB-consistent choices—Article 3

Dummel, S., & Rummel, J. (2016) Effects of Ego-Depletion on Choice Behavior in a Multi-Attribute Decision Task. *Journal of Cognitive Psychology.* doi: 10.1080/20445911.2015.1135929

The main question addressed in the previous articles was whether decision makers who consistently made choices in line with TTB ignored information or not. Our main goal in article 3 was to further our understanding of the conditions under which decision makers would become more likely to make TTB-consistent choices at all. The findings from article 1 suggest that TTB-CCs make non-compensatory TTB-choices because they perceive the cues as being non-compensatory. This complements findings from previous studies on adaptive decision making, where participants in a decision environment with high cue dispersion (i.e., non-compensatory) were also found to become more likely to make TTB-consistent choices (e.g., Bröder, 2000). Research on adaptive decision making also examined other factors that have been found to increase participants' likelihood of making TTB-consistent choices, such as the redundancy of cues in a decision environment (Dieckmann & Rieskamp, 2007) or time pressure (Glöckner & Betsch, 2008; Rieskamp & Hoffrage, 2008). Of importance with regard to article 3, the factors considered in this research were all factors directly related to the decision situation itself. The question addressed in article 3, in contrast, was whether individuals' choice behavior in a decision task would also be affected by a situation (task) completely unrelated to the choice situation. Research on ego-depletion suggests that engaging in self-control in one task may reduce one's cognitive resources available for another subsequent task (e.g., Baumeister, Bratslavsky, Muraven, & Tice, 1998). TTB has been suggested to reduce cognitive effort, and there has also been some support for this assumption[12](Bröder & Schiffer, 2003b; Mata, Schooler, & Rieskamp, 2007). The study of article 3 therefore examined whether decision makers in a state of ego-depletion (induced prior to the decision task) would become more likely to make TTB-consistent choices than participants who were not depleted. Before I continue with the outline of the study and the results, I want to briefly discuss one point that may need some clarification.

In our previous research (Dummel et al., 2016; Experiment 2), we found that participants' choice behavior remained largely unaffected by a time pressure manipulation, and we suggested that this may have been due to the routinization of a strategy during validity learning. Indeed, in most studies on adaptive decision making where effects on choice behavior had been found, cue validities were instructed rather than had to be learned. Therefore, as our interest in article 3 was to study the effects of ego-depletion on choice behavior, we told participants the exact validity values in the instructions of the decision task rather than having them learn the validities. Furthermore, the validity values we provided in the instructions pointed to a compensatory environment; findings from previous research suggested that under these conditions, participants generally prefer to make choices in line with compensatory strategies like WADD. We deemed this important, because our assumption was that ego-depletion might increase participants' likelihood of making a choice in line with the non-compensatory TTB strategy. We therefore thought the depletion-effect most likely to occur in a compensatory environment. Note that this also meant that we expected depleted participants not to consistently make TTB-consistent choices, but rather to become more likely to deviate from the preferred, but more effortful compensatory choices. In our previous research, we used a strategy-classification approach to identify individual strategies. However, as we assumed participants to generally prefer to make compensatory choices and to only become more likely to deviate from these

[12] There has been some debate, however, on whether TTB, in comparison to compensatory strategies, indeed reduces effort. We discussed this issue in detail in the article. The bottom line of this discussion was that the mere execution of a TTB strategy (i.e., the processing of cues as suggested by TTB) indeed seems to be less effortful than, for example, the execution of a WADD strategy. However, what seems to be difficult for participants is to figure out that in a decision environment, a TTB strategy would be more profitable than a WADD strategy. As our focus in article 3 was on participants' application of a TTB-like strategy and not on the learning of strategies, we considered it warranted to suggest that TTB may reduce cognitive effort.

choices under ego-depletion (and make TTB-consistent choices) we used a different approach to analyze individual choices (see below).

Figure 1 shows the decision task we used in article 3. Participants were to choose the more profitable of two funds and for each fund, the recommendations of six experts (cues) of varying validities were shown. Participants were shown 50 pairs of funds for which the non-compensatory TTB and compensatory strategies[13] made opposing choice predictions. Consistent with our previous studies, the pairs varied regarding the validity rank of the best discriminating cue (1st, 2nd, or 3rd) [14]. Of greatest importance, however, *prior* to the decision task, participants performed a completely unrelated task (copying a text), where we manipulated ego-depletion in a way it has commonly been done in ego-depletion research (simply copying the text vs. copying but skipping specific letters).

We analyzed participants' choices with a multi-level logistic regression analysis thereby taking into account the dependency among data and the dichotomous nature of the dependent variable (TTB-consistent vs. compensatory-consistent). Consistent with our hypothesis, the analysis revealed that, for depleted participants, the likelihood of making a TTB-consistent choice was 2.7 times higher than for non-depleted (which was significant). The validity rank manipulation also had a significant effect on choice behavior, such that the likelihood of making a TTB-consistent choice increased with the validity rank of the best cue increasing. This latter finding was somewhat surprising—that participants become more likely to rely on the best cue when this cue had a lower rather than a higher validity. Our suggestion in the article was that, when the first-rank cue was the best discriminating cue, then the evidence provided by the remaining cues may probably have been perceived as stronger (favoring compensatory choices) than when the second- or third-rank cue were best cues (favoring TTB-consistent choices).

We further discussed several explanations for why ego-depletion increased participants' likelihood of making TTB-consistent choices. Our initial assumption was that ego-depletion reduces cognitive resources. According to this account then, depleted participants more frequently made simple TTB-choices because they had less cognitive resources available for the decision task. A motivational account, however, might also seem plausible, suggesting that depleted participants were less motivated for the decision task. This account, however, would also suggest that depleted decision makers may probably have made faster decisions than non-depleted participants (to get the task over with). In the article, we also considered participants' decision times. Yet contrary to the 'demotivation' hypothesis, decision times did not differ between the groups. An interesting observation that we made about decision times, however, was that TTB-consistent choices were not

[13] We used the general term compensatory strategies in the article rather than referring to specific strategies (WADD or EQW) because the different strategies made identical choice predictions for almost all pairs.

[14] We did not use the consistency manipulation here. This manipulation was used in previous studies to examine whether TTB-CCs ignored information or not. In article 3, however, our interest was to examine the conditions under which participants would become more likely to make TTB-consistent choices, irrespective of whether information had been ignored or not.

made any faster than compensatory choices; the descriptive pattern was even reversed. Although not of our primary interest in article 3, this finding indicated that participants probably did not ignore information when they made TTB-consistent choices (if information had been ignored, TTB-consistent would have been expected to be faster). The decision-time findings could be reconciled with the previously mentioned cognitive resources account. Specifically, depleted participants may have perceived the task of integrating information from the six cues as being more difficult than non-depleted participants, and when integration attempts became too effortful on a trial, depleted participants may finally have resorted to a simple rule-of-thumb and followed the best cue (in the sense of 'take-the-best, if everything else fails'). As we pointed out in the article, however, all the explanations considered for why depletion affected participants' choice behavior remain rather speculative and await further research. Yet irrespective of why ego-depletion increased individuals' likelihood of making TTB-consistent choices, the important finding from article 3 is that ego-depletion had this effect. The findings suggest, therefore, that the choices we make in our lives can be affected by things that actually have nothing to do with the choice situations themselves.

3. General Discussion

The work presented in this thesis aimed to get a better understanding of the cognitive processes underlying those choices that (supposedly) rely on only one good cue, so-called TTB-consistent choices. A common explanation for such a choice behavior has been that decision makers stop information search at the discovery of the best cue and ignore additional information. In the present work, however, we found converging evidence that TTB-CCs do not ignore cue information when this information is fully shown to them or when decision accuracy is of importance (article 1). Moreover, even when cues had to be retrieved from memory, TTB-CCs were not completely unaware of additional cues (article 2). We further gained first insights into the specific processes underlying the choices of TTB-CCs. We found first evidence that TTB-CCs inhibit information that conflicts with their decisions. Finally, the present work improved our understanding of the conditions under which decision makers become more likely to make TTB-consistent choices. We found that the likelihood of making a TTB-consistent choice increased, when decision makers were ego-depleted prior to decision making as compared to when they were not depleted.

Overall, the findings presented here challenge the assumption of a strict TTB-stopping-rule, as it is suggested, for example, by the multiple-strategy view on decision making. As outlined in the previous sections, our findings were mostly in line with EAMs or PCS. Yet even those models could not fully account for the decision behavior we observed. Specifically, EAMs and PCS assume that a single process (the automatic integration of information) underlies the decision behavior of all decision makers. Our inhibition findings suggest, however, that more deliberate processes also operate during decision making, and that decision makers differ in the extent to which they engage in these processes. Most of the relevant and critical points of each study have already been discussed in the previous sections. The following section therefore takes a cross-article perspective by summarizing and discussing the results of the three articles in relation to the three questions pointed to at the very beginning of this thesis.

One of these questions asked, when or why do decision makers become more likely to rely on only one cue to make their decisions. Our findings point to two answers. First, decision makers predominantly based their choices on only one cue, when they perceived this cue as truly strong enough to outweigh additional cues—that is, when they perceived the cues as non-compensatory (article 1). This finding fits with the notion of ecological rationality (Gigerenzer et al., 1999; Gigerenzer & Gaissmaier, 2011). That is, the application of a non-compensatory strategy like TTB seems perfectly rational in a non-compensatory environment[15]. Second, the likelihood of making TTB-consistent choices in a compensatory environment increased in a state of ego-depletion. This finding fits with the notion that TTB reduces cognitive effort and might thus become more likely when cognitive resources are sparse (e.g., Bröder & Schiffer, 2003b; Mata et al., 2007).

The second question addressed with the present work is, what it means, when decision makers make choices in line with TTB; concretely, do TTB-CCs ignore information? The findings suggest that *it depends*: Under certain conditions, such as when cues were not that easily available or when decision speed was emphasized, TTB-CCs became more likely to ignore information. However, when cues were easily available or when decision accuracy was of importance, TTB-CCs tended to process cues completely. These findings are in line with the idea of the adaptive decision maker (Gigerenzer & Gaissmaier, 2011; Payne et al., 1988). However, contrary to previous research (Glöckner & Betsch, 2008a; Rieskamp & Hoffrage, 2008), suggesting that adaptive decision making is generally reflected by both a change in choice behavior and a change in the extent of information search (i.e., adaptive strategy selection), the current findings indicate that decision makers may adaptively adjust their extent of information search without necessarily changing their choice behavior. In the case of TTB-CCs who perceive cues as non-compensatory (article 1), this kind of adaptive flexibility also seems plausible—that is, the choices of these decision makers should have consistently been driven by the best cue, irrespective of the extent of information search. The finding that under accuracy instructions, TTB-CCs became less likely to ignore information points to a possible, and important, reason for why TTB-CCs may process cue information that, according to TTB, is considered irrelevant. That is, one could argue that TTB-CCs actually have no reason to process additional cues, because for their choices the one single cue would be sufficient (i.e., their behavior could be considered as irrational or inefficient). However, in many daily situations, individuals might probably not only want to make a

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[15] In this study (Dummel, et al., 2016), the cue validities of the learning environment pointed to a compensatory environment. One could argue therefore that the decision behavior of TTB-CCs was not rational under a prescriptive perspective of decision making. However, the cues in the learning environment were also positively correlated. Simulation studies showed that under these conditions the predictive power of TTB matches the predictive power of compensatory strategies like WADD (Davis-Stober, Dana, & Budescu, 2010). Thus, the decision behavior of TTB-CCs in our studies could indeed be considered as ‘ecological rational’.

choice, but they also might want to know how accurate their choice is in order to calibrate their decision behavior accordingly (see also Hausmann & Läge, 2008; Newell & Shanks, 2003; for a similar view). For example, in order to choose the more profitable of two funds, information from a single, highly recommended expert might suffice. Yet if one also were to invest some money in that fund, information from several experts might be helpful to gauge how good the choice (i.e., the fund) actually is and thus *how much* money one would be willing to invest.

Finally, the last question concerns the cognitive processes underlying the choices of TTB-CCs. More specifically, if TTB-CCs do not ignore information, how do they process this information? I have already discussed in more detail that (1) our findings were largely in line with the predictions made by EAMs or PCS, indicating that automatic information integration processes may most likely have underlain the decision behavior of TTB-CCs (and also WADD-CCs); but that (2) additional inhibitory processes apparently also operated during TTB-decision-making but not WADD-decision-making, indicating that the assumption of a single process underlying the decision behavior of TTB-CCs and WADD-CCs might probably be too constraint. This discussion mainly concerned the results from article 1. In the following, I want to further elaborate on the processes underlying decision making by focusing on the results from articles 2 and 3. And I want to specifically concentrate on the assumption that information integration is automatic.

As noted previously, Bröder and Schiffer (2003b) found that the proportion of TTB-CCs was higher in a condition where cues had to be retrieved from memory as compared to a condition where the same cue information was fully shown on screen during decision making. This finding supported the assumption that TTB reduces cognitive effort. However, the findings by Khader et al. (2013), as well as our findings (Dummel & Rummel, 2015), provide evidence for a retrieval of complete cue information even for TTB-CCs, indicating that the retrieval of cues seems to be less effortful than commonly assumed. Provided, however, that cue retrieval is not that effortful, why do decision makers nevertheless prefer TTB over WADD in a memory-based decision task? A possible explanation could be that, what actually requires cognitive effort in a memory-based decision task is not the retrieval of cues but the memory-based combination or integration of cues. This, however, would speak against the assumption that cues become automatically integrated at their retrieval (EAMs and PCS). That is, if cues were automatically retrieved and integrated (i.e., retrieval and integration without much effort), then there would be no reason for decision makers to prefer TTB over WADD—yet this is what Bröder and Schiffer found (and indeed, in our own study in article 2, there were only three WADD-CCs compared to 41 TTB-CCs). One might suggest, therefore, that the retrieval of complete cue information is probably not sufficient for a decision maker to also fully integrate the information so that an immediate choice could have been made once all cues had been retrieved. It rather seems that the memory-based combination of cues in a WADD-like manner requires a certain amount of cognitive effort—effort that decision makers may probably circumvent by (simply) focusing on the best cue to make their decisions (TTB), even when additional cues had been retrieved completely. Note that this does not mean that integration processes did not play any role at the time cues were retrieved (as decision makers of our study were sensitive to the consistency of information); but for a choice to be made, these processes might have been insufficient and decision makers may probably have relied on more strategic processes instead. Importantly, however, even though the way in which decision makers process cues in a memory-based decision task might still not be fully understood, a conclusion that one might relatively safely draw from the most current findings (Dummel & Rummel, 2015; Khader et al., 2013) is that, contrary to the TTB-stopping-rule, cue information is not ignored.

The assumption of a completely automatic information integration process underlying decision making might also be challenged to some extent by the findings from article 3. There, decision makers became more likely to make TTB-consistent choices when they had previously been depleted. An inspection of individual choice patterns revealed that, decision makers of this study showed a general preference for compensatory choices, which seems reasonable given that the instructed validities pointed to a compensatory environment. Put differently, an optimal choice in this environment would have been a compensatory choice, and a successful combination of cues should have led to this kind of choices. But in a state of ego-depletion, decision makers more frequently deviated from the ‘optimal’ choices and made TTB-consistent choices. One might suggest therefore that depleted participants had less cognitive resources available in order to successfully combine the cues. This, however, would suggest that the combination or integration of cues may not be completely automatic but may require at least some cognitive or attentional effort—effort that depleted participants seemed not able to muster consistently.

In decision research the MSF has often been directly contrasted with the EAMs framework or PCS. This approach implies (and it has often been framed explicitly in that way) that the two views—different strategies and single process—are mutually exclusive. The findings of the present research, however, may suggest that there is probably a truth to both frameworks. Certainly, our findings quite consistently showed that the assumption implied by the TTB-stopping-rule is not valid, at least not in its strictest meaning (i.e., information is not generally ignored). Yet the TTB-stopping-rule is only one specific assumption incorporated into one specific strategy. This therefore should not completely invalidate the MSF as a whole; but it may one require to reconsider the basic tenets of the framework. A core tenet of the MSF, for example, is the assumption that rule-like processes operate during decision making; specific rules are, for instance, search-, stopping-, and decision rules. Our findings indicate that decision makers apparently do not adhere to a specific stopping-rule; but this should not necessarily mean that rule-like processes play no role at all during decision making. In fact, our assumption that TTB-CCs might inhibit conflicting information was particularly inspired by the assumption that these decision makers might follow a TTB-decision-rule. The study of decision strategies, which are fix configuration of rules, might obscure somehow the view on the rules themselves. Focusing more on the rules or the rule-like processes that may operate during decision making might therefore be a more promising approach to the study of decision making than focusing on specific strategies.

Rule-like or strategic processes are not incorporated into decision making models like EAMs or PCS (but see Glöckner & Betsch, 2008b; for a first attempt). These models suppose that the decisions we make are the result of automatic information integration processes. The results of our study were quite well in line with the predictions made by EAMs or PCS. We suggest therefore that information integration processes play a prominent role in decision making. Yet the aforementioned discussion of our findings might also have demonstrated that the supposed integration processes may probably not be completely automatic but may require at least some cognitive effort. Furthermore, the finding that TTB-CCs inhibited conflicting information, whereas WADD-CCs showed no signs of inhibition, challenge the assumption of a single process. As with the MSF, however, the findings suggesting that information integration is probably not completely automatic and that information integration is probably not the only process operating during decision making—these findings do not invalidate EAMs or PCS as models of decision making per se. But these findings suggest that processes other than information integration might also be at work during decision making—processes that might probably well be captured by the rule-like processes postulated by the MSF. Therefore, EAMs/PCS and the MSF may not necessarily be mutually exclusive, and information integration processes might probably operate in parallel to more strategic processes during decision making. When full-fledged frameworks of decision making are pitted against each other (macro-level perspective), the focus might probably be too much on the differences between, and the exclusiveness of, the processes suggested by these frameworks; but the very processes supposed by these frameworks (micro-level perspective) might tend to be overlooked. A promising approach to the study of decision making might be therefore to focus on, and tap into, the specific processes postulated by the different frameworks, such as information integration, rule adherence, or inhibition. I hope the work presented here offered some interesting and novel ideas and methods how this endeavor might be started and accomplished.

References

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego depletion: is the active self a limited resource? *Journal of Personality and Social Psychology*, *74*(5), 1252–1265. doi:10.1037/0022-3514.74.5.1252

Bergert, F. B., & Nosofsky, R. M. (2007). A response-time approach to comparing generalized rational and take-the-best models of decision making. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *33*(1), 107–129. doi:10.1037/0278-7393.33.1.107

Bröder, A. (2000). Assessing the empirical validity of the "take-the-best" heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *26*(5), 1332–1346. doi:10.1037/0278-7393.26.5.1332

Bröder, A. (2003). Decision making with the "adaptive toolbox": influence of environmental structure, intelligence, and working memory load. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *29*(4), 611–625. doi:10.1037/0278-7393.29.4.611

Bröder, A., & Gaissmaier, W. (2007). Sequential processing of cues in memory-based multiattribute decisions. *Psychonomic Bulletin & Review*, *14*(5), 895–900. doi:10.3758/BF03194118

Bröder, A., & Schiffer, S. (2003a). Bayesian strategy assessment in multi-attribute decision making. *Journal of Behavioral Decision Making*, *16*(3), 193–213. doi:10.1002/bdm.442

Bröder, A., & Schiffer, S. (2003b). Take the best versus simultaneous feature matching: probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology. General*, *132*(2), 277–293. doi:10.1037/0096-3445.132.2.277

Bröder, A., & Schiffer, S. (2006). Adaptive flexibility and maladaptive routines in selecting fast and frugal decision strategies. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *32*(4), 904–918. doi:10.1037/0278-7393.32.4.904

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*(3), 432–459. doi:10.1037/0033-295X.100.3.432

Czerlinski, J., Gigerenzer, G., Goldstein, D. G. (1999) How good are simple heuristics? In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.), Simple heuristics that make us smart (pp. 141–167). Oxford: Oxford University Press.

Davis-Stober, C. P., Dana, J., & Budescu, D. V. (2010). Why recognition is rational: Optimality results on single-variable decision rules. *Judgment and Decision Making*, *5*(4), 216–229.

Dieckmann, A., & Rieskamp, J. (2007). The influence of information redundancy on probabilistic inferences. *Memory & Cognition*, *35*(7), 1801–1813. doi:10.3758/BF03193511

Dummel, S., & Rummel, J. (2015). Take-the-best and the influence of decision-inconsistent attributes on decision confidence and choices in memory-based decisions. *Memory,* advanced online publication. doi: 10.1080/09658211.2015.1117642

Dummel, S., & Rummel, J. (2016). Effects of ego-depletion on choice behavior in a multi-attribute decision task. *Journal of Cognitive Psychology.* doi: 10.1080/20445911.2015.1135929

Dummel, S., Rummel, J., & Voss, A. (2016). Additional inforamtion is not ignored: New evidence for information integration and inhibition in take-the-best decisions. *Acta Psychologica,* advanced online publication. doi: 10.1016/j.actpsy.2015.12.001

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*, 451–482. doi:10.1146/annurev-psych-120709-145346

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the Fast and Frugal Way: Models of Bounded Rationality. *Psychological Review*, *103*(4), 650–669. doi:10.1037/0033-295X.103.4.650

Gigerenzer, G., Todd, P., & the ABC Research Group (1999). Simple heuristics that make us smart. Oxford: Oxford University Press.

Glöckner, A., & Betsch, T. (2008a). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *34*(5), 1055–1075. doi:10.1037/0278-7393.34.5.1055

Glöckner, A. & Betsch, T. (2008b). Modeling option and strategy choices with connectionist networks : Towards an integrative model of automatic and deliberate decision making. *Judgment and Decision Making*, *3*(3), 215–228.

Glöckner, A., & Betsch, T. (2012). Decisions beyond boundaries: When more information is processed faster than less. *Acta Psychologica*, *139*(3), 532–542. doi:10.1016/j.actpsy.2012.01.009

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction theory for decision making, *133*, 641–666. doi:10.1016/j.cognition.2014.08.017

Hausmann, D., & Läge, D. (2008). Sequential evidence accumulation in decision making : The individual desired level of confidence can explain the extent of information acquisition. *Judgment and Decision Making*, *3*(3), 229–243.

Khader, P. H., Pachur, T., & Jost, K. (2013). Automatic activation of attribute knowledge in heuristic inference from memory. *Psychonomic Bulletin & Review*, *20*(2), 372–7. doi:10.3758/s13423-012-0334-7

Lee, M. D., & Cummins, T. D. R. (2004). Evidence accumulation in decision making: unifying the “take the best” and the “rational” models. *Psychonomic Bulletin & Review*, *11*(2), 343–352. doi:10.3758/BF03196581

Marí-Beffa, P., Estévez, a F., & Danziger, S. (2000). Stroop interference and negative priming: problems with inferences from null results. *Psychonomic Bulletin & Review*, *7*(3), 499–503. doi:10.3758/BF03214362

Mata, R., Schooler, L. J., & Rieskamp, J. (2007). The aging decision maker: cognitive aging and the adaptive selection of decision strategies. *Psychology and Aging*, *22*(4), 796–810.

doi:10.1037/0882-7974.22.4.796

Newell, B. R. (2005). Re-visions of rationality? *Trends in Cognitive Sciences*, *9*(1), 11–15. doi:10.1016/j.tics.2004.11.005

Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing “one-reason” decision making. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *29*(1), 53–65. doi:10.1037/0278-7393.29.1.53

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. doi:10.1037/0278-7393.14.3.534

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics, and how can we tell? In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.). *Simple Heuristics That Make Us Smart*, 141–167. Oxford: Oxford University Press.

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276. doi:10.1016/j.actpsy.2007.05.004

Rieskamp, J., & Otto, P. E. (2006). SSL: a theory of how people learn to select strategies. *Journal of Experimental Psychology. General*, *135*(2), 207–236. doi:10.1037/0096-3445.135.2.207

Simon, H. (1995). A behavioral model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99–118.

Söllner, A., Bröder, A., Glöckner, A., & Betsch, T. (2014). Single-process versus multiple-strategy models of decision making: Evidence from an information intrusion paradigm. *Acta Psychologica*, *146*(1), 84–96. doi:10.1016/j.actpsy.2013.12.007

Söllner, A., Bröder, A., Söllner, A., & Bröder, A. (2015). Toolbox or adjustable spanner: A critical comparison of two metaphors for adaptive decision making. *Journal of Experimental Psychologiy: Learning, Memory, and Cognition*.

Tipper, S. P. (2001). Does negative priming reflect inhibitory mechanisms? A review and integration of conflicting views. *The Quarterly Journal of Experimental Psychology, 54*(2), 321–343. doi:10.1080/02724980042000183

Todd, P., & Gigerenzer, G. (2000). Precis of simple heuristics that make us smart. *Behavioral and Brain Sciences*, 727–780.

Voss, A., Nagler, M., & Lerche, V. (2013). Diffusion models in experimental psychology. *Experimental Psychology*, *60*(6), 385–402. doi:10.1027/1618-3169/a000218

Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: an empirical validation. *Memory & Cognition*, *32*(7), 1206–1220. doi:10.3758/BF03196893

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Appendix A1 – Article 1

Note:

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Additional information is not ignored: New evidence for information integration and inhibition in take-the-best decisions

Sebastian Dummel, Jan Rummel, and Andreas Voss

Heidelberg University

Author Note

Sebastian Dummel, Jan Rummel, Andreas Voss, Department of Psychology, Heidelberg University, Germany.

Correspondence concerning this article should be addressed to Sebastian Dummel, Department of Psychology, Heidelberg University, Hauptstrasse 47-51, 69 117 Heidelberg, Germany. E-mail: sebastian.dummel@psychologie.uni-heidelberg.de

Abstract

Ignoring information when making a decision is at the heart of the take-the-best (TTB) strategy, according to which decision makers only consider information about the most valid cue (TTB-relevant) and ignore less valid cues (TTB-irrelevant). Results of four experiments, however, show that participants do not ignore information when cues are easily available (Experiments1a, 1b, and 3) or when task instructions emphasize decision accuracy (Experiment 2). In all four experiments we found that the consistency between the TTB-relevant cue and a supposedly TTB-irrelevant cue systematically affected decision times and confidence ratings of even those participants whose choices were consistently driven by only the TTB-relevant cue. In Experiments 1a and 1b, we also found that these participants were more likely to ignore information when cues had to be acquired sequentially, suggesting that whether or not participants ignore information depends on information availability. Experiment 2 further showed that different task instructions (emphasizing decision accuracy vs. speed) affect whether or not participants ignore information. Finally, Experiment 3 addressed the question of how participants process information that, according to TTB, is considered irrelevant for their choices. We find first evidence that participants who consistently make choices in line with TTB inhibit information about a TTB-irrelevant cue when this information conflicts with their decisions. Findings are considered and discussed in relation to current models of decision making.

Keywords: decision-making; take-the-best heuristic; evidence accumulation; inhibition

Additional information is not ignored: New evidence for information integration and inhibition in take-the-best decisions

Introduction

Choosing between two options is not always easy, especially when the options differ on several decision-relevant attributes and neither option is unequivocally favored by all attributes: Some attributes are in favor of the first option, others in favor of the second option. To illustrate, consider a doctor who needs to decide which of two patients is more severely infected and should be treated first. The doctor may have a symptom check-list for each patient where each list indicates the presence/absence of four symptoms, referred to as cues. The symptoms differ in their extent to which they predict a patient's level of infection, referred to as cue validity. The symptoms may be: fever, dizziness, nausea, and abdominal pain (from high to low validity). The list of Patient 1 indicates the presence of fever but no further symptoms, whereas the list of Patient 2 shows the presence of dizziness, nausea, and abdominal pain, but not fever (written here as P1: 1-0-0-0, and P2: 0-1-1-1).

As illustrated in this example, cue information can be in conflict: a highly valid cue points to P1 (fever), whereas three less valid cues point to P2 (dizziness, nausea, abdominal pain). Decision-making researchers have long been interested in studying how people respond in such situations (Gigerenzer & Gaissmaier, 2011; Gigerenzer, Tood, & The ABC Research Group, 1999; Payne, Bettman, & Johnson, 1988), and there seems to be common agreement that some people resolve the conflict by integrating *all available information* about the options. Other people, in contrast, are assumed to not notice the conflicting information because they seem to just look for the most valid cue and if it allows them to make a decision (i.e., if it discriminates between the options) they will stop collecting further information and base their choice on only *parts of the available information* (Lee & Cummins, 2004; Newell & Lee, 2011). This latter approach is at the heart of the fast-and-frugal-heuristics framework of decision making (e.g., Gigerenzer & Gaissmaier, 2011). A key heuristic specifically formulated for tasks of multi-cue decision-making, like the one above, is the *take-the-best* (TTB) strategy.

Decision makers following TTB are assumed to process cues in descending order of their validity. As soon as a cue discriminates between the options, the decision maker will stop looking for further information and chooses the option pointed to by the first discriminating cue (the *best cue*). TTB can thus be said to consist of three building blocks (Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2011): a *search rule*, a *stopping rule*, and a *decision rule*. Following all three rules, a decision maker confronted with the two patients from above would start comparing the patients on the most relevant symptom, fever (search rule); because this symptom discriminates between the two patients, the decision maker would stop looking for further information (stopping rule) and will choose the patient with the symptom being present (P1; decision rule). Hence, a decision maker following TTB would only inspect one cue for her choice.

In decision-making research, TTB is often contrasted with decision strategies which assume that all information is being processed before a choice is made. One such strategy that we considered for the present research is the *weighted additive rule* (WADD; Payne, Bettman, & Johnson, 1988). Decision makers following WADD are assumed to weight all cues of an option by their validity, sum up the weighted evidence for each option, and choose the option with the higher amount of evidence. Following WADD, a decision maker confronted with the two patients above would multiply the symptoms with their validity and sum up the weighted symptoms for each patient. If the weighted sum of the less valid cues exceeds the validity of the most valid cue, the decision maker would choose P2. Because WADD allows for the possibility that a highly valid cue can be compensated for by two or more less valid cues, WADD is often called *compensatory*, whereas TTB is called *non-compensatory*.

As illustrated by the introductory example, for some binary decisions (e.g., 1-0-0-0 vs. 0-1-1-1), TTB and WADD make different choice predictions (provided that the weighted sum of the less valid cues exceed the validity of the best discriminating cue): TTB predicts the choice of option (1-0-0-0), whereas WADD predicts the choice of option (0-1-1-1). The choices participants make in a decision experiment are commonly used to classify them as users of TTB, WADD, or any other decision strategy under consideration (Bergert & Nosofsky, 2007; Bröder, 2000; Bröder & Schiffer, 2003; Lee & Cummins, 2004; Newell & Lee, 2011). Moreover, choice outcomes are often used to draw conclusions about the *processes* underlying participants' choices (Lee & Cummins, 2004; Newell & Lee, 2011). It is often—implicitly or explicitly—concluded that participants who show an outcome in line with the TTB-decision-rule stopped information search earlier than did participants who made choices as predicted by WADD.

Importantly, however, the mere analysis of participants' choice outcomes only allows for drawing conclusions about which participants most likely *did not* ignore information, that is, participants who made choices in line with WADD. Participants who make choices in line with the best discriminating cue (TTB), however, may have done so because they stopped information search after discovering this cue—as suggested by the TTB-stopping-rule. Yet it is also possible that these participants processed cue information completely and nevertheless chose the option favored by the best discriminating cue, because they perceived this cue as important enough to outweigh all less valid cues jointly (see also Glöckner, Hilbig, & Jekel, 2014). In the next paragraph(s), we will outline the possible implications of a strategy mimicking the outcomes of TTB (i.e., choices) but without following the strategy's stopping rule. To avoid confusion, we will refer to decision makers who show a choice outcome in line with TTB as TTB-consistent choosers (TTB-CCs). Note that this term only implies that individuals classified as TTB-CCs show a decision outcome in line with TTB; it does not make any assumptions about the possible processes underlying these outcomes (i.e., whether a stopping-rule is adopted or not).

One might argue that TTB-CCs do not need to process additional cues because these cues have no bearing on their choices. However, in line with other researchers (e.g., Hausmann & Läge, 2008;

Newell, Weston, & Shanks, 2003), we suggest that, in addition to making choices in a decision task, decision makers also want to know how confident they can be with their choices. Especially when cue information is easily available, the processing of additional cue information comes with very little cognitive costs but it provides decision makers with important information regarding decision confidence. One of the questions we therefore want to address in this research is whether TTB-CCs actually ignore cue information in decision tasks where information is easily available (i.e., openly displayed). As argued, we suggest that TTB-CCs have good reasons to not ignore information when it can easily be processed, and the reason for why they finally go with the best discriminating cue may be that they consider this cue as most important for their decisions. It should be noted that we do not generally question the assumption that decision makers ignore information. The TTB strategy has originally been postulated for inferences from memory, that is, decision situations where cues are not easily available but have to be retrieved (Gigerenzer, Hoffrage, Kleinbölting, 1991; Gigerenzer & Goldstein, 1996). The cognitive costs of retrieving and processing cue information can be considered relatively high compared with the costs of processing openly displayed information, and here decision makers may have good reasons to ignore cues. Therefore, our assumption that decision makers would not ignore information specifically refers to situations where cues are easily available.

The strategy we suggest to underlie the decision behavior of TTB-CCs resembles the one described by a certain class of decision-making models, the so called evidence accumulation models (EAMs, Lee & Cummins, 2004). EAMs assume that, when facing a choice between two options, decision makers sequentially sample information about the cue values of the options at hand and automatically integrate this information. Information sampling terminates as soon as the amount of evidence in favor of one option passes a decision maker's decision threshold and the option favored by the evidence is then chosen. Psychologically, a decision threshold can be understood as an individual’s desire for decision confidence (Hausmann & Läge, 2008). Lee and Cummins (2004) were the first to suggest that the strategies TTB and WADD can be accounted for by a *unifying* EAM. According to this model, TTB-CCs are assumed to set a threshold that is passed by information from any single cue, suggesting therefore that TTB-CCs would stop information search in line with the TTB-stopping-rule, whereas WADD-CCs are assumed to set a threshold that guarantees the processing of all cue information.

As just argued, however, we suggest that TTB-CCs will *not* necessarily stop information search in line with the TTB-stopping-rule when information is easily available. In terms of EAMs, the decision threshold of TTB-CCs may thus be said to be higher than the information provided by one cue alone, even when it is the most valid cue. Yet because TTB-CCs give most weight to the best discriminating cue, this cue consistently outweighs less valid cues and therefore drives TTB-CCs' choices. WADD-CCs, in contrast, weight the cues more equally, so that a highly valid cue can be compensated for by less valid cues. One reason for this difference in cue weighting between TTB-CCs (non-compensatory weighting) and WADD-CCs (compensatory weighting) could be that the former perceive relatively high dispersion among cue validities, whereas the latter perceive rather low cue dispersion and treat the cues more equally (see Glöckner et al., 2014, or Bröder, 2000, for systematic investigations of how differences in validity dispersions between different environments affects decision making). To summarize, in line with Lee and Cummins (2004), we consider EAMs as an overarching framework for the present research and for explaining the decision behavior of both TTB-CCs and WADD-CCs. Yet, whereas Lee and Cummins' unifying model assumes that TTB-CCs actually ignore information about cues lower in validity than the best discriminating cue (and therefore choose the option favored by this cue), we suggest that TTB-CCs would not ignore this information when it is easily available, but that they would integrate the cues in a non-compensatory manner.

To examine this assumption, we measured participants' decision times (and decision confidence) in a task where cue information was directly accessible, and we manipulated the consistency between the choice-relevant best cue and the choice-irrelevant next-best cue: The best and the next-best cue were either consistent (e.g., 1-**1**-0-0 vs. 0-**0**-0-0) or inconsistent (e.g., 1-**0**-0-0 vs. 0-**1**-0-0). If participants followed the TTB-stopping-rule and thus ignore cues lower in validity than the best discriminating cue, information about the next-best cue should not affect decision times or confidence. However, if, TTB-CCs did *not* ignore less valid cues, EAMs would predict slower decisions and lower decision confidence when cue information is inconsistent rather than consistent. According to EAMs, decision time and decision confidence depend on the difference in evidence between the two choice options: The higher the evidence difference is (higher information consistency), the faster and the more confident decision makers (both TTB and WADD) are expected to be.

In addition to manipulating the status of the next-best cue (consistent vs. inconsistent with best cue), we varied the validity rank of the best discriminating cue, that is, the ordinal position of the discriminating cue within the validity hierarchy. The best discriminating cue either was the most valid (cue 1), the second-most-valid (cue 2), or the third-most valid cue (cue 3). Previous studies found that the decision times of TTB-CCs increased with the validity of the best discriminating cue decreasing (Bergert & Nosofsky, 2007; Bröder & Gaismaier, 2007). It has been reasoned that, when decision makers search the cues in descending order of their validity (TTB-search-rule), then they need to inspect more cues the later in the validity hierarchy the best discriminating cue occurs (i.e., the lower the validity of this cue is). In our view, the number of cues to be inspected until a discriminating cue is found, may indeed contribute to an increase in decision times as previously observed. However, the original explanation for this effect supposes that TTB-CCs actually stop information sampling after discovering a discriminating cue. That is, only when TTB-CCs did not continue information sampling once a discriminating cue had been found, they would have had to inspect only one cue when cue 1 was the best discriminating cue, and three cues, when cue 3 was the best discriminating cue. Our assumption, however, is that TTB-CCs would not stop information sampling at the discovering of the discriminating cue, but that they would process cue information completely. Yet even though we expect TTB-CCs to process cue information completely, we nevertheless expect their decision times to increase with the validity rank of the best discriminating cue decreasing, not only because of the cue's ordinal position in the validity hierarchy and thus the number of cues inspected until the discriminating cue is found; but also because of the cue's *validity* itself. According to EAMs, decision time is a function of the amount of evidence in favor of a certain decision option, and the amount of evidence depends on the validity of the provided information. Assuming that, as outlined previously, TTB-CCs perceive high dispersion among cue validities, they may perceive stronger evidence in favor of an option when this option is favored by cue 1 (**1**-0-0-0 vs. **0**-0-0-0) than when it is favored by cue 2 (1-**1**-0-0 vs. 1-**0**-0-0). The perceived stronger evidence, in turn, may then accelerate the decision. Therefore, we expect the validity rank of the best discriminating cue to influence decision times of those participants perceiving high dispersion among cue validities (TTB). For participants perceiving only few differences among cue validities (WADD), the validity rank of the best cue should have less influence on decision times.

The assumption that TTB-CCs may be sensitive to cue information considered to be irrelevant according to the TTB-stopping-rule recently received first support. In a study by Söllner, Bröder, Glöckner, and Betsch (2014), participants learned to use a TTB strategy in a decision task where participants had to pay virtual money to purchase cue information and where the payoff function of the decision environment favored the use of a TTB strategy. On some trials of the task, however, TTB-irrelevant information popped up for free. This information was either consistent or inconsistent with the best cue. Contrary to the ignorance assumption implied by the TTB-stopping-rule, however, the TTB-irrelevant information affected participants' decision behavior as predicted by EAMs: Participants continued information purchase more frequently and they were less confident in their decisions, when the up-popping information was inconsistent rather than consistent with the best cue. Söllner and Bröder (2015) recently extended these findings by showing that TTB-CCs continue information search more frequently in the presence of inconsistent information when this information was acquired by participants themselves rather than being experimenter-provided, ruling out that the aforementioned finding was due to mere cue saliency (Platzer & Bröder, 2012). In sum, using decision tasks with sequential information search, Söllner and colleagues found converging evidence that TTB-CCs do not consistently stop their information search as predicted by the TTB-stopping-rule, especially when cues are inconsistent.

The present experiments aimed to extend the findings—that TTB-CCs are not completely ignorant of additional information—to a decision task with cue information directly accessible to participants. Information search behavior has been found to vary systematically as a function of whether cue information has to be acquired sequentially or is openly displayed (e.g., Lohse & Johnson, 1996). It is not clear, therefore, whether the findings by Söllner and colleagues directly translate to a decision task with cues directly accessible. Recent findings by Glöckner et al. (2014; see also Glöckner & Betsch, 2012) suggest that this may be the case. In their decision task, cue information was directly accessible during decision making and they showed that decision times and decision confidence of TTB-CCs were affected by the overall consistency of the information. Although this finding suggests that TTB-CCs are not ignorant of directly accessible cues, there may have been some specific task settings in the studies by Glöckner and colleagues that may have encouraged participants to process more information than considered necessary for their choices. Specifically, in their decision tasks, the arrangement of cues, and hence the position of the TTB-relevant best cue, changed from trial to trial (but see Glöckner et al., 2014, Experiment 2); thus, by searching for the best cue on a decision trial, participants may have processed irrelevant cues inadvertently. Furthermore, participants of the studies by Glöckner and colleagues were asked to indicate their decision confidence after each decision they made. It is possible that these consistent confidence prompts heightened participants' desire for confidence (and thus their decision thresholds), thereby prompting them to look for more cues than just the TTB-relevant cue. Finally, for their decision task, Glöckner et al. (2014) used a set of six decision pairs, and for five of the six pairs, the TTB-relevant cue was always the cue with the highest validity (cue 1). Thus, the cue on which TTB-CCs based their choices was almost always the same one, which might have further encouraged TTB-CCs to not stop information search at the discovery of this cue but to process additional cues in order to counteract the otherwise rather monotonous task routine.

A first goal of the present research was therefore to demonstrate that, even when information about single cues could easily be ignored in a task with directly accessible information, and when participants are not consistently prompted for decision confidence, TTB-CCs would still not ignore additional cues. Furthermore, by systematically varying both the validity-rank of the best discriminating cue and the status of the next-best cue, we aimed to examine how participants' decision behavior is affected by both factors.

Our assumption that TTB-CCs would not ignore cue information specifically refers to decision situations where cues are directly accessible. However, there may be situations, both in real-life and in the laboratory, where cues are not that easily available but have to be acquired sequentially, as in the study by Söllner and Bröder (2015). Their findings suggest that even under these conditions, TTB-CCs do not consistently ignore information, though other research found relatively strong support for the TTB-stopping-rule when information search was sequential (e.g., Newell & Shanks, 2003, Experiment 3). A second goal of our research was to examine whether TTB-CCs would adjust their decision thresholds as a function of information availability. That is, we tested whether TTB-CCs would not ignore information when cues are directly accessible, but that they would be more likely to ignore information when cues have to be acquired sequentially (Experiments 1a and 1b). We also examined how different task instructions, rather than information availability, affect participants' decision thresholds, and whether focusing participants on decision confidence would make them more likely to look for TTB-irrelevant cues (Experiment 2). Finally, in addition to further our understanding of the conditions under which TTB-CCs may most likely not ignore information, we aimed to get a better understanding of what TTB-CCs are doing with the information they processed. Concretely, we tested whether TTB-CCs inhibit irrelevant cue information when it is conflicting with their choices (Experiment 3).

The Present Paradigm

In all four experiments presented here we used a decision-task paradigm introduced by Bergert and Nosofsky (2007). Participants of this task had to decide which of two bugs, described by four binary cues (*body*, *legs*, *antennae*, and *fangs*) of varying validities, was more poisonous. All experiments consisted of a validity *learning phase* and two *test phases*. In the learning phase, participants performed the bug decision task and received feedback on their decisions; the feedback allowed participants to figure out the cue validities, which were .94, .83, .79, and .71 (to facilitate learning, participants received a hint regarding the correct validity ranking halfway through the learning phase; cf. Newell & Shanks, 2003). In the subsequent test phase, participants performed the same decision task without feedback. In the first part of the test phase (Test Phase 1) cue information was directly accessible, whereas in the second part (Test Phase 2) information about single cues had to be acquired sequentially.

There were two types of bug pairs we used for the test phase. The *diagnostic pairs* were those pairs for which TTB and WADD make different choice predictions (see Table 2). Diagnostic pairs enabled us to classify participants as TTB and WADD, respectively. For the classification, we also considered the possibility that participants used an equal-weight strategy (EQW), meaning that they considered all cues and weighted them equally. The *experimental pairs* of the test phase were those pairs we obtained by crossing the two experimental factors introduced above: validity-rank of the best discriminating cue (cue 1, cue 2, cue 3), and status of the next-best cue (consistent vs. inconsistent).

Experiments 1a and 1b

In Experiments 1a and 1b we tested the hypothesis that TTB-CCs would not ignore cue information when cues are directly accessible. Cues in our task were presented in a way that cues of certain validities always occurred at the same positions. Participants therefore knew where to look for the TTB-relevant best discriminating cue and could easily ignore other cues if they wanted. In Experiment 1a we used holistic pictures of bugs (cf. Figure 1, top panel). In all other experiments, pictures of the single features of the bugs were presented in a list-wise format and cues were presented in descending order of their validities (cf. Figure 1, bottom panel). This format should make it especially easy for TTB-CCs to ignore TTB-irrelevant cues. Our main dependent variable for Test Phase 1 was decision times. In Experiment 1b, we further asked participants to bet on their decisions in a separate, final block of the task. Previous studies found that information consistency affects participants' decision confidence (Söllner et al., 2014; Glöckner et al., 2014, Glöckner & Betsch, 2012). Assuming that decision confidence plays an important role when participants bet on their decisions, Experiment 1b examined whether information consistency would likewise affect participants' betting behavior. Finally, Experiments 1a and 1b addressed the question of whether TTB-CCs would behave more in line the TTB-stopping-rule when information has to be acquired sequentially rather than being directly accessible, which may suggest that TTB-CCs adjust their decision thresholds as a function of information availability.

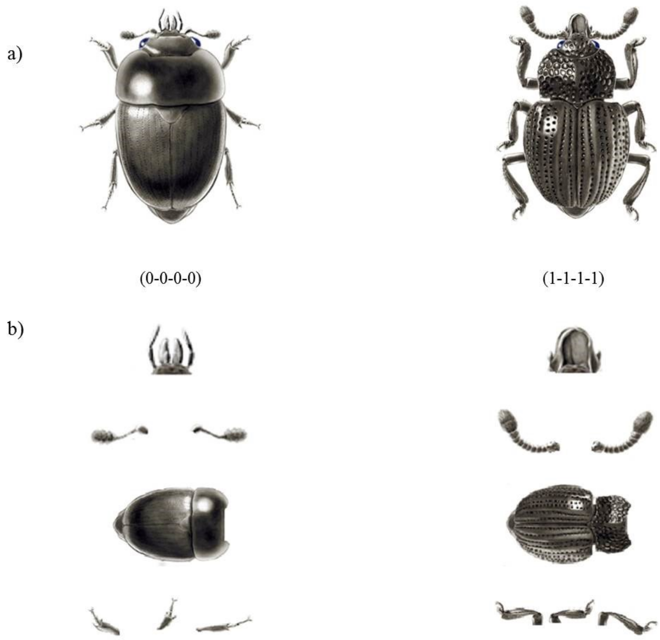

Figure 1. Example of a pair of bugs that differ on all features. In Experiment 1a, bugs were presented holistically (a). In all other Experiments, bugs were presented as lists of their features (b).

Method

Participants. Heidelberg University students participated for partial course credit or monetary compensation (8€). In addition to receiving either course credit or monetary compensation, all participants could earn a bonus of up to 6.45 € contingent on task performance (Experiment 1a: N = 50, 39 female, mean age = 21.82; Experiment 1b, N = 74, 55 female, mean age = 22.5).

Materials and design. Our stimulus set comprised sixteen pictures of bugs taken from the stimulus set by Bergert and Nosofsky (2007). The bugs were described by four binary cues, represented as physical features, and each cue could take on two different physical appearances (*cue values*; e.g., *short* vs. *long* legs). Figure 1 depicts two bugs that differ on all cues. Fully combining the four cues resulted in our set of 16 different bugs. Table 1 shows the cue patterns for the 16 bugs (the value “1” denotes the cue value indicative of poisonousness). The 10 cue patterns displayed in the upper part of Table 1 were used to create the learning environment. A complete pairing of the 10 patterns yielded 45 learning pairs.

Table 1

Abstract Cue Patterns Used in Experiments 1 – 3

Stimulus Number	Cue 1 (.94)	Cue 2 (.83)	Cue 3 (.79)	Cue 4 (.71)	Criterion Variable (poison index rank)
Cue patterns for the learning phase					
1	1	1	1	1	10
2	1	1	1	0	9
3	1	0	1	1	8
4	1	1	0	1	7
5	0	1	0	1	6
6	1	0	1	0	5
7	0	1	0	0	4
8	0	0	1	0	3
9	0	0	0	1	2
10	0	0	0	0	1
Cue patterns to create diagnostic pairs					
11	1	0	0	0	
12	1	1	0	0	
13	1	0	0	1	
14	0	1	1	1	
15	0	1	1	0	
16	0	0	1	1	

Note. The cue values 1 and 0 were realized as physical appearances of a bug's different features. In the learning phase only the ten patterns on top were presented.

The learning phase consisted of two blocks, each consisting of the 45 learning pairs. The cue patterns in Table 1 (top) are ranked by their level of poisonousness, and cue validities were calculated as suggested by Bergert and Nosofsky (2007; see also Lee & Cummins, 2004):

$$v(i) = \frac{number\ of\ correct\ decisions\ made\ by\ cue(i)\ +\ 1}{number\ of\ all\ discriminations\ made\ by\ cue(i)\ +\ 2}$$

This formula takes into account both the number of times a cue discriminates between a pair and the number of times a correct choice can be made based on this cue. Cue validities were randomly assigned to the four cues for each participant anew, and for each cue, the cue value associated with poisonousness was randomly chosen. Note that as in previous studies (Bergert & Nosofsky, 2007; Lee & Cummins, 2004) only pairs for which TTB and WADD make identical choice predictions were presented during validity learning. Therefore, participants should not have been biased toward TTB- or WADD-decision-making, respectively.

The cue patterns not shown during the learning phase were used to create the diagnostic pairs for the test phases (Table 2). For the diagnostic pairs, TTB predicts the choice of option A, whereas WADD and EQW predict the choice of option B. The 12 consistent and 12 inconsistent pairs shown in Table 3 were the test pairs obtained when crossing the factor *validity-rank of the best discriminating cue* (cue 1, cue 2, cue 3) with the factor *status of the next-best cue* (consistent vs. inconsistent). Both factors were manipulated within subjects.

Table 2

Pairs for Which the Strategies Predict Opposing Choices

Diagnostic pairs	
Option A	Option B
1000	0111
1000	0110
1000	0101
1000	0011
1001	0111
1010	0111
1100	0111
0100	0011

The test phase was further subdivided in two phases: In Test Phase 1, cue information was directly accessible; in Test Phase 2, cue information had to be acquired sequentially. In Test Phase 1, individual choices were used for the strategy classification and decision time was our main dependent variable. To attain both reliable decision time estimates for each within-subjects condition (cf. cells in Table 3) and a reliable strategy classification, we presented all 24 consistent and inconsistent pairs as well as all eight diagnostic pairs four times each, yielding 128 decision trials. Presentation order of pairs was randomly determined with the constraint that each of the 32 pairs had to be presented once before a pair was repeated.

In Experiment 1b, Test Phase 1 was extended by an additional block where the consistent, inconsistent, and diagnostic pairs were presented only once and where participants were asked to bet on each decision (*betting block*).

In Test Phase 2 (both experiments), the consistent, inconsistent, and diagnostic pairs were also presented only once. In this phase, cues were not directly accessible but participants could uncover the cues sequentially (see Procedure section).

Table 3

Pairs Used in the Decision Tasks of Experiments 1 - 3

	Status of the next-best cue					
Validity-rank of the best discriminating cue	Consistent pairs		Inconsistent pairs		Non-discriminating (Experiment 3 only)	
	Option A	Option B	Option A	Option B	Option A	Option B
Cue 1	1111	0011	1011	0111	1111	0111
	1110	0010	1010	0110	1110	0110
	1101	0001	1001	0101	1101	0101
	1100	0000	1000	0100	1100	0100
Cue 2	1111	1001	1101	1011	1111	1011
	1110	1000	1100	1010	1110	1010
	0111	0001	0101	0011	0111	0011
	0110	0000	0100	0010	0110	0010
Cue 3	1111	1100	1110	1101	1111	1101
	1011	1000	1010	1001	1010	1001
	0111	0100	0110	0101	0110	0101
	0011	0000	0010	0001	0010	0001

Procedure. We used a cover story to enhance plausibility of the task. Participants were told that they were doctors and would soon travel in a tropical country to take up employment at the hospital there. The country was said to be known for its poisonous bugs and participants should learn about some specific cues of these bugs.

The experiment started with the learning phase which was identical for all experiments. On each trial, participants were shown a bug pair and had to choose the more poisonous bug, using the left and right arrow keys. After each choice, the German words for correct or incorrect appeared on the screen and the correct (i.e., more poisonous) bug was additionally highlighted by a red frame. Participants could study the feedback as long as they liked and started the next trial by pressing the space bar. At the end of the first learning block, participants received feedback about their overall accuracy. They were next told that the cues varied in their *usefulness* to predict poisonousness and they were given the validity hierarchy (ranking) of the cues (they were not given the cue directions though). Participants were also told that they would receive 2 cent for each correct decision in a second learning block. The procedure of the second block was identical to that of the first block.

Afterwards, participants received instructions for Test Phase 1. They were told that they had arrived at the tropical country and started their work as doctors. They were now confronted with the following situation: Two Patients A and B had been bitten by differently poisonous bugs. As doctors, participants had to decide which of the two patients needed to be treated first and thus which bug was more poisonous. Participants were also told that they would receive a bonus of 2 € if accuracy in the following task was above 80%. In the test phase, participants no longer received feedback. Instead, bug pairs remained on the screen for another 500 ms after a response was given, and the next trial started after an inter-stimulus-interval of 1000 ms.

After Test Phase 1, the procedure continued with instructions for Test Phase 2 in Experiment 1a (see below). In Experiment 1b, participants were told that another 32 trials of the same task would follow and that subsequent to each decision, they would be asked to bet on their choice (betting block). To this end, the screen depicting the bug pair turned to a screen prompting participants' bets once a choice had been made. Participants could bet between 1ct and 10ct, using the keys F1 (1ct) to F10 (10ct). They were told that their bet, and hence the money they would get, would double if their choice was correct, but they would lose their bet if their choice was false. Participants did not receive direct feedback on their decisions but were informed that the computer kept track of their decisions and their bets and would update their earnings.

For Test Phase 2, which was identical for both experiments, participants were informed that they were now required to make inquiries about the bugs' cues before making their decisions, and that they could ask the two to-be-compared patients up to four questions—one question for each cue (*What did the legs/antennae/body/fang of the bugs look like?).* The questions were presented in a fixed order, one below the other. Each question was associated with a key (F1 to F4) which participants were required to press to ask a question. Having asked a question, the corresponding features of the bugs (shown as pictures of the single cues; cf. Figure 1, bottom) appeared on the screen for both patients. Participants were free to ask as many questions as they wanted without order restrictions.

Following Test Phase 2, participants received feedback about their accuracy in the decision task and were told their bonus. Next, they were asked to indicate for each of the four cues the predictive utility it had for them in the learning phase (on a scale ranging from 1 = *not useful* to 9 = *very useful*). Predictive utility ratings were used to check (1) whether participants were aware of the cue validity ranking and (2) whether TTB-CCs perceived higher dispersion among cue validities than did WADD-CCs. Finally, participants were shown the eight cue values and were to indicate those cue values pointing to poisonousness. This cue-knowledge test was used to assess whether participants had correctly learned which of the two cue values was indicative of poisonousness.

Results

The alpha-level for each test was set at 0.05. The reported effect size is generalized eta square (η^2_G). When sphericity was violated Greenhouse-Geisser corrected results are reported. All analyses were conducted in *R* (*R* Core Team, 2013); for planned contrasts analyses the R-package nlme was used (Pinheiro, Bates, DebRoy, Sarkar, & the *R* Development Core Team, 2013).

Learning phase and cue-knowledge test. Data from the learning phase showed that accuracy was good in both experiments and increased from block 1 (Experiment 1a: 80.76%, SD = 7.29; Experiment 1b: 80.36%, SD = 9.01) to block 2 (Experiment 1a: 93.20%, SD = 3.85; Experiment 1b: 92.6%, SD = 3.42), $F_{1a}(1, 49) = 145.02$, $p < .001$, $\eta^2_G = 0.54$; $F_{1b}(1,74) = 147.55$, $p < 0.001$, η^2_G = 0.45. Data from the final cue-knowledge test revealed that all but one participant of Experiment 1a

(98%) and all but four participants of Experiment 1b (95%) learned the eight cue values correctly. Non-learners were omitted from subsequent analyses.

Test Phase 1: Strategy classification. We used the strategy-classification method by Bröder and Schiffer (2003) to classify participants into TTB-CCs, WADD-CCs, or EQW-CCs, respectively[1]. For the classification, choices to all pairs were considered. As noted above, TTB and WADD/EQW make opposing choice predictions for the diagnostic pairs. For consistent pairs, all strategies make identical choice predictions (option A in Table 3). For the inconsistent pairs, TTB and WADD predict identical choices, whereas EQW assumes guessing. In a nutshell, the idea of the classification method is to estimate the likelihood of a participant's *observed choice pattern*, given each of the strategies *predicted choice patterns*, plus a constant error term ε (estimated from the data).

This way, participants were classified according to the strategy with the highest likelihood provided that ε was smaller than .40. If ε was greater than .40, a guessing strategy (guess) was assumed. If two strategies had identical likelihoods, the participant remained unclassified. Table 4 depicts the obtained strategy proportions for all experiments. In Experiment 1a, the majority of participants were classified as TTB-CCs; in Experiment 1b, the proportion of TTB-CCs and WADD-CCs was roughly equal.

Table 4

Number of Participants Classified According to the Best-Fitting Strategy in the Test-Phases of Experiments 1 – 3

	Strategy							
Test-phase	TTB	ε	WADD	ε	EQW	ε	unclassifed	Total
Experiment 1a								
Test Phase 1	31 (62%)	0.04	11 (20%)	0.06	7 (14%)	0.06	-	49
Test Phase 2	29 (60%)	0.04	14 (28%)	0.05	5 (10%)	0.06	1 (2%)	49
Experiment 1b								
Test Phase 1	30 (43%)	0.04	30 (43%)	0.07	8 (11%)	0.04	2 (3%)	70
Betting Block	30 (43%)	0.03	32 (46%)	0.04	7 (10%)	0.03	1 (1%)	70
Test Phase 2	31 (44%)	0.05	27 (39%)	0.05	10 (14%)	0.05	2 (3%)	70
Experiment 2								
Test Phase 1	23 (50%)	0.07	18 (39%)	0.08	5 (11%)	0.02	-	46
Accuracy Block	22 (48%)	0.04	16 (35%)	0.07	8 (17%)	0.04	-	46
Speed Block	23 (50%)	0.04	16 (35%)	0.06	5 (11%)	0.03	2 (4%)	46
Experiment 3								
Test Phase 1	37 (54%)	0.05	24 (35%)	0.04	5 (7%)	0.01	3(4%)	69
Confidence Block	34 (49%)	0.03	29 (41%)	0.04	3 (4%)	0.00	3 (4%)	69

Note. TTB = take the best; WADD = weighted additive; EQW = equal weights; ε = error term. Proportions in brackets.

Test Phase 1: Decision times. For the statistical analysis of decision times, responses inconsistent with a participant's strategy were removed (Experiment 1a: 4.21%; Experiment 1b: 4.29%) as were outliers, defined as RTs smaller than 300ms or RTs greater than individual mean plus

2.5 standard deviations (Experiment 1a: 0.36%; Experiment 1b: 0.19%). Decision times were analyzed separately for each of the three strategy groups.[2] For each group, data were submitted to a 3 (validity-rank of the best discriminating cue: cue 1, cue 2, cue 3) × 2 (status of the next-best cue: consistent, inconsistent) within-subjects ANOVA. The decision times of participants of both experiments are depicted in Figure 2.

The TTB-stopping-rule predicts that the decision times of TTB-CCs should not be affected by the next-best cue. Contrary to this prediction, the status of the next-best cue had a significant effect on TTB-CCs' decision times in both experiments, Experiment 1a: $F(1, 30) = 12.35$, $p = 0.001$, $\eta^2_G = 0.024$, and Experiment 1b: $F(1, 29) = 18.32$, $p < 0.001$, $\eta^2_G = 0.027$. Furthermore, in both experiments the decision times of TTB-CCs were significantly affected by the validity-rank of the best discriminating cue, Experiment 1a: $F(2, 60) = 50.61$, $p < 0.001$, $\eta^2_G = 0.12$; Experiment 1b: $F(2, 58) = 8.83$, $p < 0.001$, $\eta^2_G = 0.017$. The interaction was not significant in Experiment 1a, $F < 1$; but it was significant in Experiment 1b, $F(1.5, 43.5) = 3.83$, $p = 0.027$, $\eta^2_G = 0.005$. As evident from Figure 2 (bottom), TTB-CCs' decision times were most strongly affected by the status of the next-best cue when the most valid cue was the best discriminating cue. Follow-up analyses revealed, however, that the status of the next-best cue significantly affected participants' decision times on all levels of the validity-rank factor, ps < 0.04.

In Experiment 1a, decision times of both WADD-CCs and EQW-CCs were only affected by the status the next-best cue, $F_{WADD}(1, 10) = 54.91$, $p < 0.001$, $\eta^2_G = 0.395$, and $F_{EQW}(1, 6) = 10.21$, $p = 0.019$, $\eta^2_G = 0.101$. WADD- and EQW-CCs were slower when the next-best cue was inconsistent with the best cue ($M_{WADD} = 5055.7$, $SE = 233.6$; $M_{EQW} = 4562.0$, $SE = 471.4$), than when both cues were consistent ($M_{WADD} = 3150.5$ $SE = 131.6$; $M_{EQW} = 2853.6$ $SE = 251.9$). In both groups, neither the effect of the validity-rank of the best discriminating cue nor the interaction was significant, Fs < 1.63, ps > 0.236.

In Experiment 1b, decision times of WADD-CCs were significantly affected by both the validity rank of the best discriminating cue, $F(1.56, 45.24) = 15.26$, $p < 0.001$, $\eta^2_G = 0.04$, and the status of the next-best cue, $F(1, 29) = 115.59$, $p < 0.001$, $\eta^2_G = 0.21$. Furthermore, the interaction was significant, $F(2, 58) = 8.45$, $p < 0.001$, $\eta^2_G = 0.02$. As evident from Figure 2, when cue 3 was the best discriminating cue, the status of the next-best cue had a less pronounced effect on participants' decision times than when cue 1 or cue 2 were best discriminating cues. Follow-up analyses revealed that the effect of the next-best cue was significant on all levels of the validity-rank factor, ps < 0.001. The decision times of EQW-CCs of Experiment 1b were also affected by both the validity rank of best discriminating cue, $F(2, 14) = 4.90$, $p < 0.05$, $\eta^2_G = 0.018$, and the status of the next-best cue, $F(1, 7) = 8.66$, $p < 0.05$, $\eta^2_G = 0.25$. The interaction approached significance, $F(2, 14) = 3.72$, $p = 0.051$, $\eta^2_G = 0.04$.

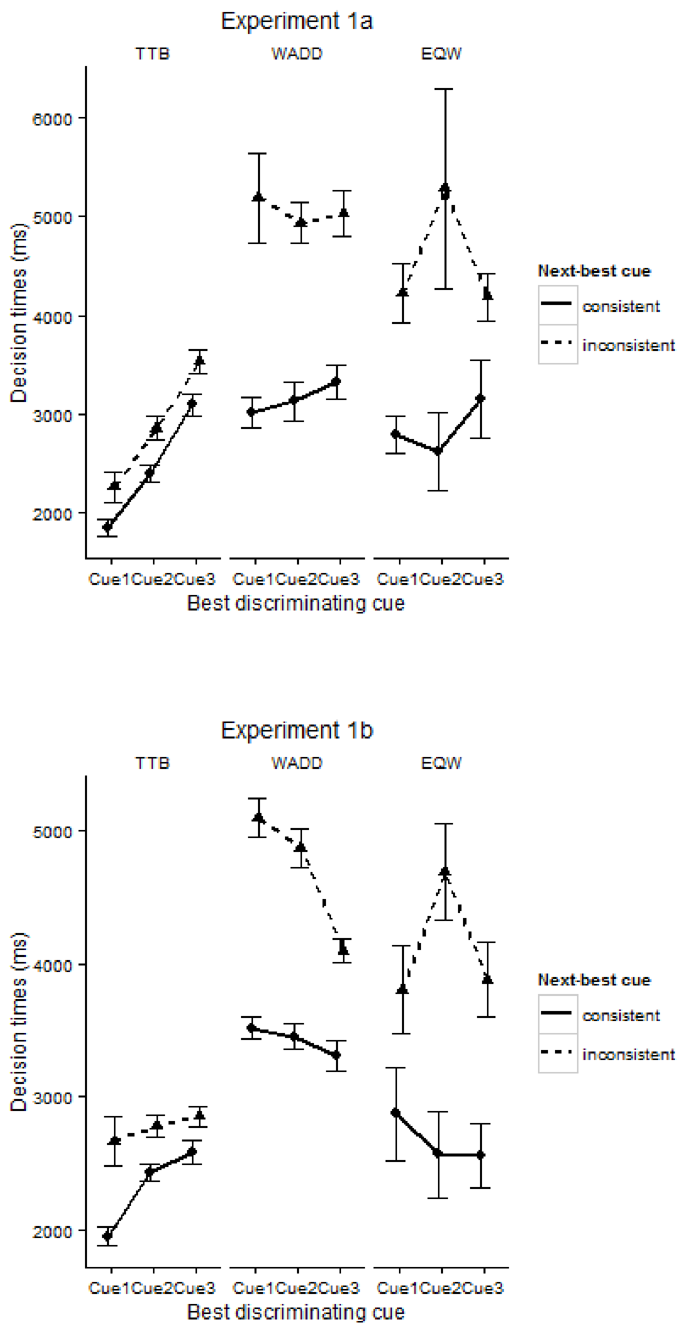

Figure 2. Mean decision times in milliseconds as a function of participants' strategy, the validity-rank of the best discriminating cue and the status of the next-best cue. Top panel: Experiment 1a; bottom panel: Experiment 1 b. TTB = take the best; WADD = weighted additive; EQW = equal weights. Error bars represent ±1 standard error of the mean.

Betting block results (Experiment 1b). Strategy-classification was done anew (as described previously) with the choices participants of Experiment 1b made in the betting block. Strategy proportions are depicted in Table 4. As can be seen, strategy proportions differed only slightly across test phases and inspection of the individual strategies revealed high consistency of participants' strategy use across test phases. Two participants previously classified as TTB were re-classified as WADD-CCs as did one EQW-CCs and one unclassified participant. Two WADD-CCs were re-classified as TTB-CCs.

For the analyses of bets, trials on which participants' decisions were inconsistent with their strategy were removed (3.54%). Bets of each group of participants were submitted to a 3 (validity-rank of the best discriminating cue; cue 1, cue 2, cue 3) × 2 (status of the next-best cue: consistent, inconsistent) within-subjects ANOVA.

The analysis of TTB-CCs' bets revealed that they bet less on their decisions, when information about the best and next-best cue was inconsistent ($M = 8.42$, $SE = 0.15$) than when cue information was consistent ($M = 9.45$, $SE = 0.12$), $F(1, 29) = 25.29$, $p < 0.001$, $\eta^2_G = 0.10$. No other effects were significant, Fs < 1.46, ps > 0.239.

The status of the next-best cue also had an effect on WADD-CCs' bets, $F(1, 30) = 14.45$, $p < 0.001$, $\eta^2_G = 0.087$. The interaction was also significant, $F(1, 60) = 3.35$, $p < 0.042$, $\eta^2_G = 0.01$. Follow-up analyses revealed that the next-best cue affected WADD-CCs' bets on all levels of the validity-rank factor, all ps < 0.043. Overall, WADD-CCs bet less when cue information was inconsistent ($M = 8.76$, $SE = 0.16$) than when it was consistent ($M = 9.67$, $SE = 0.10$).

For EQW-CCs, the main effect of the status of the next-best cue was also significant, $F(1, 6) = 6.41$, $p = 0.044$, $\eta^2_G = 0.25$. For this group, no other effects were significant, Fs < 1.4, ps > 0.284. EQW-CCs bet less on their decisions when cue information was inconsistent ($M = 7.74$, $SE = 0.44$) than when it was consistent ($M = 9.63$, $SE = 0.33$).

In brief, the decision-time results of both experiments as well as the betting behavior of participants of Experiment 1b provide evidence that TTB-CCs do not ignore information about (supposedly) TTB-irrelevant cues when cues are directly accessible. We will next consider whether TTB-CCs would be more likely to ignore TTB-irrelevant cues, when information about single cues has to be acquired sequentially.

Test Phase 2: Strategy classification. Strategy classification was achieved as in Test Phase 1. Strategy proportions are depicted in Table 4. Again, participants were highly consistent in their strategy use across test phases.

Test Phase 2: Process-tracing measures. In Test Phase 2, cue information was no longer directly accessible but participants could sequentially uncover as much cues as they wanted without order restrictions. We were specifically interested in participants' search- and, most importantly, their stopping-behavior. To examine participants' search behavior, the computer recorded which cue was acquired first, second, third, and last, on each trial. For each participant search orders on each trial were averaged across all trials. The mean individual search orders for both experiments can be found in Tables A.1 and B.1 of the Appendix. The majority of participants (77% in Experiment 1a and 76%

in Experiment 1b) searched the cues in descending order of their validity. This finding is well in line with the TTB-search-rule.

We next considered the average amount of cues a participant acquired before making a decision as an indicator of the participant's decision threshold (cf. Newell & Lee, 2011). A maximum of four cues could be acquired on each trial. In both experiments, TTB-CCs acquired less cues per trial than did both WADD- and EQW-CCs (Experiment 1a: $M_{\text{TTB}} = 1.84$, $SE_{\text{TTB}} = 0.07$, $M_{\text{WADD}} = 3.57$, $SE_{\text{WADD}} = 0.05$, $M_{\text{EQW}} = 3.01$, $SE_{\text{EQW}} = 0.42$; Experiment 1b: $M_{\text{TTB}} = 2.5$, $SE_{\text{TTB}} = 0.63$, $M_{\text{WADD}} = 3.44$, $SE_{\text{WADD}} = 0.06$, $M_{\text{EQW}} = 3.54$, $SE_{\text{EQW}} = 0.13$). A one-way ANOVA with decision strategy as between-subjects factor showed a significant effect in both experiments, $F_{1a}(2, 45) = 82.12$, $\eta^2 = 0.78$, $p < 0.001$; $F_{1b}(2, 65) = 33.09$, $\eta^2 = 0.50$, $p < 0.001$.

These results indicate that TTB-CCs stopped information search sooner than WADD- and EQW-CCs. To get a more direct test of whether TTB-CCs behaved in line with the TTB-stopping-rule, we finally considered the frequency of trials on which participants continued information search after discovering a discriminating cue for the first time. The TTB-stopping-rule predicts that information search would terminate as soon as a cue discriminates between options.

In Experiment 1a, the average frequency of continued search was 12% (SE = 4.2) for TTB, 85% (SE = 1.8) for WADD, and 72% (SE = 18.1) EQW. In Experiment 1b, the average frequency of continued search was 41% (SE = 6) for TTB, 79% (SE = 12) for WADD, and 93% (SE = 8) for EQW.

Utility ratings of the four cues. At the end of the experiment participants rated the predictive utility of each of the four cues. We used these ratings to check (1) whether participants learned the correct validity hierarchy and (2) whether TTB-CCs perceived higher dispersion among cue validities than WADD-CCs. Utility ratings are shown in Table 5 separately for each strategy group. As can be seen, with the exception of EQW-CCs of Experiment 1b, the utility ratings of the four cues decreased significantly with the objective cue validities, suggesting that participants learned the correct validity hierarchy. Theoretically, the lack of a significant trend for EQW-CCs is consistent with the assumption that EQW-CCs perceive cues as equally useful. However, the ratings of EQW-CCs of Experiment 1b may also suggest that some of them may have learned a different validity hierarchy and therefore only appeared to rely on an EQW strategy. Conclusions about this group should thus be drawn with caution.

To further examine whether TTB-CCs perceived higher cue dispersion than did WADD-CCs and EQW-CCs, for each participant the standard deviation across the four ratings was calculated (cf. Pachur & Marinello, 2013). In Experiment 1a, the average standard deviation of TTB-CCs' ratings was significantly higher ($M = 2.74$, $SE = 0.17$) than that of WADD-CCs ($M = 2.01$, $SE = 0.21$) and EQW-CCs ($M = 2.14$, $SE = 0.29$), $F(2, 45) = 3.729$, $p = 0.038$. In Experiment 1b, there was a non-significant trend, $F(2, 65) = 2.691$, $p = 0.075$ ($M_{\text{TTB}} = 2.56$, $SE_{\text{TTB}} = 0.17$; $M_{\text{WADD}} = 2.00$, $SE_{\text{WADD}} = 0.19$; $M_{\text{EQW}} = 2.16$, $SE_{\text{EQW}} = 0.26$). A planned contrast between TTB-CCs and WADD-/EQW-CCs approached significance, $t(45)$, 1.99, $p = 0.051$.

Table 5

Utility Ratings for the Different Cues in Experiments 1 – 3 for the Different Strategy Groups and the Corresponding Statistical Test Results

		Mean utility ratings (*SE*)				Trend statistics	
Experiment	Strategy	Cue 1	Cue 2	Cue 3	Cue 4	*t* (linear)	*t* (quadratic)
1a	TTB (n = 31)	8.61 (0.29)	7.29 (0.21)	5.61 (0.21)	3.10 (0.37)	$t(90) = -14.4$***	$t(90) = -2.2$*
	WADD (n = 11)	8.64 (0.31)	7.18 (0.14)	5.91 (0.12)	4.18 (0.33)	$t(30) = -11.9$***	$t(30) = -0.5$
	EQW (n = 7)	8.0 (0.61)	7.57 (0.58)	6.14 (0.53)	4.14 (0.52)	$t(18) = -4.1$***	$t(18) = -1.3$
1b	TTB (n = 30)	8.83 (0.18)	7.30 (0.16)	5.63 (0.18)	3.67 (0.28)	$t(87) = -17.6$***	$t(87) = -1.6$
	WADD (n = 30)	8.57 (0.26)	7.30 (0.22)	5.87 (0.20)	4.60 (0.30)	$t(87) = -10.1$***	$t(87) = 0.0$
	EQW (n = 8)	4.63 (1.08)	7.63 (0.59)	6.38 (0.54)	6.50 (0.74)	$t(21) = 1.2$	$t(21) = -1.8$
2	TTB (n = 23)	8.57 (0.35)	7.61 (0.16)	6.09 (0.31)	4.83 (0.34)	$t(66) = -9.4$***	$t(66) = -0.5$
	WADD (n = 18)	8.83 (0.31)	7.78 (0.22)	6.78 (0.19)	4.83 (0.36)	$t(51) = -10.5$***	$t(51) = -1.6$
	EQW (n = 5)	6.4 (1.59)	7.0 (0.77)	6.6 (0.29)	5.4 (1.14)	$t(12) = -0.8$	$t(12) = -1.0$
3	TTB (n = 37)	8.70 (0.27)	7.65 (0.23)	6.57 (0.79)	4.78 (0.35)	$t(108) = -10.7$***	$t(108) = -1.4$
	WADD (n = 24)	8.54 (0.25)	7.88 (0.28)	7.17 (0.19)	6.21 (0.39)	$t(69) = -6.0$***	$t(69) = -0.5$
	EQW (n = 5)	6.6 (1.39)	6.4 (0.91)	6.4 (0.41)	5.2 (1.75)	$t(12) = -0.8$	$t(12) = -0.4$

Note. TTB = take the best; WADD = weighted additive; EQW = equal weights. Standard errors in brackets.

*** $p < 0.001$ (two-tailed)

* $p < 0.05$ (two-tailed)

Discussion

Experiments 1a and 1b yielded unequivocal evidence that TTB-CCs do not ignore cue information when cues are directly accessible, even when single cues could be easily ignored. The decision-time results of both experiments generally replicated the findings by Glöckner and Betsch (2012; Glöckner et al., 2014) and Söllner et al. (2014; Söllner & Bröder, 2015), and show that even TTB-CCs consider supposedly decision-irrelevant cue information. However, in the Glöckner studies the cue screen-positions in the decision task changed from trial to trial, which may have encouraged an inadvertent processing of complete cue information. In the Söllner studies, the cue information had to be acquired sequentially. In the present experiments, cue information was directly accessible and cue positions were held constant. In Experiment 1b cue positions on the screen even matched the cue-validity hierarchy. For these reasons, single cues could have been ignored easily in our experiments. Our results therefore suggest that TTB-CCs purposely look for more cues than just the best discriminating cue. This is nicely in line with Söllner and Bröder's (2015) findings that decision makers more frequently search for additional cues on purpose when the information they previously acquired was inconsistent rather than consistent. Furthermore, participants' betting behavior in Experiment 1b shows that the processing of additional cue information is consequential for both TTB-CCs and WADD-/EQW-CCs. Participants bet less on their choices when cue information was inconsistent than when it was consistent. This finding is in line with previous research showing that information consistency affects participants' decision confidence (Glöckner et al., 2014; Söllner et al., 2014). However, whereas decision confidence assesses the consequences of information consistency on a meta-cognitive level, the present finding points to a direct behavioral consequence (bets) of information consistency.

In terms of EAMs, the finding that TTB-CCs are sensitive to the consistency of cue information may be interpreted as evidence that, when cues are directly accessible, the decision threshold of (at least some of the) TTB-CCs is higher than the threshold implied by the TTB-stopping-rule. Overall, the decision behavior of TTB-, WADD-, and EQW-CCs can be accounted for by EAMs. According to this account, TTB- and WADD-/EQW-CCs differ specifically regarding their cue weightings: TTB-CCs weight the cues in a non-compensatory manner, whereas WADD- and EQW-CCs weight the cues in a compensatory manner. The finding that TTB-CCs of our experiments perceived stronger variability in the cues' predictive utilities than did WADD- and EQW-CCs lends support to the assumption of different cue weightings for TTB-CCs and WADD-/EQW-CCs, respectively.

In our experiments, objective cue validities were identical for all participants but participants nevertheless appeared to differ in their subjective estimates of cue validities. Glöckner et al. (2014) manipulated the objective cue validities of two decision environments and found that participants weight cue information in a non-compensatory (compensatory) manner when objective validities of the environments were non-compensatory (compensatory). Our results extend this finding by showing that not only objective validities of a decision environment but also participants' subjective perception of the cue validities affect decision behavior.

Results of Test Phase 2 provided somewhat mixed evidence regarding our assumption that TTB-CCs would behave more in line with the TTB-stopping-rule when cue information is no longer directly accessible but has to be acquired sequentially. TTB-CCs of both experiments stopped information search sooner than did WADD- and EQW-CCs, which is consistent with the assumption that TTB-CCs have lower decision thresholds than WADD- and EQW-CCs (Lee & Cummins, 2004;

Söllner & Bröder, 2015). However, only in Experiment 1a was the decision behavior of TTB-CCs considerably in line (in 88% of all trials) with the TTB-stopping-rule. In Experiment 1b, in contrast, TTB-CCs still looked for more cues than just the best discriminating cue on a relatively large proportion of trials (41%). The main differences between Experiments 1a and 1b were the presentation format of the stimuli (i.e., holistic pictures vs. pictures of single cues in a list-wise format) and the additional betting block in Experiment 1b. It may be that the betting in Experiment 1b, which preceded Test Phase 2, generally increased participants' desire for decision confidence—that is, their desire to know how certain they could be with their decisions in order to adjust their bets accordingly. This heightened desire for confidence (increased decision threshold) may then have transferred to Test Phase 2. Experiment 2 will more directly examine how focusing participants on decision confidence may affect participants' decision thresholds.

The central conclusion to be drawn from Experiments 1a and 1b is that TTB-CCs do not strictly follow a TTB-stopping-rule, even when cues have to be acquired sequentially (see also Söllner & Bröder, 2015). The next experiment aimed to further our understanding of the conditions under which TTB-CCs will look for more cues than just the best discriminating cue.

Experiment 2

Experiment 2 tests whether focusing participants on decision confidence via accuracy task instructions, would encourage TTB-CCs to look for more cues than focusing them on decision speed, which may suggest that participants adaptively adjust their decision thresholds to different situational demands (accuracy vs. speed). Initial evidence that participants increase their decision thresholds when task instructions stress accuracy comes from studies investigating the cognitive processes underlying simple response tasks (Voss, Rothermund, & Voss, 2004; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008). Voss et al. (2004; Experiment 1) had participants perform two blocks of a color discrimination task. For the first block, participants read common task instructions which did not specifically refer to accuracy. For the second block, participants were explicitly instructed to be accurate. The researchers found that participants increased their decision thresholds from the first to the second block. We similarly hypothesize that in our more complex decision task, TTB-CCs would also increase their decision thresholds (i.e., acquire more cues) when accuracy is stressed compared to when speed is stressed. Indeed, under speed instructions the decision threshold of TTB-CCs might correspond closely to the TTB-stopping-rule (e.g., Glöckner & Betsch, 2008a, Experiment 2).

The different instructional foci may also affect the decision thresholds of WADD-/EQW-CCs, who previously (Experiments 1a and b) showed a tendency to acquire the maximum of four cues. Although a focus on accuracy may thus not result in an additional increase in WADD-/EQW-CCs' decision thresholds, a focus on decision speed might make these decision makers look for fewer cues. The interesting question is, however, how strongly WADD-/EQW-CCs may restrict their information search (decision threshold) under speed instructions. One possibility is that WADD-/EQW-CCs acquire fewer cues under speed than under accuracy instructions; but that they still acquire enough cues to figure out whether a highly-valid cue can be compensated for by less valid cues. If so, we expect WADD-/EQW-CCs to remain classified as WADD-/EQW-CCs even under speed instructions.

Evidence for an alternative hypothesis, however, comes from a study by Glöckner and Betsch (2008a, Experiment 2; see also Rieskamp & Hoffrage, 1999) in which time pressure was manipulated. The authors found a higher proportion of TTB-classifications under high time pressure and a higher proportion of WADD-classifications under low time pressure indicating that participants switched from WADD to TTB when time was constraint. Or in terms of EAMs, participants classified as WADD, lowered their decision thresholds to the level of the TTB-stopping-rule under time constraints. Accordingly, one could also expect participants of Experiment 2 to generally adjust their decision thresholds to the level of the TTB-stopping-rule under time pressure. If so, a large proportion of WADD-/EQW-CCs in Experiment 2 would be re-classified as TTB-CCs under speed instructions.

Method

Participants. Forty-nine Heidelberg University students participated for partial course credit and monetary compensation (39 were female). Mean age was 22.74, ranging from 18 to 35.

Materials, design, and procedure. Participants performed the same validity-learning phase as in the previous experiments. They then performed a shortened version of the decision task with cue information completely given (i.e., Test Phase 1, where cues were presented list-wise as in Experiment 1b). The main purpose of this phase was to familiarize participants with the decision task and to identify a reference strategy for each participant. The subsequent Test Phase 2 (sequential search) was divided into (a) a block where instructions stressed accuracy (accuracy block) and (b) a block where instructions stressed speed (speed block). Block order was counterbalanced.

The instructions and the cover story for the learning phase and the subsequent test phase with cues directly accessible (Test Phase 1) were identical to that previously used. In Test Phase 1, the 24 experimental pairs (cf. cells in Table 3, except for the last column), and the 8 diagnostic pairs (Table 2) were presented only once. The design of Test Phase 1 was a 3 (validity-rank of the best discriminating cue: cue 1, cue 2, cue 3) × 2 (status of the next-best cue: consistent, inconsistent) within-subjects design.

After Test Phase 1, participants received instructions for Test Phase 2. As in the previous experiments, participants were told that they were now required to make inquiries about the bugs' features before making their decisions. Test Phase 2 comprised two blocks: an accuracy and a speed block (order counterbalanced). For the accuracy block, participants were instructed that the hospital was currently undergoing a quality assessment, the aim of which was to reduce false diagnoses. To further stress the importance of decision accuracy, participants were asked to rate their confidence after each decision (from 1 = *rather uncertain* to 12 = *absolutely certain*). For the speed block, participants were instructed that they had to help out the staff in the emergency room. In order to save as many lives as possible, decision speed was said to be of particular importance in the emergency room. To make the instructions and the procedure of the two blocks most comparable, participants were further asked to estimate the time it took them to come up with their decisions (from 1 to 12 seconds). Note that the confidence and estimated-time ratings were only meant to stress the instructions and to maintain the accuracy/speed focus throughout the blocks; the ratings were not analyzed.

Each block consisted of 20 trials. The decision pairs used for these trials were the eight diagnostic pairs and 12 pairs from the experimental pairs (i.e., two randomly drawn from each cell of Table 3). As in the previous experiments, participants could ask the patients up to four questions per trial before making a decision. Furthermore, after each decision a confidence-rating-scale (accuracy block) or a time-scale (speed block) popped up. To make the task more user friendly and to allow for making quick decisions, all inputs could be made via the computer mouse in this experiment. At the end of the experiment, participants were asked to rate the predictive utility of each of the four cues, and they had to indicate for each cue which of the two cue values was associated with poisonousness (cue-knowledge test).

Our main dependent variable in this experiment was the average amount of cues participants acquired on a decision trial. The research design was a 2 (instructional focus: accuracy, speed) × 2 (strategy: TTB, WADD, EQW) × 2 (order: speed first, accuracy first) design, with the first factor measured within subjects.

Results

Learning phase and cue-knowledge test. Data from the learning phase showed that accuracy was good and increased from 80.22% (SD = 9.25) in block 1 to 91.57% (SD = 6.14) in block 2, $F(1, 48) = 101.27$, $p < .001$, $\eta^2_G = 0.35$. Data from the final cue-knowledge test revealed that all but three participants (omitted from all analyses) learned the eight cue values correctly (i.e., 92%).

Test Phase 1: Strategy classification. The main purpose of this phase was to get a baseline strategy for each participant, which we used as between-subjects factor for the subsequent analyses. As shown in Table 4, the majority of participants were classified as TTB-CCs, followed by WADD-CCs and EQW-CCs.

Test Phase 1: Decision times. For the analysis of decision times, strategy-inconsistent decisions were removed (7%); according to our criteria, there were no outliers. Decision times were analyzed separately for the three strategy groups and are depicted in Figure 3. The decision times of TTB-CCs were significantly affected by both the validity of the best discriminating cue, $F(2, 46) = 6.25$, $p = 0.004$, $\eta^2_G = 0.042$, and the consistency of the next-best cue, $F(1, 23) = 4.96$, $p = 0.036$, $\eta^2_G = 0.023$. The interaction was also significant, $F(2, 46) = 3.85$, $p = 0.029$, $\eta^2_G = 0.012$. Follow-up analyses revealed that, as shown in Figure 3, consistency of the next-best cue had no effect when cue 3 was best discriminating cue, $F < 1$, but it had an effect when the best discriminating cue was cue 1, $F(1, 23) = 15.57$, $p < 0.001$, $\eta^2_G = 0.040$, or cue2, $F(1, 23) = 4.24$, $p = 0.051$, $\eta^2_G = 0.06$.

For both WADD-CCs and EQW-CCs, only the consistency of the next-best cue had a significant effect, $F_{WADD}(1, 17) = 65.00$, $p < 0.001$, $\eta^2_G = 0.27$, $F_{EQW}(1, 4) = 30.00$, $p = 0.005$, $\eta^2_G = 0.31$. No other effects were significant, all ps > 0.189.

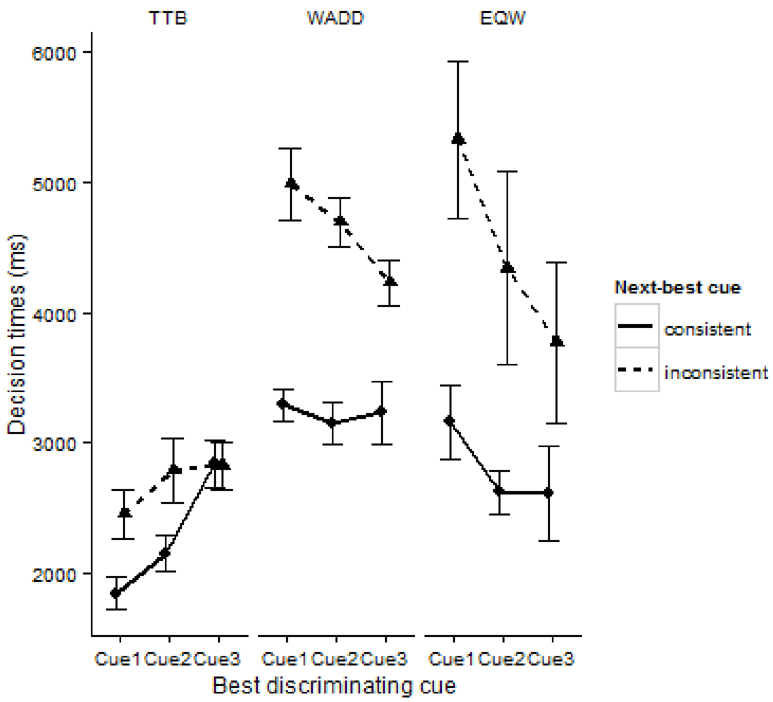

Figure 3. Mean decision times (in milliseconds) of Experiment 2 as a function of participants' strategy, the validity-rank of the best discriminating cue and the status of the next-best cue. Error bars represent ±1 standard error of the mean.

Test Phase 2: Strategy classification. The diagnostic pairs presented in each of the two experimental blocks (accuracy, speed) were used to repeat the classification procedure for each block. This allowed us to examine whether the proportion of TTB-CCs increased under speed instructions. As can be seen in Table 4, however, the strategy proportions hardly changed. Inspection of the individual strategies obtained for Test Phase 1 (baseline) and the two experimental blocks of Test Phase 2 revealed high consistency of strategy classifications across test phases: All but two TTB-CCs of Test Phase 1 remained classified as TTB-CCs in both experimental blocks. Only two of the WADD-/EQW-CCs of Test Phase 1 were re-classified as TTB-CCs in one of the experimental blocks. Classification of the majority of WADD-/EQW-CCs of Test Phase 1 did not change in Test Phase 2 or switched from WADD to EQW and vice versa. This finding suggests that, under speed instructions, WADD-/EQW-CCs did not adjust their decision thresholds to the level of the TTB-stopping-rule. It does not necessarily suggest, however, that these participants were generally insensitive to the speed instruction.

Because there were only few EQW-CCs overall in this experiment, and because some participants (four) switched between WADD and EQW across blocks, WADD- and EQW-CCs were combined to one strategy group for the following analyses.

Test Phase 2: Average amount of evidence. To examine whether TTB-CCs and WADD-/EQW-CCs adjusted their decision thresholds in response to the different instructions, we analyzed the average amount of cues participants acquired in the different experimental blocks with a 2 (instructional focus: accuracy, speed) × 2 (strategy: TTB vs. WADD-/EQW-CCs) × 2 (order: speed first vs. accuracy first) mixed-design ANOVA. As the order of blocks had no significant effect and did not interact with any of the other factors (*p*s > 0.193), this factor was not considered for the following analysis. The average amount of cues participants of the different groups acquired within the accuracy and the speed block, respectively, is depicted in Figure 4.

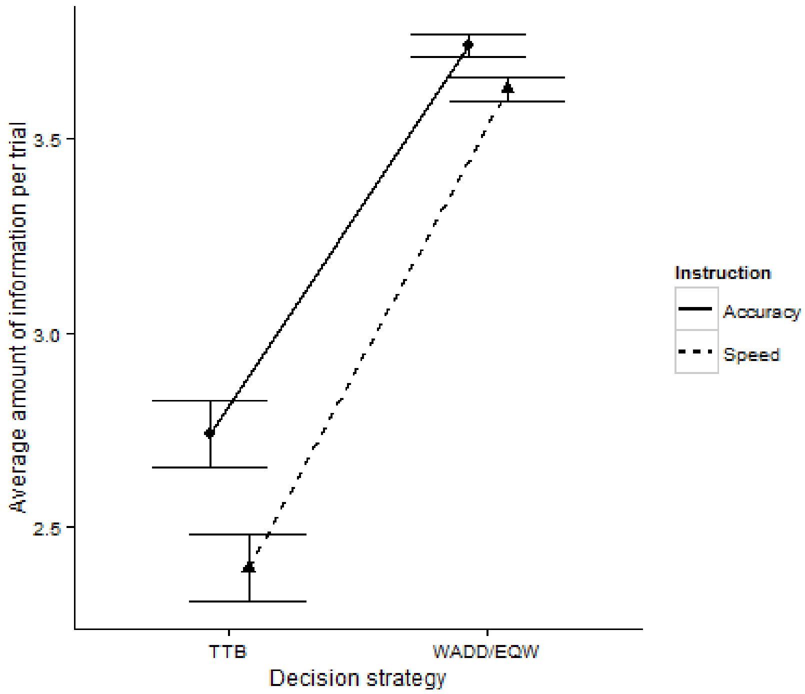

Figure 4. Average amount of information that participants of Experiment 2 acquired on a trial as a function of participants' strategy and the different instructional foci. TTB = take the best; COMP = compensatory strategy. Error bars represent ±1 standard error of the mean

The analysis revealed a significant effect of decision strategy, $F(1, 44) = 33.20$, $p < 0.001$, $\eta^2_G = 0.41$. As illustrated in Figure 4, TTB-CCs acquired less cues ($M = 2.57$, $SE = 0.14$) than did WADD-/EQW-CCs ($M = 3.68$, $SE = 0.04$). Furthermore, the instructional focus also had a significant effect, $F(1, 44) = 12.81$, $p < 0.001$, $\eta^2_G = 0.03$. As shown in Figure 4, when instructions emphasized speed, participants acquired less information ($M = 3.01$, $SE = 0.14$) than when instructions emphasized accuracy ($M = 3.24$, $SE = 0.13$). The interaction term approached significance, $p = 0.074$. However, separate analyses for the two groups revealed that instructional focus significantly affected both TTB-CCs, $F(1, 22) = 8.20$, $p = 0.009$, $\eta^2_G = 0.03$, and WADD-/EQW-CCs, $F(1, 22) = 7.07$, $p = 0.014$, $\eta^2_G = 0.04$.

Utility ratings of the four cues. As in the previous experiments, we also analyzed the utility ratings participants gave at the end of the experiment. Table 5 shows the utility ratings for the different strategy groups. The significant decrease of TTB- and WADD-CCs' ratings suggests that they had learned the validity hierarchy correctly. As in Experiment 1b, the rating pattern of EQW-CCs was less conclusive. It may be that these participants perceived the cues as equally useful or that some EQW-CCs learned a different order.

We next examined whether TTB-CCs perceived higher dispersion among cues than did WADD- and EQW-CCs, measured as in the previous experiments. Unlike in Experiments 1a and 1b, the average standard deviation of the four cues in this experiment was only slightly higher for TTB-CCs ($M = 2.02$, $SE = 0.17$) than for WADD-CCs ($M = 1.79$, $SE = 0.17$) or EQW-CCs ($M = 2.05$, $SE = 0.45$), $F < 1$. It is possible that through the explicit accuracy instructions in Test Phase 2 of this experiment even the less valid cues may have become relatively important for TTB-CCs thereby reducing the dispersion of TTB-CCs' utility ratings.

Discussion

Results of Experiment 2 provide evidence that decision makers adapt their decision thresholds in response to different situational demands: When instructions emphasized decision speed, both TTB-CCs and WADD-/EQW-CCs acquired less information than when instructions emphasized decision accuracy. Regarding TTB-CCs, this finding suggests that a focus on decision accuracy motivates participants to increase their decision thresholds relative to a focus on decision speed. The finding that WADD-/EQW-CCs also showed an adaption of their decision thresholds has at least two additional important theoretical implications. It demonstrates that WADD-/EQW-CCs are not insensitive to different situational demands—they acquired less information under speed than under accuracy instructions. Interestingly, however, and contrary to the findings by Glöckner and Betsch (2008), their adaptive behavior did not manifest itself in a shift in decision strategies. Rather, the finding that participants were highly consistent in their strategy use across blocks suggests that, even under time pressure, WADD-/EQW-CCs acquire still enough information to figure out whether a highly valid cue can be compensated for by less valid cues (otherwise they would not be classified as WADD-/EQW-CCs any more).

One possible explanation for why we found no evidence for a strategy shift, whereas Glöckner and Betsch (2008) found such a shift, may be that the latter imposed an explicit external time limit on participants' information search. Specifically, under severe time constraints, where Glöckner and Betsch found the highest proportion of TTB-classifications, participants had only 1.5 seconds to search for information. In the present experiment, in contrast, participants were told that decision speed was of particular importance, but they were free to decide how much time they would devote to each decision. It may well be that we would have found an increase in TTB-classifications with a strict external time limit, simply because participants may no longer have had sufficient time to look for enough cues. Under such conditions, relying on the best cue to make a decision may be the best strategy, even for participants actually preferring a WADD or EQW strategy.

Another reason for why WADD-/EQW-CCs in the present study stick to their strategy even under speed instructions could be that they simply did not believe that information about a single cue would be sufficient to make a correct decision. During validity learning, where participants received feedback on their decisions, WADD-/EQW-CCS may have learned that information about any cue was important to make a correct choice, and they may have routinized this decision strategy throughout learning (e.g., Rieskamp & Otto, 2006) and stick to it during the subsequent test phases (cf. Bröder & Schiffer, 2006 for routine effects in decision making). In the study by Glöckner and Betsch (2008) or Rieskamp and Hoffrage (1999), cue validities were instructed and, more importantly, participants received no feedback on their decisions. Receiving no choice feedback may therefore have prevented participants from routinizing a certain strategy and this may have enabled participants to switch more flexibly between strategies. Future studies should investigate how cue-validity learning (i.e., via instructions vs. via feedback learning) affects strategy selection in subsequent test phases.

To summarize, results of Experiment 2 demonstrate that participants adjust their information search behavior—and thus their decision thresholds—to different situational demands: Under speed instructions, TTB-CCs and WADD-/EQW-CCs acquired less information than under accuracy instructions. Importantly, whereas a pure outcome-based analysis would have yielded no evidence for an adaptive decision behavior, a closer look at their information-search behavior revealed that decision behavior was adjusted to situational requirements (see also Lee, Newell, & Vanderkerckhove, 2014; Newell & Leee, 2009).

Experiment 3

In the three experiments reported so far we found converging evidence that TTB-CCs acquire information that is supposed to be irrelevant according to the TTB-stopping-rule. With the third experiment we aimed to get a better understanding of *how* TTB-CCs process additional cue information when it is directly accessible. As in Experiment 1a and 1b we used a decision time approach to tackle this question. In the first two experiments we found that TTB-CCs' decision times were slower when cue information from the next-best cue conflicted with the best cue as compared to when there was no conflict. EAMs can explain this finding by assuming that decision makers automatically integrate information about the processed cues and that the resulting overall evidence in favor of the to-be-chosen option—which is lower when cues are conflicting than when they are consistent—determines decision time.

We theorize, however, that in addition to automatic integration processes, a more deliberate process may also be at work when TTB-CCs are confronted with conflicting cue information. Specifically, we hypothesize that TTB-CCs inhibit conflicting cue information, which is based on the following reasoning. For TTB-CCs it is always the best discriminating cue that finally drives the decision (even when additional cues have been considered). The best discriminating cue therefore has rule-like features, and we suggest that TTB-CCs, being aware of the simplicity and regularity inherent in their choice pattern, follow a TTB-decision rule rather deliberately (cf. Glöckner et al. 2014, for a different view). When this decision-rule is challenged by conflicting information from other cues, TTB-CCs may experience a cognitive conflict, and they may want to reduce this conflict by inhibiting the conflicting information. As inhibition is cognitively demanding (cf. Kane & Engle, 2003) this process may take time and may thus contribute to the previously observed slowing in decision speed. The main goal of Experiment 3 was to test this inhibition hypothesis. Note that for WADD-/ and EQW-CCs, the best discriminating cue has no such rule-like feature as it has for TTB-CCs (WADD-/EQW-CCs only choose the option pointed to by the best cue when this cue cannot be compensated for by less valid cues). The inhibition of conflicting information may therefore be of less or no importance for WADD-/EQW-CCs.

In Experiment 3, we used a decision task similar to the ones of the previous experiments comprising a learning phase and a test phase with cues being directly accessible. In addition to using pairs with a consistent and an inconsistent next-best cue in the test phase, we also used pairs for which the next-best cue did not discriminate between options (e.g., 1-**0**-0-0 vs. 0-**0**-0-0). Most importantly, to examine whether TTB-CCs inhibit conflicting cue information, we changed the test phase in the following way. Participants were still presented with bug pairs and were to choose the more poisonous one (pair trials). These pair trials, however, were interspersed with *single-cue* trials on which participants were shown only a single cue value. Their task on these trials was to decide whether the depicted cue value indicated poisonousness or not. Crucially, the cue value depicted on a single-cue trial was always a cue value of the next-best cue from the preceding pair trial. We assumed a participant's response to a single cue value to be impaired when this cue value had been inhibited on the preceding pair trial. Specifically, we hypothesized that the *poisonous cue value* of an *inconsistent next-best cue* would be inhibited on a pair trial by TTB-CCs, because this cue value interferes most with TTB-CCs' decisions (it points to the non-TTB option). The poisonous cue values of *consistent* or *non-discriminating* next-best cues, in contrast, were not assumed to be inhibited, because they do not conflict with TTB-CCs' choices. To examine the inhibition hypothesis, we therefore considered participants' decision times from single-cue trials depicting a poisonous cue value, and we compared those trials preceded by an inconsistent pair trial (assumed inhibition of the poisonous cue value) with those trials preceded by either a consistent or a non-discriminating pair-trial (no inhibition assumed).

The inclusion of pairs with a non-discriminating next-best cue further allowed us to test the following hypothesis. Relative to a non-discriminating next-best cue, a consistent next-best cue increases the overall consistency of information which, according to EAMs, should lead to a speedup in decisions. An inconsistent next-best cue, in contrast, decreases the overall consistency and should lead to a slowdown in decisions (see Glöckner & Betsch, 2012). Finally, in Experiment 3 we also examined how information consistency affects participants' decision confidence. Unlike in Experiment 1b, we used explicit confidence judgments rather than bets to assess confidence, in order to replicate our findings with a different confidence indicator.

Method

Participants. Seventy-three Heidelberg University students (49 female) participated in Experiment 3. Mean age was 22.3, ranging from 18 to 31. Participants either received 8€ for their participation or partial course credit. All participants could earn an additional bonus of up to 2.90€, contingent on their task performance.

Materials, design, and procedure. The learning phase was identical to the learning phase of the previous experiments. The test phase of Experiment 3 differed from the test phases of the first two experiments. Most importantly, the decision task also contained single-cue trials and pairs with a non-discriminating next-best cue. Furthermore, instead of Test Phase 2, participants performed an additional block of the decision task with directly accessible information where they had to indicate their decision confidence on half of the trials.

Test Phase 1 consisted of four successive sub-blocks, each consisting of 36 test pairs and eight diagnostic pairs. The 36 test pairs for the pair trials are shown in Table 3, the eight diagnostic pairs are shown in Table 2. Presentation order of the 44 pair-trials within each sub-block was randomly determined (the block structure was used for reasons of randomization only). The design of the pair trials was a 3 (validity-rank of the best discriminating cue: cue 1, cue 2, cue 3) × 3 (status of the next-best cue: consistent, inconsistent, non-discriminating) within-subjects design.

Within each sub-block, half of the 36 test pairs (Table 1) were followed by a single-cue trial. The single cue value on these trials was always of the same validity rank as the next-best cue of the preceding pair (e.g., when the next-best cue on a pair trial was antennae, the cue value shown on a subsequent single-cue trial would have been one of the two physical appearances—large or small—of antennae). The pairs preceding a single-cue trial were selected from the body of the 36 test pairs by randomly choosing two pairs from each combination of the factors *validity-rank of the best discriminating cue* and *status of the next-best cue* (cf. cells of Table 3). One of the chosen pairs from each cell was followed by a single-cue trial depicting the *poisonous* cue value of the pair's next-best cue—these were the critical trials to test our inhibition hypothesis. The other pair was followed by a single-cue trial depicting the *non-poisonous* cue value. These trials were used for methodological reasons only, because otherwise participants' responses on single-cue trials would always have been 'poisonous.' As responses to non-poisonous trials have no theoretical implications, they were not analyzed.

The design of the *single-cue*-trial analysis was a 3 × 3 within-subjects design, with the first factor being the *cue* to which the single cue value belonged (cue 2, cue 3, cue 4), and the second factor being the *preceding status* of the depicted cue, that is, whether it was part of a consistent, inconsistent, or non-discriminating next-best cue on the preceding pair trial (note that, because single-cue values always belonged to a next-best cue, cue 1 values did not occur on single-cue trials).

Instructions for Test Phase 1 were similar to those of the previous experiments, but participants were additionally told that on some trials of the task they would be presented with only a single cue value of a bug. Their task would then be to indicate whether the depicted cue value indicated poisonousness or not, using the up and down arrow keys (up = poisonous). To familiarize participants with this new task, they performed eight successive single-cue practice trials before the beginning of Test Phase 1. Furthermore, halfway through the decision task of Test Phase 1, there was an obligatory one-minute break (to reduce fatigue effects).

Following Test Phase 1, participants performed an additional block of the decision task which also consisted of 36 test-pair trials and eight diagnostic-pair trials but no single-cue trials. Half of the test pairs were randomly selected for the additional confidence ratings with the constraint that each factor combination (status of next best cue by validity rank of best discriminating cue; cf. cells in Table 3) occurred equally often (i.e., two times). For the confidence ratings, participants were asked to indicate how likely they considered the bug they chose to be actually more poisonous. To this end, they were presented with a scale running from 50% (indicating *guessing*) to 100% (indicating *absolute certainty*) in steps of five, and they used the keys *F1* (50%) - *F12* (100%) for their responses. The design for the confidence-rating analyses was a 3 (validity-rank of the best discriminating cue) × 3 (status of the next-best cue) within-subjects design. At the end of the study, participants were asked to estimate the predictive utility of each of the four cues.

Results

Learning phase. Mean accuracy increased from block 1 (M = 81.19%, SD = 7.88) to block 2 (M = 92.42%; SD = 4.29), $F(1, 72) = 147.6$, $p < 0.001$, $\eta^2_G = 0.44$. Unlike in the previous experiments, there was no cue-knowledge test in this experiment. Instead we used participants' error rates on the single-cue trials in Test Phase 1 to assess their cue-knowledge. On the single-cue trials, participants were to indicate whether a cue value was indicative of poisonousness or not. Overall, participants made very few errors on these trials (2.32%). However, four participants showed error rates higher than 40%, indicating that they did not learn the cue values correctly. These participants were omitted from all subsequent analyses.

Test Phase 1: Strategy classification. Strategy proportions obtained for Test Phase 1 are shown in Table 4. The majority of participants were classified as TTB, followed by WADD, and EQW.

Test Phase 1: Decision times. For the analysis of decision times, decisions inconsistent with a participant's strategy were removed (3.75%) as were outliers (0.27%). Decision times were analyzed separately for the three strategy groups.

There was a significant effect of the best discriminating cue on the decision times of TTB-CCs, $F(1.2, 42) = 17.43$, $p < 0.001$, $\eta^2_G = 0.06$. As illustrated in Figure 5, decision times increased with the validity of the best discriminating cue decreasing (M_{Cue1} = 1.93, *SE* = 0.08; M_{Cue2} = 2.21, *SE* = 0.04; M_{Cue3} = 2.47, *SE* = 0.07). Furthermore, the next-best cue affected TTB users' decision times, $F(1.2, 42) = 33.80$, $p < 0.001$, $\eta^2_G = 0.06$. The interaction was not significant, $F(4, 140) = 1.41$, $p = 0.233$. Two orthogonal contrasts revealed that TTB-CCs were slower when the next-best cue was inconsistent (*M* = 2.53, *SE* = 0.08) than when it was non-discriminating (*M* = 2.06, *SE* = 0.49) or consistent (*M* = 2.03, *SE* = 0.05), $t(210) = 10.38$, $p < 0.001$. However, there was no significant difference between the consistent and the non-discriminating conditions, $t < 1$.

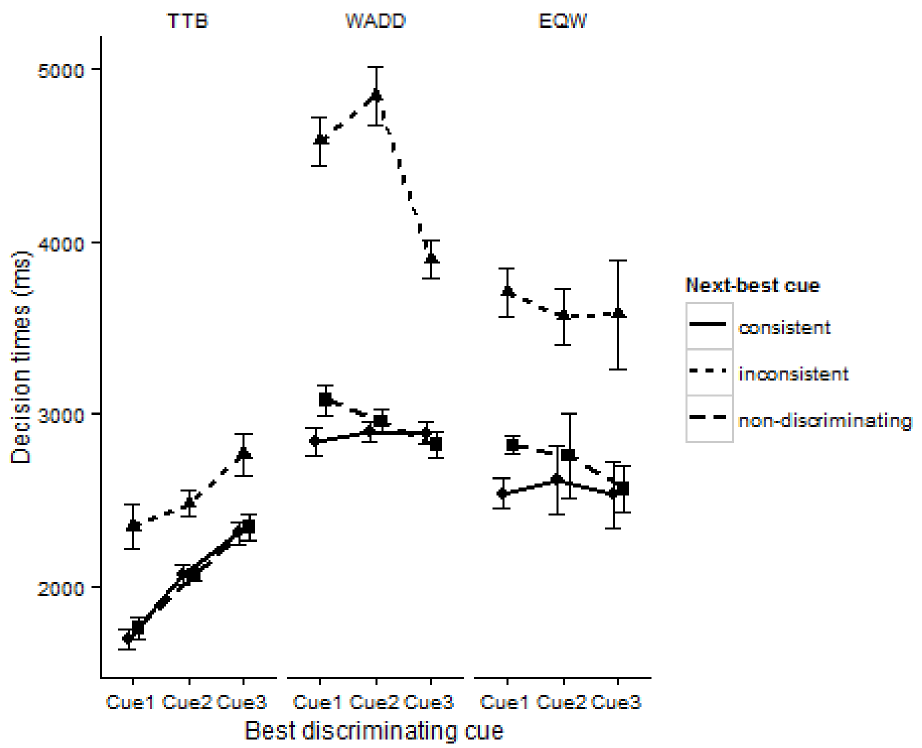

Figure 5. Mean decision times of Experiment 3, as a function of participants' strategy, the validity-rank of the best discriminating cue and the status of the next-best cue. TTB = take the best; WADD = weighted additive; EQW = equal weights. Error bars represent ±1 standard error of the mean.

For WADD-CCs, both the best discriminating cue, $F(2, 46) = 10.40$, $p < 0.001$, $\eta^2_G = 0.02$, and the next-best cue, $F(1.3, 29.4) = 185.68$, $p < 0.001$, $\eta^2_G = 0.32$, affected decision times significantly. The interaction term was also significant, $F(1.3, 30.8) = 8.13$, $p < 0.001$, $\eta^2_G = 0.03$. As evident from Figure 5, the next-best cue had a less pronounced effect for cue 3. Follow-up analyses revealed, that the next-best cue had a significant effect on all levels of the validity-rank factor: $F_{\text{Cue1}}(2, 46) = 80.70$, $p < 0.001$, $\eta^2_G = 0.35$; $F_{\text{Cue2}}(2, 46) = 88.31$, $p < 0.001$, $\eta^2_G = 0.40$; $F_{\text{Cue3}}(2, 46) = 66.25$, $p < 0.001$, $\eta^2_G = 0.21$.

Finally, the next-best cue affected the decision times of EQW-CCs, $F(2, 8) = 13.91$, $p = 0.002$, $\eta^2_G = 0.18$. No other effects were significant, *F*s < 1, *p*s > 0.463. As shown in Figure 5, EQW-CCs were significantly slower when the best discriminating cue was followed by an inconsistent cue (M = 3.62, SE = 0.14) than when it was followed by a consistent (M = 2.56, SE = 0.11) or non-discriminating cue (M = 2.72, SE = 0.42). Tukey post-hoc tests revealed significant differences between the inconsistent and consistent condition as well as the inconsistent and non-discriminating condition, both ps < 0.001. The difference between the consistent and the non-discriminating condition was not significant, $p = 0.460$.

In brief, the results replicated the previous effect that TTB-CCs were slower in making their decisions when information about the best and the next-best cue was inconsistent rather than consistent, indicating once again that TTB-CCs do not ignore cue information when cues are directly accessible. Importantly, the results showed that, in comparison to a non-discriminating cue as baseline, an inconsistent next-best cue led to slower decisions. We will next consider whether TTB-CCs inhibit information inconsistent with their decisions.

Test Phase 1: Single-cue trials. For the analyses of participants' decision times on single-cue trials, incorrect responses on these trials (1.63%) were removed. According to our criteria there were no outliers. A 3 (validity-rank of the cue: cue2, cue3, cue4) × 3 (preceding status: inconsistent, consistent, non-discriminating) within-subject ANOVA for single-cue trial decision times showed that decision times of TTB-CCs were significantly affected by the preceding status of the cue, $F(2, 68) = 4.39$, $p = 0.016$, $\eta^2_G = 0.014$. The main effect of validity-rank of the cue and the interaction were not significant, Fs < 1.49, ps > 0.233. The main effect of preceding status was further explored with two orthogonal contrasts reflecting our hypothesis regarding the inhibition of conflicting information. The first contrast compared the inconsistent condition with the other two conditions. This contrast directly tested our hypothesis that an inconsistent next-best cue but not a non-discriminating or consistent cue requires inhibition. This contrast revealed a significant effect, $t(204) = 2.60$, $p = 0.010$. TTB-CCs were slower in indicating that the depicted cue value was poisonous, when the cue value had been inconsistent with the best discriminating cue on the preceding trial (M = 1284, SE = 24.96) as compared to when it had been consistent (M = 1205, SE = 42.37) or non-discriminating (M = 1251, SE = 57.23). The second contrast, comparing the consistent with the non-discriminating condition, approached significance, $t(204) = 1.81$, $p = 0.071$.

For WADD-CCs, the type of cue had no significant effect on participants' decision times, $F(2, 46) = 1.51$, $p = 0.231$. The preceding status of the cue had a marginally significant effect, $F(2, 46) = 2.96$, $p = 0.062$, $\eta^2_G = 0.01$. When the single cue value had been consistent with the best cue on the preceding trial, WADD-CCs tended to respond faster (M = 1208, SE = 26.19) than when the cue value had previously been inconsistent (M = 1288, SE = 41.30) or non-discriminating (M = 1261, SE = 62.63). For EQW-CCs, no significant effects were obtained, ps > 0.124.

In sum, the results from the single-cue trials provide support for our assumption that information about a cue that conflicts with the decisions of TTB-CCs is inhibited.

Confidence block: Strategy classification. Strategy proportions obtained for this phase are shown in Table 4. The observable increase in WADD was mainly due to two switching EQW-CCs, and three switching TTB-CCs.

Confidence block: Confidence ratings. Because there were only three participants classified as EQW-CCs for this block, data of these participants were not analyzed. Confidence ratings of TTB-CCs and those of WADD were each submitted to a 3 (validity-rank of the best discriminating cue) × 3 (status of the next-best cue) within subjects ANOVA.

There was only a significant effect of the next-best cue on TTB users' confidence ratings, $F(2, 66) = 5.44$, $p < 0.007$, $\eta^2_G = 0.03$. No other effects were significant, *F*s < 1.08, *p*s > 0.367. TTB users were most confident in their decisions when cue information was consistent ($M = 98.19$, $SE = 0.38$), and they were least confident when information was inconsistent ($M = 95.29$, $SE = 0.79$), with the non-discriminating condition in-between ($M = 96.99$, $SE = 0.85$). Tukey post-hoc tests revealed a significant difference between the consistent and the inconsistent condition, $p = 0.001$. The non-discriminating condition did not differ from either the consistent or the inconsistent condition, *p*s > 0.099.

There was also only a significant effect of the next-best cue on the confidence ratings of WADD-CCs, $F(1.08, 30.184) = 19.11$, $p < 0.001$, $\eta^2_G = 0.16$. No other effects were significant, *F*s < 2.90, *p*s > 0.063. Participants were less confident in their decisions when cue information was inconsistent ($M = 93.94$, $SE = 0.84$) as compared to both when cue information was consistent ($M = 98.82$, $SE = 0.33$) and when the next-best cue did not discriminate ($M = 98.71$, $SE = 0.35$). Tukey post-hoc tests revealed that the inconsistent condition differed significantly from both the consistent and the non-discriminating condition, *p*s < 0.001. The consistent and the non-discriminating condition did not differ significantly, $p = 0.984$.

Utility ratings of the four cues. The cue ratings are shown separately for each strategy group in Table 5. We generally replicated our previous findings. The ratings show a significant decrease with the objective cue validities for TTB-/ and WADD-CCs but not for EQW-CCs.

We again examined the dispersion of each participant's cue-utility ratings measured by the standard deviation. For TTB-CCs, the average standard deviation of ratings was $M = 2.07$ ($SE = 0.17$), for WADD-CCs $M = 1.44$ ($SE = 0.19$), and for EQW-CCs $M = 2.17$ ($SE = 0.64$). A one-way ANOVA with decision strategy as between-subjects factor revealed a non-significant trend, $F(2, 63) = 2.98$, $p = 0.058$, $\eta^2 = 0.09$.

Discussion

In Experiment 3, we again found that TTB-CCs were sensitive to the consistency of the next-best cue. This provides further evidence that TTB-CCs do not ignore easily available cue information. Moreover, compared with a non-discriminating next-best cue, it was specifically the information provided by an inconsistent next-best cue that slowed down TTB-CCs' decisions. The interesting novel finding of Experiment 3 is that on single-cue trials, TTB-CCs required more time to indicate that a cue value pointed to poisonousness, when this cue value had previously been part of an inconsistent next-best cue compared to when it had been part of a consistent or non-discriminating next-best cue. In line with research showing that previous engagement in inhibition of certain information slows down subsequent processing of this information (e.g., Mari-Beffa, Estévez, & Danziger, 2000), this finding suggests that TTB-CCs inhibit information that conflicts with their implicit or explicit decision rule ('go with the best cue'), and this inhibition slows the decision process. The decision time pattern of WADD-CCs was less conclusive though. They showed a tendency to respond faster after a consistent next-best cue compared to an inconsistent or a non-discriminating next-best cue (which points to a facilitation effect after processing consistent information). Overall, the findings suggest that inhibitory processes are one mechanism TTB-CCs recruit to deal with conflicting information. Whether, or to what extent, inhibitory processes are also at work during WADD decision making needs to be addressed in future studies. Our findings suggest that inhibition may be less important for WADD-CCs.

The integration of cue information is one of the assumptions underlying EAMs. The results from Experiment 3 partially supported the predictions by EAMs. We found evidence for a slowdown in decisions when information consistency was decreased. However, we found no speedup in decisions when consistency was increased. This latter finding is at odds with EAMs and the findings by Glöckner and Betsch (2012) who found that an increase in consistency was associated with faster decisions. A possible reason for why we found no evidence that a consistent next-best cue would speed participants' decisions in comparison to a non-discriminating next-best cue, may be due to our materials: The bugs of non-discriminating pairs differed on only one cue (the best discriminating cue), whereas the bugs of consistent and inconsistent pairs differed on two cues (best and next-best cue; cf. Table 3). When only one cue discriminates between bugs, participants may figure out relatively quickly, which of the two bugs had the critical cue value. When two cues discriminate between the bugs, however, participants may require more time for figuring out the critical values of either cue (even when information about the two cues is consistent). Note, however, that for consistent and inconsistent pairs the number of cues on which the bugs differed was always identical, so that the decision time difference between consistent and inconsistent pairs cannot be accounted for by varying amounts of to-be-processed information.

Participants' confidence ratings in Experiment 3 closely mirrored the betting behavior of participants of Experiment 1b, and they replicate findings by Glöckner and Betsch (2012). The finding that decision confidence increased with information consistency is well in line with EAMs and suggests that participants integrate cue information when reflecting on their decision confidence.

General Discussion

Decision makers often need to evaluate how much information they consider for their decisions and how important they consider each piece of information. In the present research, we were specifically interested in the decision behavior of decision makers who rely on the best discriminating cue when making their choices, even when less valid cues contradict this cue. A common explanation for the choice-behavior of these TTB-CCs is that they stop information search at the discovery of the best cue and ignore other cues completely.

The present results demonstrate, however, that TTB-CCs do not ignore cue information when cues are directly accessible (Experiments 1–3), or when task instructions focus on decision accuracy (Experiment 2). In the present experiments, information about a supposedly TTB-irrelevant cue, the next-best cue, affected the decision behavior of TTB-CCs in several ways: TTB-CCs took more time for their decisions (Experiments 1a, 1b, and 3), they bet less on their decisions (Experiment 1b), and they showed lower decision confidence (Experiment 3), when information from the best and the next-best cue conflicted than when it converged. In addition to finding that TTB-CCs do not ignore easily available cue information, Experiment 3 yielded novel insights into how TTB-CCs process available information. We found first evidence that TTB-CCs inhibit conflicting information from a less valid cue. Although inhibition has garnered a lot of attention within the field of cognitive psychology, and evidence for inhibitory processes has been reported for tasks involving selective attention (research on negative priming; Tipper, 2001) or memory (Veling & van Knippenberg, 2004), the present experiment, to our knowledge, is the first to demonstrate inhibitory processes in the context of TTB-decision-making.

Regarding the question of when TTB-CCs do or do not ignore information, Experiments 1a and 1b revealed that information availability plays an important role: When information about cues was directly accessible, TTB-CCs did not ignore it; yet, when information about single cues had to be acquired sequentially, TTB-CCs behaved more in line with the TTB-stopping-rule, that is, they often ignored TTB-irrelevant cues. This observation—that the same TTB-CCs do not ignore information when it is directly accessible, but become more likely to ignore information when information search is sequential—suggests that TTB-CCs adaptively adjust their information-search behavior as a function of information availability. As the sequential search for information may require more time and may thus be considered more effortful than the processing of openly displayed information (e.g., Lohse & Johnson, 1996), this finding also fits nicely with the notion of an effort-accuracy trade-off in decision making (e.g., Payne et al., 1988). In this regard then the amount of information accumulated by a decision maker is a function of the effort required to accumulate the information.

Results of Experiment 2 further support the adaptive nature of TTB-CCs' information-search behavior and point to another condition under which TTB-CCs become more likely to not ignore information. When the focus of the task was on decision accuracy, TTB-CCs acquired more cues than when the focus was on decision speed.

Relation to Previous Research

The finding that TTB-CCs do not ignore information when cues are directly accessible is consistent with previous research demonstrating that TTB-CCs are sensitive to the consistency of easily available cue information (Glöckner & Betsch, 2012; Glöckner et al., 2014; Söllner et al., 2014).

Furthermore, in addition to showing that TTB-CCs do not ignore information when it is easily available, we also showed that, when cue information access is more effortful (sequential search), TTB-CCs become somewhat more likely to ignore information. In line with findings by Söllner and Bröder (2015), however, our TTB-CCs did not consistently stop their sequential information search after acquiring the best cue. Importantly, whereas in previous research either a task format with simultaneous cue presentation or a task format with sequential search was used (Glöckner & Betsch, 2008a), in the present research we varied the task format within participants. This enabled us to explore the decision behavior of decision makers under varying conditions of information availability (or processing effort) and, in this regard, to explore the adaptive nature of their behavior.

The finding that decision makers of Experiment 2 acquired less cue information under speed than under accuracy instructions mirrors the results of previous studies on adaptive decision making (Glöckner & Betsch, 2008a; Rieskamp & Hoffrage, 1999). In these studies, however, the restriction of information search under time pressure was accompanied by a shift in strategies—that is, a shift from WADD to TTB. In the present research, we found no evidence that WADD-/EQW-CCs switched to a TTB strategy under speed instructions. Rather, decision makers of our experiments (irrespective of their strategies) were highly consistent in their strategy use across different conditions—an observation more in line with findings of routine effects in decision making (Bröder & Schiffer, 2006). As already mentioned, an important difference between our time pressure manipulation and the one used in previous research is that the latter imposed an explicit time limit on participants' decisions whereas no time limits were set in our study. It seems reasonable that the explicit time limit in previous research required participants to restrict their information search to a minimum so that a TTB-like strategy became preferable to the majority of participants (even those participants who otherwise would have preferred a WADD-like strategy). Without explicit time limit, however, as in our study, there was no objective constraint that would have terminated the decision process automatically. Although our findings showed that WADD-CCs restricted their information search under time pressure, they nevertheless searched for enough cues to figure out whether a highly valid cue could have been compensated for by less valid cues.

Another difference between our experiment and previous research that might explain the discrepancies between the findings relates to the different ways in which participants learned the cue validities. In previous research, cue validities were conveyed via instructions and participants received no choice feedback. In the present experiments, participants learned the validities in a feedback learning phase. It seems likely that already during the learning phase, participants adopted a certain decision strategy. That is, some participants (TTB-CCs) may have paid particular attention to only one cue and specifically relied on this cue to make their decisions; others may have divided their attention more equally among cues and took into account information from all cues (WADD-/EQW-CCs). This could also explain why the cue utility ratings showed larger dispersions for TTB-CCs than for WADD-/EQW-CCs. That is, paying particular attention to, and relying on only one cue during learning (TTB) may have distorted the perception of the actual cue validities (i.e., perceiving higher dispersion among cue validities than there actually were in the environment). In the learning phase of our experiment, the WADD- and the TTB-strategy performed equally well (i.e., they made identical choice predictions) and the choice feedback participants received during learning therefore should not have favored one strategy over the other. However, it should be noted that there was a positive correlation among cues in our learning environment, and it has been shown that, under these conditions, a single-cue strategy like TTB fares quite well in predicting choices (Davis-Stober, Dana, & Bodescu, 2010). It is therefore possible, that the positive correlation among the cues in the learning phase may have biased some participants toward using a TTB-like learning strategy.[3] More research is necessary, to examine how participants learn cue validities, and whether participants adopt different learning strategies.[4]

Theoretical Implications

For the present research, we considered EAMs as an overarching framework to account for the decision behavior of TTB-CCs and WADD-/EQW-CCs under varying conditions. The finding that TTB-CCs and WADD-CCs are sensitive to the consistency of easily available cue information is consistent with an EAM account assuming that participants process cue information completely; but whereas TTB-CCs weight the cues in a non-compensatory way, WADD-CCs weight the cues in a compensatory way. This finding is also consistent with the neural network model proposed by Glöckner et al. (2014; Glöckner & Betsch, 2008a, 2012), which likewise supposes that TTB-CCs and WADD-CCs differ in their cue weightings (non-compensatory vs. compensatory). Like EAMs, the parallel constraint satisfaction (PCS) model predicts that decision time and confidence depend on the consistency of cue information. Unlike EAMs, however, which assume that information processing is sequential, PCS assumes that information is processed holistically and in parallel. PCS is thus specifically suited for decision tasks where cue information is simultaneously presented. When information search happens sequentially, as was also the case in the present experiments, it is less clear which predictions can be derived from the PCS model.

In the task with sequential search, we found that TTB-CCs acquired less cue information than did WADD-/EQW-CCs. This observation is consistent with the unifying EAM proposed by Lee and Cummins (2004; Newell & Lee, 2011), which assumes that TTB-CCs have lower decision thresholds than WADD-/EQW-CCs and therefore stop information search sooner than WADD-/EQW-CCs (see also Söllner & Bröder, 2015). Although the unifying model can explain the present findings from the sequential search task, it has difficulties to explain the findings from the task with directly accessible cue information—where our findings suggest that TTB-CCs do not stop information search at the discovery of the best cue. Specifically, the unifying model is based on the assumption that all participants weight the cues by their *objective* validities; that is, the model does not suppose any differences in cue weightings. Given that the objective validities of a decision environment are compensatory (as it was the case in our experiments), the unifying model predicts that participants who process cue information completely integrate the cues in a compensatory manner which necessarily leads to choices as predicted by WADD. Our results suggest, however, that some participants (which we termed TTB-CCs) process cue information completely and nevertheless go with the best cue. In our view, the unifying model could be reconciled with our findings by allowing for differences in the way in which participants weight cues (i.e., by taking into account subjective cue weights). Indeed, although TTB-CCs and WADD-CCs did not differ in their cue-utility rankings, the observation that TTB-CCs and WADD-/EQW-CCs showed a consistent tendency to perceive higher cue dispersion corroborates our assumption of individual differences in cue weightings, at least in terms of the dispersion of the weightings. It should be noted, however, that TTB-CCs' sensitivity to information consistency only suggests that their decision threshold (or at least the decision threshold of some of the TTB-CCs) is higher than the threshold implied by the TTB-stopping-rule. This does not necessarily imply that the decision thresholds of TTB-CCs and WADD-CCs are equal. It could be, for example, that in case of conflicting information, WADD-CCs try to solve the conflict by deliberately re-considering and re-evaluating the information (i.e., high threshold), whereas TTB-CCs may solve the conflict by quickly relying on the best cue instead of re-evaluating the information (i.e., lower threshold). When information is openly presented to decision makers (compared to when it is sequentially acquired), it is difficult to say how decision makers actually process the information (e.g., information search and amount). That said, it is safe to conclude from the present findings that TTB-CCs did not ignore information and this suggests higher decision thresholds for TTB-CCs than implied by the TTB-stopping-rule.

Different Strategies, Single Process, or Both?

There is an ongoing debate on whether decision making is better reflected by different strategies, such as TTB, WADD or EQW, or a single process such as evidence accumulation or parallel constraint satisfaction (Glöckner et al., 2014; Lee & Cummins, 2004; Söllner et al., 2014; Söllner & Bröder, 2015). Our research suggests that the two views need not necessarily be mutually exclusive. The finding that decision makers are generally sensitive to the consistency of easily available cue information suggests that information integration, as suggested by EAMs or PCS, is one process underlying the decision behavior of decision makers in general.

Despite this commonality, however, we also found an interesting difference between the decision behavior of TTB-CCs on one hand and WADD-/EQW-CCs on the other hand. Specifically, we found that TTB-CCs inhibit cue information that conflicts with their decisions, whereas no evidence of an inhibition process was found for WADD-/EQW-CCs. The idea that decision-inconsistent information is inhibited is closely related to the idea proposed by PCS that decision makers strive for coherence during decision making (Glöckner, Betsch, & Schindler, 2010). This coherence-striving process supposes a reciprocal relation between the evaluation of the cues (their perceived utilities) and the final choice: The evaluation of the cues affects the final choice, but the choice also affects the final evaluation of the cues in a way that information inconsistent with the chosen option will be "devalued". In this regard, PCS could explain the inhibition findings of our TTB-CCs. That is, in order to make a coherent choice and to maximize the difference between the two choice options, TTB-CCs inhibit the inconsistent information about the non-chosen option. Importantly, however, PCS would suggest that this coherence-striving process should be present in all decision makers, that is, TTB-CCs and WADD-/EQW-CCs alike. Note that for the pairs we considered for our inhibition hypothesis both TTB-CCs and WADD-CCs finally chose the option favored by the best cue. Thus, according to PCS both TTB-CCs and WADD-CCs should have inhibited information about the inconsistent next-best cue, because this information conflicted with their choices. Our findings suggest, however, that inhibition is of less importance for WADD-/EQW-CCs. We suggested that for TTB-CCs, the best discriminating cue has a rule-like function, as it consistently drives the choices of these decision makers. It seems reasonable to us, therefore, to assume that TTB-CCs consciously follow a TTB-decision-rule. For WADD-/EQW-CCs, the best discriminating cue is not tied to a certain rule. TTB-CCs are therefore supposed to experience a cognitive conflict when the next-best cue is inconsistent with the best discriminating cue; and they may want to reduce this conflict by suppressing the decision-inconsistent information. For WADD-/EQW-CCs, an inconsistent next-best cue may be perceived as less conflicting, because WADD-/EQW-CCs have no decision rule related to the best cue with which the next-best cue might conflict. WADD-/EQW-CCs may therefore not necessarily need to inhibit decision-inconsistent information, at least not to the extent that TTB-CCs do.

The assumption of deliberate or rule-like processes, which we suggest may differ between TTB-CCs and WADD-CCs and could therefore account for the difference in inhibition, is not taken into account by PCS. Rather, PCS argues for a single, automatic coherence-striving process. We think that striving for coherence is indeed an important mechanism underlying the decision behavior of decision makers in general, as suggested by PCS. But the single coherence-striving process alone cannot explain why for some decision makers, inconsistent information is perceived as more conflicting (TTB-CCs) and therefore requires more inhibition than it is for others (WADD-CCs). In our view, the additional consideration of more deliberate processes during decision making could provide such an explanation. Moreover, it can also explain why it was particularly the inconsistent information that affected decision times (slowdown) whereas the consistent information—contrary to the coherence-striving assumption—did not: there was no speedup when coherence was increased. Specifically, only when the rule 'to go with the best cue' is conflicted by additional information, an additional time consuming process (inhibition) seems to be required, whereas no additional processes seem to be necessary when additional information is neutral or confirming. Although more research is certainly necessary to deepen our understanding of the specific nature of decision processes, we think that taking into account more deliberate or rule-like processes when investigating decision making may provide a fruitful avenue for future research. Importantly, however, the idea of deliberate and inhibitory processes during decision making does not contradict the assumption that information is accumulated and integrated until a certain threshold is reached (EAM) or that information is automatically integrated in parallel on the basis of a coherence-striving process (PCS) (see also Glöckner & Betsch, 2008b, for another view on how deliberate and automatic processes might co-exist during decision making). Yet the decision processes might probably be more complex than assumed by these models. Specifically, in addition to automatic information integration processes, more deliberate and post-integrational processes (inhibition) also seem to be at work during decision making and contribute to the specific decision patterns observed in groups of decision makers whose decisions are consistent with different decision strategies.

References

Bergert, F. B., & Nosofsky, R. M. (2007). A response-time approach to comparing generalized rational and take-the-best models of decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(1), 107–129. doi: 0.1037/0278-7393.33.1.107

Bröder, A. (2000). Assessing the empirical validity of the "Take-the-best" heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(5), 1332–1346. doi: 10.1037/0278-7393.26.5.1332

Bröder A., & Gaissmaier, W. (2007). Sequential processing of cues in memory-based multiattribute decisions, *Psychonomic Bulletin & Review, 14*(5), 805–900.

Bröder, A., & Schiffer, S. (2003). Bayesian strategy assessment in multi-attribute decision making. *Journal of Behavioral Decision Making*, *16*(3), 193–213. doi:10.1002/bdm.442

Bröder, A., & Schiffer, S. (2006). Adaptive flexibility and maladaptive routines in selecting fast and frugal decision strategies. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*(4), 904–918. doi:10.1037/0278-7393.32.4.904

Davis-Stober, C. P., Dana, J., & Budescu, D. V. (2010). Why recognition is rational: Optimality results on single-variable decision rules. *Judgment and Decision Making*, *5*, 216–229.

Gigerenzer, G., & Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science*, *1*(1), 107–143. doi: 10.1111/j.1756-8765.2008.01006.x

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*, 451–482. doi: 10.1146/annurev-psych-120709-145346

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

Gigerenzer, G., Hoffrage, U., & Kleinbölting, H. (1991). Probabilistic mental models: A Brunswikian theory of confidence. *Psychological Review*, *98*, 506–528.

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

Glöckner, A., & Betsch, T. (2008a). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(5), 1055–1075. doi:10.1037/0278-7393.34.5.1055

Glöckner, A., & Betsch, T. (2008b). Modelling option and strategy choices with connectionist networks: Towards an integrative model of automatic and deliberate decision making. *Judgment and Decision Making*, *3*(3), 215–228.

Glöckner, A., & Betsch, T. (2012). Decisions beyond boundaries: When more information is processed faster than less. *Acta Psychologica*, *139*(3), 532–542. doi:10.1016/j.actpsy.2012.01.009

Glöckner, A., Betsch, T., & Schindler, N. (2010). Coherence shifts in probabilistic inference tasks. *Journal of Behavioral Decision Making*, *23*(5),439–462. doi: 10.1002/bdm.668

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is Adaptive about Adaptive Decision Making? A Parallel Constraint Satisfaction Theory for Decision Making, *Cognition 133*, 641–666. doi:10.1016/j.cognition.2014.08.017

Hausmann, D., & Läge, D. (2008). Sequential evidence accumulation in decision making: The individual desired level of confidence can explain the extent of information acquisition. *Judgment and Decision Making*, *3*(3), 229–243.

Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to Stroop interference. *Journal of Experimental Psychology: General*, *132*(1), 47–70. doi:10.1037/0096-3445.132.1.47

Lee, M. D., & Cummins, T. D. (2004). Evidence accumulation in decision making: Unifying the "take the best" and the "rational" models. *Psychonomic Bulletin & Review*, *11*(2), 343–352. doi: 10.3758/BF03196581

Lee, M. D., Newell, B. R., & Vandekerckhove, J. (2014). Modelling the adaptation of search termination in human decision making. *Decision*, *1*, 223–251. http://dx.doi.org/10.1037/dec0000019

Lohse, G. L., & Johnson, E. J. (1996). A comparison of two process tracing methods for choice tasks. *Organizational Behavior and Human Decision Processes, 68*(1), 28–43. http://dx.doi.org/10.1109/hicss.1996.495316

Mari-Beffa, P., Estévez, A. F., & Danziger, S. (2000). Stroop interference and negative priming: Problems with inferences from null results. *Psychonomic Bulletin & Review, 7*(3), 499–503. doi: 10.3758/BF03214362

Newell, B. R., & Lee, M. D. (2009). Learning to adapt evidence thresholds in decision making. In N. Taatgen, H. van Rijn, J. Nerbonne, & L. Schomaker (Eds.), *Proceedings of the 31st Annual Conference of the Cognitive Science Society* (pp. 473–478). Austin, TX: Cognitive Science Society.

Newell, B. R., & Lee, M. D. (2011). The right tool for the job? Comparing an evidence accumulation and a naive strategy selection model of decision making. *Journal of Behavioral Decision Making*, *24*(5), 456–481. doi: 10.1002/bdm.703

Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing "one-reason" decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(1), 53. doi: 10.1037/0278-7393.29.1.53

Newell, B. R., Weston, N. J., & Shanks, D. R. (2003). Empirical tests of a fast-and-frugal heuristic: Not everyone "takes-the-best". *Organizational Behavior and Human Decision Processes*, *91*(1), 82–96. doi: 10.1016/S0749-5978(02)00525-3

Nosofsky, R. M., & Bergert, F. B. (2007). Limitations of exemplar models of multi-attribute probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(6), 999–1019. doi: 10.1037/0278-7393.33.6.999

Pachur, T., & Marinello, G. (2013). Expert intuitions: How to model the decision strategies of airport customs officers? *Acta Psychologica*, *144*(1), 97–103. doi:10.1016/j.actpsy.2013.05.003

Pachur, T., & Olsson, H. (2013). Type of learning task impacts performance and strategy selection in decision making. *Cognitive Psychology*, *65*(2), 2077–240. doi: 10.1016/j.cogpsych.2012.03.003

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. doi: 10.1037/0278-7393.14.3.534

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & the R Development Core Team (2013). nlme: Linear and nonlinear mixed effects models. R package version 3.1–111.

Platzer, C., & Bröder, A. (2012). Most people do not ignore salient invalid cues in memory-based decisions. *Psychonomic Bulletin & Review*, *19*(4), 654–661. doi:10.3758/s13423-012-0248-4

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics, and how can we tell? In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.), S*imple heuristics that make us smart* (pp. 141 – 167). New York: Oxford University Press.

Söllner, A., & Bröder, A. (2015). Toolbox or adjustable spanner? A critical comparison of two metaphors of decision making. *Journal of Experimental Psychology: Learning Memory, & Cognition*.

Söllner, A., Bröder, A., Glöckner, A., & Betsch, T. (2014). Single-process versus multiple-strategy models of decision making: Evidence from an information intrusion paradigm. *Acta Psychologica*, *146*(1), 84–96. doi:10.1016/j.actpsy.2013.12.007

Tipper, S. P. (2001). Does negative priming reflect inhibitory mechanisms? A review and integration of conflicting views. *The Quarterly Journal of Experimental Psychology, 54*(2), 321–343. doi: 10.1080/02724980042000183

Veling, H., & van Knippenberg, A. (2004). Remembering can cause inhibition: Retrieval-induced inhibition as cue independent process. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*(2), 315–318. doi: 10.1037/0278-7393.30.2.315

Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: an empirical validation. *Memory & Cognition*, *32*(7), 1206–1220. doi: 0.3758/BF03196893

R Core Team (2013). R: A language and enviornment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Wagenmakers, E. J., Ratcliff, R., Gomez, P., & McKoon, G. (2008). A diffusion model account of criterion shifts in the lexical decision task. *Journal of Memory and Language*, *58*(1), 140–159. doi: 10.1016/j.jml.2007.04.006

Footnotes

[1]The strategy-classification approach requires a decision researcher to determine a set of decision strategies that participants might potentially apply and that are of interest for the research question. We focused on TTB, WADD, and EQW here, because they are commonly considered in decision research and because they were of most interest for our research question. Another class of decision strategies that has received some attention in decision research is the class of exemplar-based strategies. However, recent research using similar or identical stimulus material as we did, similar decision environments (linear), and similar decision tasks (paired comparison task) found only little support for exemplar-based decision strategies (Nosofsky & Bergert, 2007; Pachur & Olsson, 2013). Thus, assuming that exemplar-based strategies may probably only have played a minor for the type of decision task we used, we did not additionally test for these strategies.

[2]For all experiments, an initial overall ANOVA was conducted with decision strategy as between-subjects factor. In all experiments, the three-way interaction between decision strategy, best discriminating cue, and next-best cue was significant, *p*s < 0.026. For the sake of conciseness, however, only the follow-up analyses for the separate groups are reported in this paper.

[3]We thank an anonymous reviewer for this careful observation and interpretation

[4]An analysis of participants' decision times of the validity learning phase provides initial support for our assumption that participants used different strategies already during learning. Specifically, participants later classified as TTB-CCs were found to make faster decisions on a learning trial ($M = 4.63$, $SE = 2.27$) than participants later classified as WADD-/EQW-CCs ($M = 5.74$, $SE = 2.51$), $F(1, 44) = 6.017$, $p = 0.018$, $\eta^2 = 0.11$.

Appendix A

Table A.1

Individual Orders of Cue Acquisition and Decision Strategies in Test Phase 2 of Experiment 1a.

Participant	Decision strategy	Order of acquired cues			
		First	Second	Third	Last
1	TTB	1.00	2.10	2.89	-
2	TTB	1.00	2.00	3.00	-
3	TTB	1.00	2.00	3.00	-
4	WADD	1.20	1.95	3.72	3.06
5	TTB	1.00	2.00	3.25	3.25
6	TTB	1.00	2.00	3.00	-
7	WADD	1.00	2.00	3.00	4.00
8	TTB	1.07	2.00	3.00	-
9	TTB	1.00	2.00	3.00	-
10	WADD	1.05	1.98	2.97	4.00
11	WADD	1.00	2.00	3.09	3.82
12	WADD	1.00	2.05	3.10	3.84
13	EQW	1.98	1.25	2.82	4.00
14	TTB	1.00	2.00	3.12	3.00
15	WADD	1.00	2.08	2.92	4.00
16	EQW	1.00	2.00	4.00	3.00
17	TTB	1.02	1.95	3.00	-
18	EQW	1.00	2.88	2.13	4.00
19	TTB	1.00	2.00	3.00	-
20	WADD	1.32	1.90	3.11	3.56
21	TTB	1.07	1.95	2.88	3.00
22	EQW	2.15	3.85	1.00	3.00
23	TTB	1.02	1.95	3.00	-
24	TTB	1.07	2.27	2.92	3.89
25	TTB	1.02	1.95	3.00	-
26	TTB	1.07	2.03	2.82	3.86
27	TTB	1.00	2.00	3.00	4.00
28	TTB	1.20	1.90	2.87	3.80
29	TTB	1.00	3.00	-	-
30	WADD	1.00	2.00	3.02	3.96
31	TTB	1.00	2.00	3.00	-
32	TTB	1.07	1.97	3.07	3.67
33	TTB	1.00	3.00	2.00	-
34	TTB	1.68	2.09	3.00	-
35	WADD	1.07	1.92	3.08	3.89
36	TTB	1.00	2.16	3.09	2.00
37	WADD	1.00	2.10	2.94	3.92

38	TTB	1.07	2.00	2.75	-
39	EQW	1.98	1.11	3.00	-
40	TTB	1.00	2.00	3.00	-
41	TTB	1.00	2.05	2.89	-
42	WADD	1.00	2.00	3.00	4.00
43	WADD	1.00	2.10	2.89	4.00
44	WADD	1.05	2.00	2.94	4.00
45	TTB	1.05	2.00	3.00	-
46	WADD	1.00	2.00	3.00	4.00
47	TTB	1.02	1.95	3.12	3.00
48	unclassified	1.00	2.00	3.05	3.94
49	TTB	1.00	2.00	3.00	-

Note. TTB = take the best; WADD = weighted additive; EQW = equal weights.

Appendix B

Table B.1

Individual Orders of Cue Acquisition and Decision Strategies in Test Phase 2 of Experiment 1b

Participant	Decision strategy	Order of acquired cues: First	Second	Third	Fourth
1	WADD	1.00	2.06	2.96	3.92
2	TTB	1.00	2.00	3.00	4.00
3	TTB	1.00	2.00	3.00	-
4	WADD	1.00	2.06	3.00	3.88
5	EQW	3.94	2.09	2.96	1.00
6	TTB	1.00	2.00	3.00	-
7	TTB	1.00	2.00	3.00	4.00
8	TTB	1.00	2.00	3.00	-
9	TTB	1.00	2.00	3.12	3.00
10	WADD	1.00	2.07	3.06	3.89
11	TTB	1.00	3.00	2.23	3.20
12	WADD	1.00	2.09	3.00	3.86
13	WADD	1.00	2.00	3.13	3.73
14	WADD	1.00	2.00	3.00	4.00
15	WADD	1.00	2.03	2.96	4.00
16	TTB	1.00	2.00	3.00	-
17	TTB	1.09	2.03	2.91	4.00
18	WADD	2.00	2.14	3.14	2.58
19	TTB	1.00	2.12	2.78	-
20	EQW	1.78	2.03	2.81	3.35
21	WADD	1.12	1.97	2.9	4.00
22	EQW	1.09	2.03	3.03	3.90
23	TTB	1.06	1.94	3.17	3.69
24	WADD	1.00	2.00	3.00	4.00
25	TTB	1.16	1.85	3.00	4.00
26	WADD	1.00	2.00	3.00	4.00
27	EQW	1.00	3.91	3.03	2.20
28	WADD	1.25	1.97	2.88	3.91
29	WADD	1.09	2.03	2.93	3.89
30	TTB	1.03	1.97	3.00	4.00
31	EQW	2.41	2.22	2.00	3.38
32	WADD	1.00	3.94	2.03	3.03
33	WADD	1.00	2.03	3.00	3.95
34	EQW	1.00	3.00	4.00	2.00
35	unclassified	1.16	2.06	2.76	4.00
36	TTB	1.00	2.00	3.00	-
37	WADD	1.44	2.12	3.10	3.20
38	TTB	1.00	3.19	2.54	3.00

39	TTB	1.00	2.00	3.00	4.00
40	WADD	1.00	2.03	2.96	4.00
41	WADD	1.00	2.00	3.00	4.00
42	TTB	1.00	2.00	3.00	4.00
43	WADD	1.00	2.00	3.00	4.00
44	WADD	1.00	2.00	3.07	3.94
45	TTB	1.00	2.00	3.00	-
46	TTB	1.00	2.00	3.00	4.00
47	TTB	1.12	1.94	2.90	4.00
48	TTB	1.00	2.10	2.86	4.00
49	EQW	1.19	3.72	2.19	2.91
50	WADD	1.03	1.97	3.00	4.00
51	TTB	1.00	2.00	3.00	4.00
52	TTB	1.00	2.13	3.08	3.33
53	TTB	1.00	2.00	3.00	4.00
54	EQW	3.41	2.47	2.56	1.72
55	EQW	2.06	3.69	3.13	-
56	WADD	1.03	2.03	3.06	3.82
57	TTB	1.00	2.14	3.00	4.00
58	WADD	1.00	2.09	2.93	4.00
59	TTB	1.09	3.56	2.71	2.6
60	TTB	1.06	2.09	3.15	3.67
61	EQW	1.00	2.00	4.00	3.00
62	WADD	1.12	2.03	2.9	4.00
63	WADD	1.03	3.03	1.97	3.97
64	unclassified	1.03	1.97	3.04	4.00
65	TTB	1.00	2.07	3.07	4.00
66	TTB	1.03	1.94	3.00	-
67	TTB	3.72	3.00	1.22	2.06
68	TTB	1.00	2.06	2.94	3.75
69	WADD	1.00	2.00	3.00	4.00
70	WADD	1.00	2.00	3.00	4.00

Note. TTB = take the best; WADD = weighted additive; EQW = equal weights.

Appendix A2 – Article 2

Note:
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Take-the-best and the Influence of Decision-inconsistent Attributes on Decision Confidence and Choices in Memory-based Decisions

Sebastian Dummel and Jan Rummel

Heidelberg University

Author Note

Sebastian Dummel, Jan Rummel, Department of Psychology, Heidelberg University, Germany.

Correspondence concerning this article should be addressed to Sebastian Dummel, Department of Psychology, Heidelberg University, Hauptstrasse 47-51, 69 117 Heidelberg, Germany. Phone: +49 (0)6221/54 - 7120. E-mail: sebastian.dummel@psychologie.uni-heidelberg.de

Abstract

Take-the-best (TTB) is a decision strategy according to which attributes about choice options are sequentially processed in descending order of validity, and attribute processing is stopped once an attribute discriminates between options. Consequently, TTB-decisions rely on only one, the best discriminating, attribute, and lower-valid attributes need not be processed because they are TTB-irrelevant. Recent research suggests, however, that when attribute information is visually present during decision-making, TTB-irrelevant attributes are processed and integrated into decisions nonetheless. To examine whether TTB-irrelevant attributes are retrieved and integrated when decisions are made memory-based, we tested whether the consistency of a TTB-irrelevant attribute affects TTB users' decision behavior in a memory-based decision-task. Participants first learned attribute configurations of several options. Afterwards, they made several decisions between two of the options, and we manipulated conflict between the second-best attribute and the TTB-decision. We assessed participants' decision confidence and the proportion of TTB-inconsistent choices. According to TTB, TTB-irrelevant attributes should not affect confidence and choices, because these attributes should not be retrieved. Results showed, however, that TTB-users were less confident and made more TTB-inconsistent choices when TTB-irrelevant information was in conflict with the TTB-decision than when it was not, suggesting that TTB-users retrieved and integrated TTB-irrelevant information.

Keywords: Decision making, Memory-based decisions, Take-the-best strategy, Evidence accumulation, Parallel constraint satisfaction

Take-the-best and the Influence of Decision-inconsistent Attributes on Decision Confidence and Choices in Memory-based Decisions

Facing a choice between two options, decision makers often have knowledge about decision-relevant attributes associated with the options, which they may retrieve from memory. For example, being asked whether Berlin or Frankfurt has the larger population, one might know that Berlin is the capital of Germany and has an airport (coded as 1-1), whereas Frankfurt is not the capital, but also has an airport (0-1). Information about these attributes can be used to make a decision, and decision-making researchers suggested different decision strategies as to how this information may be used (Payne, Bettman, & Johnson, 1988). According to the take-the-best heuristic (TTB; Gigerenzer & Goldstein, 1999), decision makers search their memories for information about the most valid attribute first—that is, the attribute most predictive of the criterion (e.g., the attribute 'being the capital' in case of the criterion 'population size'). The options are compared on this attribute and if it discriminates (Berlin is the capital, Frankfurt not), memory search is stopped (stopping-rule). At this point, so the assumption, no further attributes are retrieved and the option with the critical attribute value is chosen (decision-rule). If the most valid attribute had not discriminated, memory would have been searched for information about the second-most valid attribute (e.g., having an airport) and so on, until a discriminating attribute was found (search-rule).

Due to the stopping rule, TTB considers only part of the options' attributes. In decision-making research, TTB is often contrasted with decision strategies that take into account all attributes, such as the weighted-additive strategy (WADD). Using WADD, decision makers would retrieve all decision-relevant attributes associated with the options, weight (multiply) each attribute by its validity and sum up the products for each option. The option with the higher weighted sum would then be chosen. With regard to the Berlin-Frankfurt example, decision makers would thus have to retrieve all four attribute values for WADD but only two for TTB. If people consider all attributes but weight them equally they use an equal-weight strategy (EQW). Differences between TTB and other strategies have been investigated in decision contexts where attribute information had to be retrieved from memory (i.e., memory-based inferences; e.g., Bröder, Newell, & Platzer, 2010; Platzer & Bröder 2012; Khader, Pachur, & Jost, 2013; Renkewitz & Jahn, 2012), but also in contexts where attribute information was visually presented to participants throughout decision making (i.e., inferences from given information; e.g., Lee & Cummins, 2004; Newell & Shanks, 2003; Söllner, Bröder, Glöckner, & Betsch, 2014). Bröder and Schiffer (2003b) compared the two types of contexts and found that participants are more likely to use a TTB strategy when attributes have to be retrieved from memory than when the same attributes are visually present while participants make their decisions. They therefore suggest that TTB reduces the costs of information search (i.e., it reduces memory retrieval) and may thus be preferred for memory-based decisions.

However, recent research on memory-based decision making found evidence for an automatic retrieval of complete attribute information even during TTB-decision-making (Khaderet al., 2013). For example, Khader et al. (2013) asked participants to learn several items (companies) each of which was described by a distinct attribute-value pattern (e.g., company location, company manager, etc.). Importantly, the companies differed regarding the number of to-be-associated attributes, with the number ranging from one to three. After learning, participants were presented with company pairs and were asked to choose the prospectively more successful company on the basis of their acquired attribute knowledge. For their decisions, participants were instructed to follow a TTB strategy. The analysis of decision times revealed that, the more attributes were associated with the to-be-compared companies the longer it took participants to decide. For instance, in cases where, according to TTB, participants had to inspect only one attribute, participants made faster decisions when the to-be-compared companies were associated with only one attribute than when the companies were associated with two or three attributes. The authors interpreted these results as evidence for an automatic retrieval of complete attribute information even when participants were instructed to use a TTB strategy and thus to stop information search.

From Khader et al.'s (2013) findings that decisions take longer when the number of attributes per option increase, it becomes evident that TTB-irrelevant attributes are (automatically) retrieved even during TTB-decision-making. It remains unclear, however, how deeply this supposedly irrelevant attribute information is processed. It could be, for instance, that TTB-irrelevant attributes become activated but are then completely ignored while making the decision. In line with this idea, one could assume that the prolonged decision times reflect participants' attempt to ignore the irrelevant information. Ignoring easily available but irrelevant information requires inhibitory effort (e.g., Platzer & Bröder, 2012) which may come with decision-time costs. Alternatively, participants may not ignore automatically retrieved attributes but integrate them into their decisions. If so, the retrieved TTB-irrelevant attributes, though they may not necessarily alter a participants' decisions, they may affect decision-related processing, such as the confidence with which a decision is made. In line with this idea, the present study investigated how the consistency of attribute information will affect higher-order processing of participants who consistently make choices in line with TTB (referred to as *TTB-consistent choosers*, TTB-CCs). Because we were interested in effects of information *quality* and not information *quantity*, unlike Khader et al. (2013) we held the number of attributes associated with each decision option constant across all options and examined how the consistency of a supposedly TTB-irrelevant attribute—the *next-best attribute*—affects participants' decision confidence. In detail, the decision options of our task were all described on four attributes, and the next-best attribute was either consistent with the best discriminating attribute (e.g., 1-**1**-0-0 vs. 0-**0**-0-0) or inconsistent (1-**0**-0-0 vs. 0-**1**-0-0), or did not discriminate any further (e.g., 1-**0**-0-0 vs. 0-**0**-0-0). We further manipulated the validity rank of the best discriminating attribute, that is, whether it was the most valid, the second-most valid or the third-most valid attribute. Further, rather than instructing participants to use a specific strategy (as in Khader et al., 2013), we classified participants on the basis of their individual choice patterns into those who consistently make choices in line with TTB (TTB-CCs) and those who consistently make choices in line with WADD (WADD-CCs) or EQW (EQW-CCs). To this end, our decision task further included pairs for which TTB and WADD/EQW make opposing choice predictions, such as (1-0-0-0 vs. 0-1-1-1), and we used a well-established strategy-classification method (Bröder & Schiffer, 2003a, 2003b; Bröder & Gaissmaier, 2007; Bröder, Newell, & Platzer, 2010), which is described in detail in the Results section. Note however, that we use the terms TTB-CCs and WADD-/EQW-CCs only to refer to the *outcomes* (i.e., choices) associated with the different strategies and not to the specific *processes* suggested by these strategies (i.e., the TTB-stopping-rule). That is, participants classified as TTB-CCs made choices consistent with TTB; but this classification does not necessarily imply that TTB-CCs ignored TTB-irrelevant information, as implied by the TTB-stopping-rule. Our interpretation of the classification outcomes thus involves fewer assumptions than the assumptions imposed in previous research—where it has commonly been assumed that TTB-CCs ignored information (e.g., Bröder & Schiffer, 2003b). Our main dependent variable was the confidence with which decisions were made.

The theory of Probabilistic Mental Models (*PMM*; Gigerenzer, Hoffrage, & Kleinbölting, 1991) predicts that the confidence with which TTB-CCs make decisions solely depends on the validity rank of the best discriminating attribute: The higher the validity of the best discriminating attribute is the more confident TTB-CCs should be. TTB-irrelevant attributes, in contrast, should not affect decision confidence because they are assumed not to be retrieved (as implied by the TTB-stopping-rule). However, the finding of a complete attribute retrieval (Khader et al., 2013) suggests that the confidence of TTB-CCs may additionally be affected by the supposedly irrelevant next-best attribute. For example, evidence accumulation models (*EAM*s; e.g., Busemeyer & Johnson, 2004; Lee & Cummins, 2004) or Parallel Constraint Satisfaction models (*PCS*; Glöckner & Betsch, 2008; Glöckner & Hodges, 2011) assume that information available to a decision maker (e.g., when being retrieved) becomes automatically integrated during decision making. In this regard, TTB-CCs who retrieve attributes completely may be assumed to integrate the attributes by using non-compensatory weights, whereas WADD-CCs may be assumed to integrate the attributes by using compensatory weights. Decision confidence, according to EAMs or PCS, is said to be a function of the difference in evidence between the two choice options. Thus, relative to a non-discriminating next-best attribute, a consistent next-best attribute should increase decision confidence (higher evidence difference), whereas an inconsistent next-best attribute should decrease decision confidence (lower evidence difference; Glöckner & Betsch, 2012). Moreover, assuming that TTB-CCs weight the attributes in a non-compensatory manner and thus perceive relatively large differences among the attributes' validities, EAMs and PCS also predict that TTB-CCs' decision confidence would increase with the validity of the best discriminating attribute (as suggested by PMM).

Söllner, et al. (2014; see also Glöckner & Betsch, 2012; Glöckner, Hilbig, & Jekel, 2014) recently found evidence that TTB-CCs are affected by TTB-irrelevant information as predicted by EAMs. In their task, attribute information had to be purchased by participants and was visually presented to them throughout decision making on an information board (i.e., inferences from given information). On some trials, however, information about TTB-irrelevant attributes popped up for free. This information was either consistent or inconsistent with the best attribute. In line with EAMs/PCS, TTB-CCs were found to be less confident with their decisions when cue information was inconsistent than when it was consistent. Furthermore, participants were found to make more TTB-inconsistent choices when cue information was inconsistent rather than consistent, indicating that supposedly choice-irrelevant information became integrated not only for post-choice confidence judgments but also for the choices themselves (i.e., pre-choice integration). This latter finding is also in line with EAMs assuming a probabilistic choice-rule. That is, the probability for making a TTB-consistent choice depends on the evidence difference between two decision options: The lower the evidence difference is, the lower is the probability for making a TTB-consistent choice.

In sum, the results from the aforementioned studies suggest that, at least when decisions are made from given information, TTB-CCs do not ignore TTB-irrelevant information. In the present study, we examined whether the findings by Söllner et al. (2014) extend to memory-based decisions—i.e., where the options' attributes have to be retrieved from memory rather than being visually present during decision making. Specifically, we examined whether decision confidence of TTB-CCs as well as their choices would be affected by the consistency of information considered to be irrelevant by TTB, which would indicate that those decision makers retrieved and, more importantly, that they integrated attribute information. Using a memory-based decision task, Glöckner and Hodges (2011) found that a large proportion of their participants integrated attribute information as suggested by PCS. In this study, however, participants were predominantly classified as WADD on the basis of their choices. Note that the choices of WADD-CCs indicate already that those participants retrieved attribute information completely. This is not the case for TTB-CCs though. TTB-CCs may have made their choices either because they ignored attributes lower in validity than the best discriminating attribute (as implied by the TTB-stopping-rule) or because they retrieved attribute information completely and integrated it in a non-compensatory way (which may suggest that the decision behavior of TTB-CCs are probably better be described by some kind of evidence accumulation strategy). Therefore, the main goal of this study was to examine the decision behavior of TTB-CCs in order to get a better understanding of the cognitive processes underling their decisions.

Method

Participants

Seventy-four students (62 female) participated for either partial course credit or monetary compensation (10€). An additional bonus up to 4€ could be earned, contingent on task performance. Mean age was 21.16 (18–33).

Materials and Design

The general setup and cover story was similar to that of Bröder and Schiffer (2003b). Participants were told that a murder had been committed and that there were nine male suspects. Participants initially learned to associate each of the nine suspects with a distinct attribute-value pattern, consisting of three clothing articles and a car (attributes and possible attribute values were headpiece: hat or beret, coat: jacket or blouson, shoes: loafers or leather shoes, and car: Mini Cooper or Beetle). They then received information about the ranking of the attributes' validities which, as in previous studies (e.g., Platzer & Bröder, 2012), was determined by the level of agreement among eyewitnesses[1]. Finally, participants performed a decision phase, in which they were presented with pairs of suspects and had to choose the more suspicious one, given their knowledge about the suspects' attributes and the attributes' validities. Because we wanted to investigate how participants behave when they use the decision strategies that most naturally occur to them, we did not instruct participants to use a specific strategy, as Khader et al. (2013) did. Instead, as in previous decision-making studies (Bröder & Schiffer, 2003b; Bröder & Gaissmaier, 2007; Platzer & Bröder, 2012), we had participants spontaneously adopt their decision strategies and then classified them based on whether they relied on only the best attribute to make their choices—TTB—, or considered all attributes—WADD/EQW.

Table 1 depicts the attribute patterns of the nine suspects. The attributes differed regarding their validity, with Attribute 1 being the most valid attribute, Attribute 2 the second-most valid, and so on. The value "1" in Table 1 denotes the critical attribute value, that is, the specific item indicative of suspiciousness. Assignment of the validities to the clothing articles and cars was randomly determined for each participant anew, as was assignment of the critical attribute values to the specific items.

For the decision phase, the nine suspects were combined to pairs that differed with regard to (1) whether Attribute 1, Attribute 2, or Attribute 3 was the best discriminating attribute and (2) whether the next-best attribute was inconsistent or consistent with the best one, or did not discriminate. This resulted in the nine pairs listed in Table 2, which represent a full two-factorial design with the factors *rank of the best discriminating attribute* and *status of the next-best attribute* orthogonally crossed. Furthermore, another six pairs were created and only for whose so called *diagnostic pairs* the different decision

[1] Specifically, participants were told that 20 eyewitnesses had been interrogated and consensus was highest for Attribute 1 (e.g., shoes), second-highest for Attribute 2 (e.g.., coat), and so on. We provided participants only with the ranking of validities and not with numerical validities (e.g., 0.8, 0.7, etc.), because the latter may have biased participants towards either a compensatory or a non-compensatory interpretation of the attribute weights. The validity ranking, in contrast, allowed for the possibility that some participants would give most weight to the best discriminating attribute (TTB) whereas others would weigh the attributes more equally (WADD or EQW).

strategies made opposing choice predictions. The strategies we considered were TTB, WADD, and EQW. Table 3 shows the diagnostic pairs for our decision task. For these pairs, TTB predicts selection of Suspect A whereas WADD and EQW predict selection of Suspect B. Diagnostic pairs were critical for classifying participants into TTB-CCs, WADD-CCs, or EQW-CCs, respectively. For the classification, however, participants' choices to all pairs were considered (which further allowed for distinguishing between WADD- and EQW-CCs; see Results sections).

Table 1

Abstract Attribute Patterns Used in the Study

Attribute patterns	Attribute 1	Attribute 2	Attribute 3	Attribute 4
1	1	1	0	1
2	1	0	0	1
3	1	0	0	0
4	0	1	1	1
5	0	1	1	0
6	0	1	0	1
7	0	1	0	0
8	0	0	1	1
9	0	0	0	1

Note. Attributes 1–4 were the different clothing articles (i.e., headpiece, coat, and shoes) and cars. The values 1 and 0 were realized as different clothing articles (e.g., hat and beret for headpiece) and cars (Mini Cooper and Beetle).

Table 2

Test Pairs Used in the Decision Phase

	Next-best attribute					
Best discriminating attribute	Consistent pairs		Inconsistent pairs		Non-discriminating	
	Option A	Option B	Option A	Option B	Option A	Option B
Attribute 1	1101	0001	1001	0101	1001	0001
Attribute 2	0111	0001	0101	0011	1101	1001
Attribute 3	0111	0100	0110	0101	0110	0100

Note. Options A and B were the two suspects participants had to choose between. Attributes 1, 2, 3 were the different clothing articles and cars associated with the suspect.

Table 3
Diagnostic Pairs Used in the Decision Phase

Diagnostic pairs	
Option A	Option B
1000	0111
1000	0110
1000	0101
1000	0011
1001	0111
0100	0011

Our main dependent variable for the decision phase was participants' decision confidence. Therefore, each of the nine test pairs (cf. cells in Table 2) was presented four times in the decision phase, and participants were asked to indicate their confidence for two out of the four presentations. Furthermore, to increase the reliability of the choice-based strategy classification, the six diagnostic pairs were repeated once. Thus, the decision phase consisted of 48 trials (4 × 9 test pairs + 2 × 6 diagnostic pairs). Presentation order of the 48 pairs was determined randomly for each participant with the following constraints. (1) Each time a test pair was repeated all other test pairs had to be presented once. (2) A diagnostic pair was not repeated until all diagnostic pairs had been presented once. (3) Between a pair and its repetition had to be at least six other pairs, hence reducing the likelihood that participants recalled an earlier decision to a pair to make their actual decision. (4) Pairs that had one attribute pattern in common (e.g., **0-1-1-0** vs. 0-1-0-1 and **0-1-1-0** vs. 0-1-0-0) could not directly follow each other.

Furthermore, as in Söllner et al. (2014), we also considered the proportion of TTB-inconsistent choices as a dependent variable, and we examined whether/how the choice-behavior of TTB-CCs is influenced by the consistency of the next-best attribute.

Procedure

First, participants learned which clothing articles and car was associated with each suspect. On each trial, participants were presented with the name and portrait of one suspect. Below the portrait, the category labels of the four attributes were presented one below the other. Next to each attribute, the two attribute values possible for this attribute were presented as response buttons (see Figure 1; note, attribute order on screen matched attribute validities). For each attribute, participants were to select the correct attribute value associated with the suspect (by clicking the button) – on initial trials by guessing, later by recalling. Upon selection of an attribute value, participants received feedback: the correct attribute value was revealed to them (verbally and pictorially). Once all attribute values had been correctly recalled for a suspect, the next suspect was presented. Having learned the attribute values of all suspects this way, there was a test in which all suspects were presented once and participants had to indicate the correct attribute values of each suspect. The learning-plus-test cycles were repeated until memory performance in the test was above 89%. Participants not achieving this criterion within one hour were automatically forwarded to the subsequent decision phase. In the tests, participants received 1 Cent for each correct attribute value. Participants achieving the learning criterion within less than 8 learning-plus-test cycles received an additional bonus of 1€.

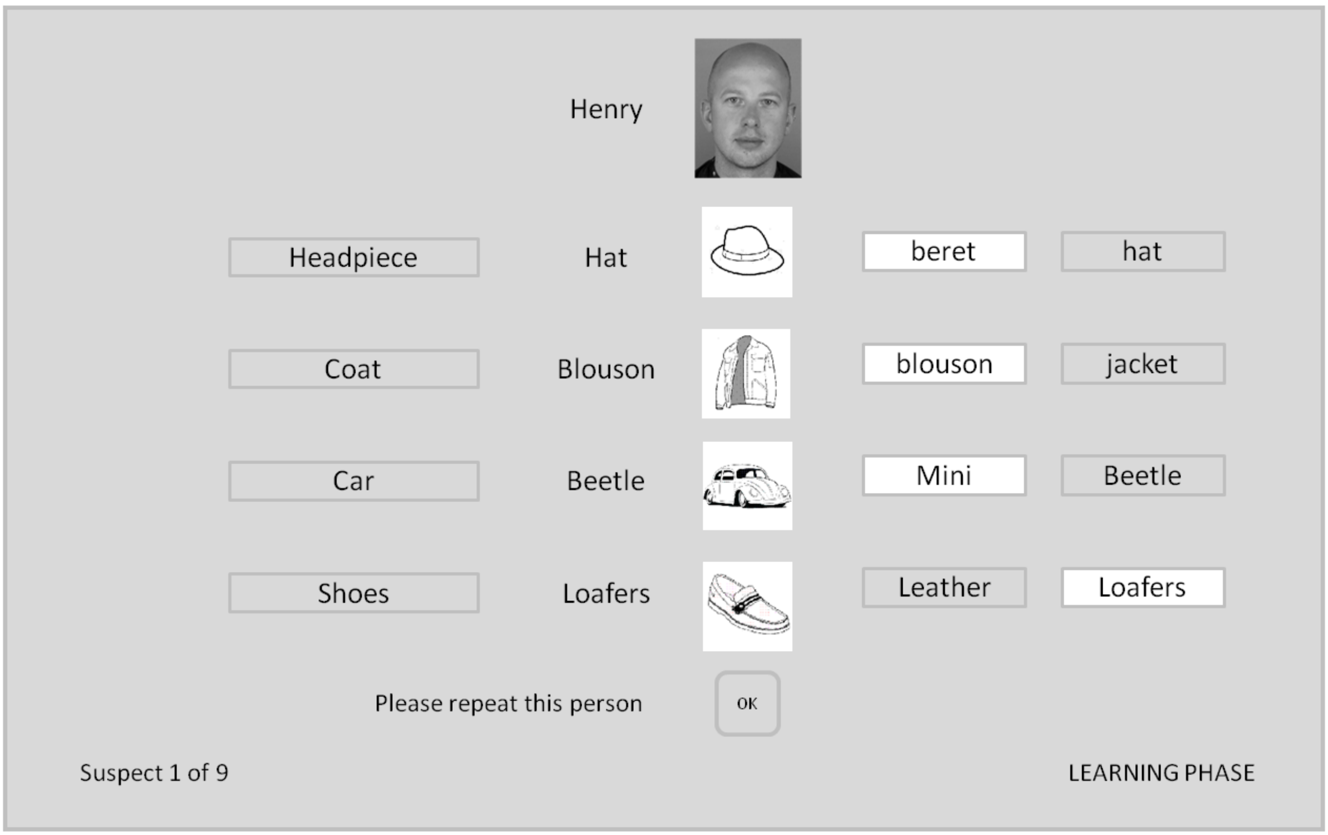

Figure 1. Example trial of the learning phase. On the left side the four attributes were listed (labels were originally in German and are translated here). On the right side, participants could select one out of two possible values for the respective attributes. Once an attribute value was selected (e.g., beret), the correct attribute value was shown for this attribute in the middle of the screen, both verbally and pictorially (e.g., hat).

After the learning phase, participants received information about the attribute validities. They were told that the level of agreement among eyewitnesses was highest with regard to Attribute 1 (e.g., Shoes), and witnesses reported to have seen a specific attribute value (e.g., loafers); and that level of agreement was second-highest for Attribute 2 (e.g., Headpiece), with a specific attribute value (e.g., hat); and so on (see Footnote 1).

Participants then performed the decision phase. On each trial, they were presented with the names and portraits of two suspects and were to decide which of the suspects was more likely to have committed the crime. On half of the decision trials, participants were further asked to indicate their decision confidence. Confidence ratings were made on a scale ranging from 1 (*very uncertain*) to 100 (*absolutely certain*).

The decision phase was followed by a final memory test where participants were to recall the attribute patterns of all suspects.

Results

Attribute Pattern Learning

Five participants failed to learn the attribute patterns within one hour. They were excluded from subsequent analyses leaving $N = 69$. Mean performance in the final memory test was 87%, indicating that attribute patterns were learned reasonably well.

Decision Phase

Strategy classification. The classification method by Bröder and Schiffer (2003a) was used to identify individual decision strategies. For the classification, a participant's choices on all 48 pairs were considered. For the consistent, inconsistent, non-discriminating, and diagnostic pairs (Tables 2 and 3), each strategy makes specific choice predictions: For the consistent and non-discriminating pairs, all strategies predict selection of Suspect A. For the diagnostic pairs, TTB predicts selection of Suspect A, whereas WADD and EQW predict selection of Suspect B. For the inconsistent pairs TTB and WADD predict selection of Suspect A; EQW predicts guessing, because both suspects have the same number of favorable attributes. In essence, the classification method is a *comparative* test of the different strategies, where each strategy is considered as a *multinomial model* with the consistent, inconsistent, non-discriminating and diagnostic pairs as different response categories (i.e., the different response categories imply a multinomial distribution of participants' choice patterns). Based on a maximum likelihood estimation, for each strategy a strategy-parameter (or its complementary error term), indicating a given participant’s probability of applying that strategy, is estimated from the data (Bröder & Schiffer, 2003a). In doing so, one can estimate the likelihood of each strategy given a participant’s data, and a participant is classified as a user of the strategy with the highest likelihood. Participants for whom two strategies had identical likelihoods remained unclassified; furthermore, participants with an error term > 0.4 are classified as guessers.

The classification analysis revealed a clear preference for TTB, with 60% (n = 41) of participants being classified as TTB-CCs, 20% (n = 14) as EQW-CCs, 12% (n = 8) as guessers, 4% (n = 3) as WADD-CCs, and 4% (n = 3) remained unclassified.[2] The subsequent analyses of participants' confidence ratings were run separately for the different strategy groups[3]. As there were only three WADD-CCs, EQW and WADD were combined into a compensatory strategy group (COMP). Data from unclassified and guessing participants were not analyzed.

Decision confidence. For the analysis of confidence ratings, decisions inconsistent with a participant's strategy were removed (on average, 17%, SD = 9.12). For each of the nine test pairs (cf. Table 2), participants gave two confidence ratings. The two ratings were averaged for each pair[4]. The design of the confidence ratings was thus a 3 (rank of the best discriminating attribute: Attribute 1, Attribute 2, Attribute 3) × 3 (status of the next-best attribute: inconsistent, non-discriminating, consistent) within-subjects design. Due to the removal of strategy-inconsistent decisions, however, the full design contained missing values (for TTB 12%, SD = 10.06; for COMP 3.27%, SD = 5.22).

To overcome the problem of missing values, we used a multilevel modelling approach to analyze participants' confidence ratings. Multilevel models (MLM) are extensions of regression models (also called hierarchical regressions), and hypothesis testing in MLM follows the same rationale as hypothesis testing in regression analyses. The advantage of MLM is that they can be applied to incomplete data sets without losing the remaining information from participants with incomplete data. Further, they can account for dependencies within a data set and are thus well suited to analyze data from repeated-measures designs. Dependency in our data was modelled by treating the two experimental factors as being nested within the variable *participant*. The participant variable was treated as a random (Level 2) factor.

As stated above, hypothesis testing in MLM is done similarly as in regression. That is, our outcome variable confidence was regressed on the predictors *best discriminating attribute*, *next-best*

[2] Because the classification method is comparative, the classification of a participant as TTB-CC only indicates that the choices of this participant were *more likely* to be produced by a TTB- rather than a WADD-/EQW-strategy. It does not tell, however, whether the proportion of TTB-inconsistent choices of a participant classified as TTB-CCs significantly deviated from zero. A more conservative approach for classifying a participant as TTB-CC would be to only consider choices to the 12 diagnostic pairs (6 different pairs, each presented twice) and to conduct a binomial test. The binomial test becomes significant when a participant makes TTB-inconsistent choices in three or more cases ($p < 0.05$). When applying this more conservative classification criterion, of the 41 participants classified as TTB-CCs with the Bröder-and-Schiffer method, 27 also had a non-significant binomial test, indicating that they chose the non-TTB option by (non-systematic) mistake. As analyzing only these 27 TTB-CCs rather than the 41 TTB-CCs did not change the present results, we decided to report the analysis of TTB-CCs including all 41 participants because this classification method is widely used in this research area. The average proportion of TTB-inconsistent choices was 17% for the 41 TTB-CCs (i.e., 2 out of 12 pairs, which corresponds to a probability of $p <$ 0.05 using the binomial criterion).

[3] Separate analyses were conducted because our primary research goal was to specifically examine the effects of TTB-irrelevant attributes on the decision-behavior of TTB-CCs. Considering strategy group as between-subjects factor would have yielded significant interactions with both within-subject factors. For sake of clarity, therefore, only results from the separate analyses are reported.

[4] The correlation between the two confidence ratings was .70, suggesting that participants were quite consistent in their confidence judgments.

attribute, and the interaction of both. We tested the significance of the predictors using a stepwise procedure. A Maximum-Likelihood algorithm was used to assess the fit of the model. Changes in model fit due to the inclusion of additional factors were assessed with a likelihood ratio test.

The confidence ratings of TTB-CCs and COMP-CCs are depicted in Figure 2. Confidence ratings of TTB-CCs were significantly affected by both the best attribute, $\chi^2(2) = 20.90$, $p < 0.001$, and the next-best attribute, $\chi^2(2) = 11.03$, $p = 0.004$. The interaction effect was not significant, $\chi^2(4) = 4.62$, $p = 0.328$. The effect of the best attribute was further explored with planned contrasts. Both PMM theory and EAMs/PCS predict that decision confidence of TTB-CCs would decrease with the validity of the best attribute. A monotonic trend analysis revealed a significant linear trend, $b = 9.08$, $t(79) = 4.82$, $p < 0.001$. The quadratic trend was not significant, $p = 0.716$. Decision confidence of TTB-CCs was highest for Attribute 1 as best discriminating attribute ($M = 70.94$, $SE = 1.76$) second highest for Attribute 2 ($M = 63.82$, $SE = 2.00$), and lowest for Attribute 3 ($M = 57.89$, $SE = 1.85$)[5].

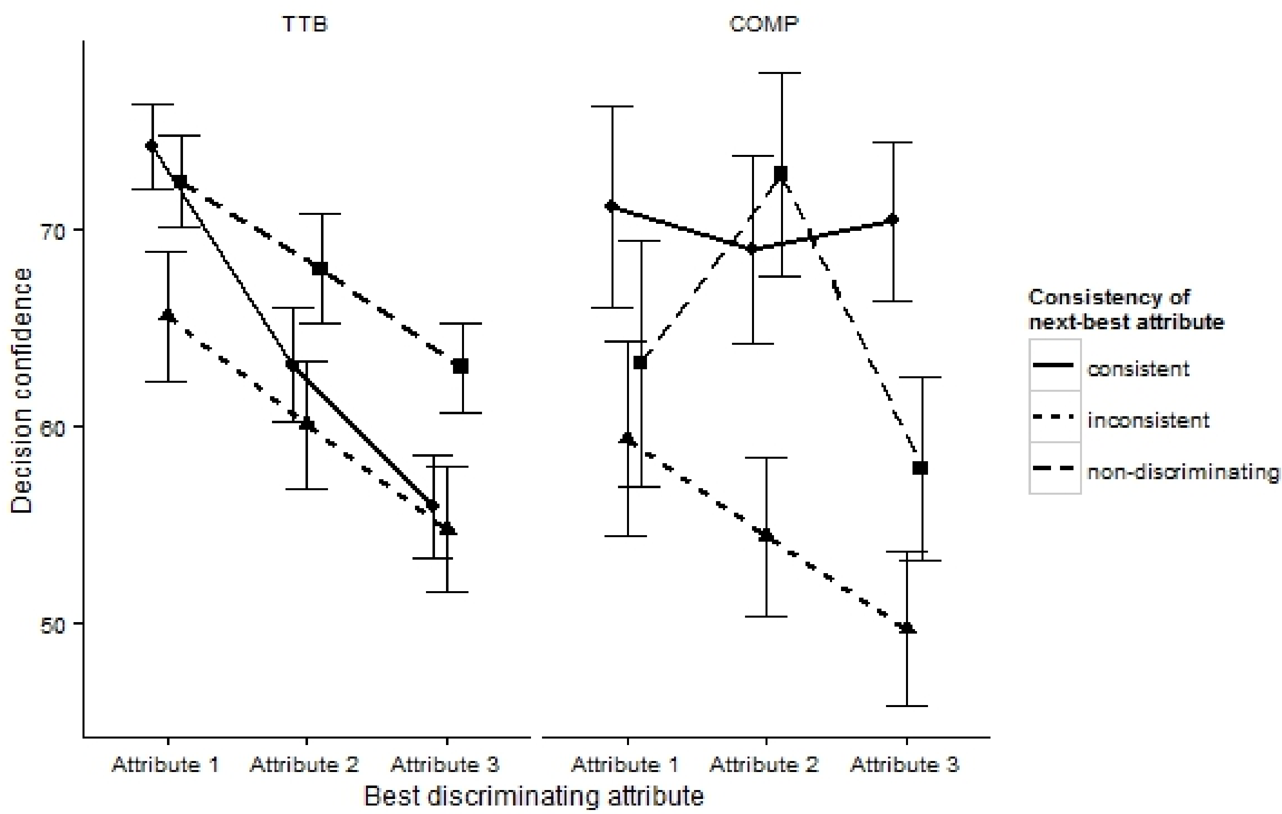

Figure 2. Mean decision confidence for TTB-CCs and COMP-CCs as a function of the validity of best discriminating attribute and the consistency of the next-best attribute. *Note*: TTB = take-the-best; COMP = compensatory strategies.

[5] All single comparisons were significant, *p*s < 0.042.

EAMs and PCS predict that relative to a non-discriminating attribute, an inconsistent next-best attribute should decrease confidence, and a consistent next-best attribute should increase decision confidence. Two contrasts were conducted to test this hypothesis. The first contrast compared the non-discriminating with the inconsistent condition and revealed a significant effect, $b = 7.33$, $t(201) = 3.33$, $p = 0.001$. Confidence of TTB-CCs was lower when the next-best attribute was inconsistent ($M = 60.69$, $SE = 2.22$) than when it was non-discriminating ($M = 68.22$, $SE = 1.70$). The second contrast compared the non-discriminating with the consistent condition and revealed no significant effect, $b = 3.10$, $t(201) = 1.46$, $p = 0.145$. Descriptively, confidence ratings even showed a reverse pattern: Confidence was lower when the next-best attribute was consistent ($M = 64.701$, $SE = 1.90$) than when it was non-discriminating ($M = 68.22$, $SE = 1.70$).

Confidence ratings of COMP-CCs were significantly affected by the next-best attribute, $\chi^2(2) = 15.68$, $p < 0.001$. No other effects were significant, ps > 0.404. The effect of the next-best attribute was explored with the same two contrasts that were conducted for TTB-CCs. The first contrast revealed that COMP-CCs were less confident when the next-best attribute was inconsistent with the best attribute ($M = 54.62$, $SE = 2.89$) than when it was non-discriminating ($M = 64.22$, $SE = 3.66$), $b = -9.54$, $t(95) = -2.44$, $p = 0.017$. The second contrast revealed no significant difference between the consistent and the non-discriminating condition, $b = 5.83$, $t(95) = 1.50$, $p = 0.137$. Descriptively, however, there was a trend in the right direction: Confidence ratings were higher when the next-best attribute was consistent ($M = 70.08$, $SE = 3.04$) than when it was non-discriminating.

TTB-inconsistent choices. We also examined the proportion of TTB-inconsistent choices for TTB-CCs. EAMs predict higher proportions of TTB-inconsistent choices the lower the consistency of the attribute information is. In line with this hypothesis, the proportion of TTB-inconsistent choices was highest when the next-best attribute was inconsistent ($M = 0.28$, $SE = 0.02$) and lowest when it was consistent ($M = 0.13$, $SE = 0.02$), with the non-discriminating condition lying in-between ($M = 0.19$, $SE = 0.02$), $F(2, 80) = 12.23$, $p < 0.001$, $\eta^2 = 0.15$.

Discussion

The present results demonstrated that participants who made choices in line with TTB were affected by attribute information considered to be irrelevant according to the TTB-stopping-rule. TTB-CCs were less confident with their decisions when the supposedly irrelevant next-best attribute was inconsistent with the best discriminating attribute than when it was non-discriminating or consistent. Furthermore, TTB-CCs made more TTB-inconsistent choices when the consistency of attribute information was low rather than high. The findings indicate that TTB-irrelevant information had been retrieved during TTB-decision-making and hence support the findings by Khader et al. (2013). These authors found evidence for a retrieval of complete attribute information by showing that the amount of attributes associated with the decision options affects participants who follow a TTB strategy. In the present study, we showed that it is not only the amount of information that has a bearing on TTB-CCs but also the consistency of the information. As all of our decision options were associated with the same amount of information (i.e., four attributes), the present findings demonstrate that not only the quantity of the supposedly irrelevant information but also its quality (consistency) affects TTB-CCs' decisions. This is first evidence that, in memory-based decision making TTB-irrelevant attributes, in addition to being retrieved, also become integrated during the decision process, as suggested for example by theoretical information-integration models like EAMs or PCS.

Support for the assumption that TTB-CCs would integrate attribute information in a PCS-/EAMs-manner has specifically been found in studies using an inferences-from-given-information paradigm, where attribute information is visually present throughout decision making and thus must not be retrieved from memory (Söllner et al., 2014, Glöckner & Betsch, 2012. Glöckner et al., 2014). The present study extends those findings to memory-based decision making. Overall, the decision behavior of both TTB-CCs and COMP-CCs is generally in line with EAMs/PCS, assuming that the former weight the attributes in a non-compensatory manner whereas the latter weight the attributes in a compensatory manner (Glöckner, Hilbig, & Jekel, 2014). Glöckner and Hodges (2011), in their memory-based study, report evidence that participants classified as WADD and EQW integrate attributes as suggested by EAMs/PCS. The present findings further suggest that even TTB-CCs may integrate attributes in a EAMs-/PCS-manner. Thus, although the choices of TTB-CCs were generally in line with the TTB strategy, and we therefore classified those participants as TTB-CCs, the present results suggest that the decision behavior of TTB-CCs may probably better be described by an evidence accumulation strategy rather than a TTB-strategy.

It is important to note, however that, as in other studies (Khader et al., 2013, Söllner et al., 2014), the decision behavior of participants was analyzed at the group-level. That is, on average, TTB-CCs seem to behave in a EAMs-/PCS-manner, which does not rule out that some TTB-CCs may have behaved in line with the TTB strategy. Moreover, the present findings could also be reconciled with a TTB strategy that relaxes the assumption of a strict stopping-rule. That is, it is possible that TTB-CCs may initially have retrieved attribute information in a rather automatic way and then compared the attributes in a TTB-manner; and to come up with a decision, TTB-CCs may have followed a TTB-decision-rule (for a similar interpretation, see Khader et al., 2013). Future research is necessary to disentangle these candidate processes potentially underlying the decision patterns observed in the present study.

Although the confidence ratings of TTB-CCs suggest that these participants retrieved TTB-irrelevant information, our results are not completely in line with EAMs/PCS models. Specifically, we found no evidence for an increase in decision confidence due to an increase in information consistency. TTB-CCs' confidence ratings were even somewhat lower when the next-best attribute was consistent compared to when it was non-discriminating (see Figure 2).[6] This unexpected finding might be due to our materials: The non-discriminating option pairs differed on only one, the best discriminating, attribute. The option pairs with a next-best consistent (and inconsistent) attribute, in contrast, differed on both the best and the next-best attribute (cf. Table 2). Therefore, on non-discriminating trials, there is no need to evaluate which of the retrieved values of the next-best attribute was the critical one and which was not. However, on consistent and inconsistent trials, participants had to recall which of the two attribute values was critical. Assuming that participants' memory for the cue hierarchy and the critical attribute values was less than perfect, the additional recall of the critical attribute values might have increased participants' uncertainty. Thus, even when the next-best attribute was consistent, the possible uncertainty related to the recall of the critical attribute values might have generally decreased participants' confidence relative to pairs with non-discriminating attributes. From a methodological point of view, this means that decision confidence assessed in memory-based decision studies may not only reflect decision-related uncertainty but also memory-related uncertainty. Future studies are necessary to investigate this assumption systematically in order to disentangle both types of uncertainty in a memory-based decision task.

Whereas participants’ confidence ratings may have been subjected to processes beyond retrieval and integration, such as meta-cognition or meta-memory (cf. Nelson, 1990), participants’ choices may have been less influenced by such meta- processes. In line with this reasoning, the choices of TTB-CCs, or better the proportion of their TTB-inconsistent choices, fully support the predictions made by EAMs/PCS. That is, compared with when the next-best attribute was non-discriminating, TTB-CCs made more TTB-inconsistent choices when the next-best attribute was inconsistent, and they made less TTB-inconsistent choices when the next-best attribute was consistent with the best attribute. This finding is important because it rules out the alternative explanation that the information on which our participants based their choices differed from the information on which they based their confidence ratings. In detail, it could be argued that TTB-CCs only retrieved information about the best discriminating attribute to make their decisions, and they subsequently retrieved additional information for their confidence judgments (Pleskac & Busemeyer, 2010). Yet, the finding that participants’ choices themselves were affected by attribute consistency provides strong evidence for a retrieval and integration of the complete attribute information *before* participants made their decisions.

TTB is a decision strategy that decision makers can only apply if they have knowledge about either of the decision options at hand. If decision makers have knowledge about only one option but they do not know the other options at all, Goldstein and Gigerenzer (2002) showed that decision makers use a recognition heuristic, that is, decision makers choose the recognized object. The recognition heuristic

[6] Note, however, that neither the interaction between the two predictors nor the contrast between the consistent and the non-discriminating condition was significant. The contrast between inconsistent and consistent pairs approached significance, $p = 0.053$

works best when knowledge about options is medium (i.e., some options are known others not). Thus, the recognition heuristic puts forward the somewhat paradoxical notion that knowledge may become detrimental for decisions. Although somewhat differently, the present results also point to the possible downside that knowledge may have for decision makers. That is, when knowledge is automatically retrieved and integrated, and when this knowledge is inconsistent (i.e., attributes are in conflict), decision makers make more strategy-inconsistent choices, which objectively are also wrong decisions. Importantly, however, participants' confidence ratings suggest that decision makers make such erroneous decisions not without awareness. Rather, when information consistency decreases and thus the likelihood of an error increases, decision makers seem to become more cautious. Thus, the possible downside of (too much) knowledge is counteracted by the upside of one's meta-cognitive awareness.

References

Bröder, A., & Gaissmaier, W. (2007). Sequential processing of cues in memory-based multiattribute decisions. *Psychonomic Bulletin & Review*, *14*(5), 895–900. doi:10.3758/BF03194118

Bröder, A., Newell, B. R., & Platzer, C. (2010). Cue integration vs . exemplar-based reasoning in multi-attribute decisions from memory : A matter of cue representation. *Judgement and Decision Making*, *5*(5), 326–338.

Bröder, A., & Schiffer, S. (2003a). Bayesian strategy assessment in multi-attribute decision making. *Journal of Behavioral Decision Making*, *16*(3), 193–213. doi:10.1002/bdm.442

Bröder, A., & Schiffer, S. (2003b). Take the best versus simultaneous feature matching: probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology. General*, *132*(2), 277–293. doi:10.1037/0096-3445.132.2.277

Busemeyer, J. R., & Johnson, J. G. (2004). Computational models of decision making. In D. J. Koehler & H. Harvey (Eds.), *Blackwell Handbook of Judgment and Decision Making* (pp. 133–154). Oxford: Blackwell Publishing.

Gigerenzer, G., Hoffrage, U., & Kleinbölting, H. (1991). Probabilistic Mental Models: A Brunswikian Theory of Confidence. *Psychological Review*, *98*, 506–528.

Gigerenzer, G., & Goldstein, D. G. (1999). Betting on One Good Reason: The Take The Best Heuristic. In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.), S*imple heuristics that make us smart* (pp. 141–167). New York: Oxford University Press.

Glöckner, A., & Betsch, T. (2008). Modeling option and strategy choices with connectionist networks: Toward an integrative model of automatic and deliberate decision making. *Judgment and Decision Making*, 3, 215–228.

Glöckner, A., & Hodges, S. D. (2011). Parallel constraint satisfaction in memory-based decisions. *Experimental Psychology*, 58(3), 180–195.

Glöckner, A., & Betsch, T. (2012). Decisions beyond boundaries: When more information is processed faster than less. *Acta Psychologic*a, 139, 532–542.

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A Parallel Constraint Satisfaction Account. *Cognition*, 133, 641–666.

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: the recognition heuristic. *Psychological Review*, *109*(1), 75–90. doi:10.1037/h0092846

Khader, P. H., Pachur, T., & Jost, K. (2013). Automatic activation of attribute knowledge in heuristic inference from memory. *Psychonomic Bulletin & Review*, *20*, 372–377.

Lee, M. D., & Cummins, T. D. (2004). Evidence accumulation in decision making: Unifying the "take the best" and the "rational" models. *Psychonomic Bulletin & Review*, *11*(2), 343–352.

Nelson, T. O. (1990). Metamemory: A theoretical framework and new findings. *Psychology of Learning and Motivation, 26*, 125–173.

Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing "one-reason" decision making. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *29*(1), 53–65. doi:10.1037/0278-7393.29.1.53

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*, 534–552.

Platzer, C, & Bröder, A. (2012). Most people do not ignore salient invalid cues in memory-based decisions. *Psychonomic Bulletin & Review*, *19*(4), 654–661.

Pleskac, T. J., & Busemeyer, J. R. (2010). Two-stage dynamic signal detection: A theory of choice, decision time, and confidence. *Psychological Review, 117*, 864–901.

Renkewitz, F., & Jahn, G. (2012). Memory indexing: A novel method for tracing memory processes in complex cognitive tasks. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(6), 1622–1639. doi:10.1037/a0028073

Söllner, A., Bröder, A., Glöckner, A., & Betsch, T. (2014). Single-process versus multiple-strategy models of decision making: Evidence from an information intrusion paradigm. *Acta Psychologica*, 146, 84–96.

Appendix A3 – Article 3

Note:

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Effects of Ego-Depletion on Choice Behavior in a Multi-Attribute Decision Task

Sebastian Dummel and Jan Rummel

Heidelberg University

Author Note

Sebastian Dummel, Jan Rummel, Department of Psychology, Heidelberg University, Germany.

Correspondence concerning this article should be addressed to Sebastian Dummel, Department of Psychology, Heidelberg University, Hauptstrasse 47-51, 69 117 Heidelberg, Germany. Phone: +49 (0)6221/54 - 7120. E-mail: sebastian.dummel@psychologie.uni-heidelberg.de

Abstract

When a choice has to be made between two options and decision-relevant information about the options is completely available, the Take-The-Best (TTB) heuristic only considers the most important information that discriminates between the options and bases its choice on it. Choices in line with TTB thus allow a decision maker to save time and effort, and they may become more likely therefore under conditions of limited self-control strength (ego-depletion). Ego-depletion was manipulated prior to making a series of choices in a multi-attribute decision task. Choices could have been in line with either TTB or more effortful compensatory decision strategies. As predicted, compared with non-depleted participants, ego-depleted participants were more likely to make TTB-consistent choices.

Keywords: decision-making; heuristics; self-control strength; ego depletion

Effects of Ego-Depletion on Choice Behavior in a Multi-Attribute Decision Task

The decisions we make in our daily lives differ, among others, in the amount of information on which they are based. For some decisions, we may rely on only a single piece of information, even when additional information is easily available. For other decisions, in contrast, we may consider all information available and integrate it in a rather sophisticated manner. The former approach to decision making is often called heuristic, whereas the latter integrative approach is referred to as rational (Lee & Cummins, 2004). A prominent framework of decision making assumes that decision makers have a repertoire of different strategies among which they choose adaptively (Gigerenzer & Gaissmaier, 2011). Some of the strategies belong to the “fast-and-frugal” heuristic category, whereas others belong to the more effortful rational-integration category. Because heuristic decisions rely on only part of the information and do not require a decision maker to trade-off information, we hypothesize that they should be preferred under conditions of limited cognitive resources. That is, from an adaptive point of view, a decision maker may be assumed to more frequently make choices in line with a simple decision heuristic when her cognitive resources are sparse. In the present research, we sought to examine the effects of ego-depletion—a state of diminished self-control and cognitive resources—on decision makers’ reliance on a simple decision heuristic.

The term ego-depletion was originally conceptualized as a state of limited self-control resources. The assumption underlying ego-depletion research is that acts of self-control, such as resisting temptations or inhibiting pre-potent responses, all draw upon a general willpower resource (Baumeister, Bratslavsky, Muraven, & Tice, 1998). As this resource is limited, engaging in acts of self-control in one task may reduce self-control available for a subsequent unrelated task. Support for the assumption that decision making indeed draws on limited self-control resources, comes from a study by Vohs, Baumeister, Schmeichel, Twenge, Nelson, and Tice (2008). Those participants of this study who had to make choices in an initial depleting task phase showed impairments in a variety of subsequent self-control tasks (e.g., pain tolerance, solving puzzles) compared to participants who were not ego-depleted. This finding suggests that decision making draws upon a limited self-control resource thereby affecting subsequent tasks involving self-control. A study by Pocheptsova, Amir, Dhar, and Baumeister (2009) further showed that participants who were experimentally depleted in an initial task phase relied more strongly on intuitive rather than deliberative reasoning in subsequent preferential-choice tasks. This finding suggests that, in a state of ego-depletion, individuals switch to a more heuristic mode of information processing compared to non-depleted individuals. Whereas there is strong evidence that states of ego-depletion affect performance in various tasks (see Hagger, Wood, Stiff, & Chatzisarantis, 2010; for a meta-analysis), it is not clear which processes drive these effects. Some researchers argue that ego-depletion effects are due to temporarily hampered executive control (Schmeichel, 2007). Others argue, however, that ego-depletion effects rather reflect a state of a lack of motivation to engage in effortful processing (Muraven & Slessareva, 2003). In the present study, we were interested in whether and how temporary ego-depletion due to performing a self-control task would affect individuals' choice behavior in an unrelated multi-attribute decision task. The present study was not designed to investigate the processes underlying the ego-depletion effect though. Thus any observed effect could be due to temporary reductions in executive control abilities, reduced motivation to engage in demanding processing, or both (cf. Inzlicht & Schmeichel, 2012). We will further discuss this issue in the Discussion section.

In multi-attribute decision tasks decision makers have to choose between two options the one that scores higher on a certain criterion value (e.g., choosing the more profitable of two shares). The options are described on several attributes or *cues*, each of which is predictive of the criterion to a certain degree (cue validity), and decision makers have access to each option's cue values (e.g., whether a share is noted or not; whether the company is established or not; and so on). Most interesting for the present research are situations with conflicting cue information such as when a highly valid cue points to one option, whereas several less valid cues point to the other option. Decision researchers suggested that decision makers might resolve this conflict in different ways. For instance, a decision maker may focus mainly on the one single cue for her choice that is of most importance (i.e., has the highest validity) and that discriminates between the two options. Such a choice behavior is in line with the so-called take-the-best strategy (TTB), according to which a decision maker searches the cues in descending order of their validities and stops information search as soon as a cue discriminates between the options. The option favored by this 'best' cue will then be chosen. Basing one's choice on the best cue may reduce cognitive effort because additional cues need no longer be integrated. An alternative way of resolving conflicting information might be to consider all cues and integrate information about these cues. Integration might be done, for example, by summing up the validity-weighted cues for each option, as suggested by the weighted-additive strategy, or by counting the critical cue values per option, as suggested by the equal-weight strategy. In either case, the option with the higher sum will be chosen. Thus, both the weighted-additive and the equal-weight strategy allow for the possibility that a highly valid cue, which guides the TTB-decision, can be compensated for by less valid cues, which is why we refer to these strategies as compensatory strategies (COMP). In cases where the (weighted) sum of less valid cues exceed the validity of the best discriminating cue, TTB and COMP make opposing choice predictions. Compared with the straightforward process underlying TTB, the processes underlying COMP can be considered more complex as they involve the consideration and integration of several cues. Therefore, when being in a state of ego-depletion, decision makers may be assumed to more frequently make choices in line with TTB rather than compensatory strategies.[1]

[1] Lee and Cummins (2004) proposed an alternative framework of decision making suggesting that TTB and the weighted-additive strategy are not qualitatively different strategies but represent the two ends of a continuous information search process. According to this view, information search proceeds continuously until the decision maker has gathered enough evidence. The stopping point is assumed to be variable (inter- and intra-individually) and decision makers are assumed to set their stopping points or *evidence thresholds* adaptively. Note that our research question applies to both frameworks in the same way as we examine how ego-depletion affects the selection process (selection of strategies or evidence thresholds). We used the strategy-selection terminology

Support for the assumption that TTB may be less effortful than COMP and may thus be preferred in a state of ego-depletion, comes from studies in which participants' cognitive resources were manipulated via time pressure (Rieskamp & Hoffrage, 1999; 2008). Putting participants under time pressure was found to increase their reliance on the TTB strategy, that is, participants were more likely to search the cues by their validity and to base their choice on the best cue. Unlike the time pressure manipulation used in previous studies, however, the ego-depletion paradigm considered here does not affect individuals' processing capacities at the time of decision making. Rather, the ego-depletion task, which precedes the decision task, is assumed to affect individuals' decision making by depleting individuals' self-control resources *prior* to any decision making. This distinction is important, as it may demonstrate that some (depleting) activities can impinge on one's decisions, even when the activities themselves are completely unrelated to the decision situation (cf. Pocheptsova, Amir, Dhar, & Baumeister, 2009).

Also in line with the assumption that TTB may reduce cognitive effort, is the finding that older adults, who show a decline in cognitive functioning, behave more in line with a TTB strategy in a decision task than younger adults (Mata, Schooler, & Rieskamp, 2007). Furthermore, Bröder and Schiffer (2003) found that, when cue information has to be retrieved rather than being openly presented during decision making, participants are more likely to make choices in line with TTB suggesting that TTB may reduce retrieval and integration effort. These findings suggest that TTB may be less effortful than COMP strategies and may thus be preferred under ego-depletion. However, findings from other research challenge the assumption that COMP strategies are actually as effortful as commonly assumed.

For example, participants of a study by Bröder (2003) made a series of choices where cue information was available on screen. One group of participants made their choices under working-memory load, the other group made their choices without load. Memory load had no effect on participants' decision behavior, that is, it did not lead to an increase in TTB-consistent behavior. The finding that participants of the Bröder study showed compensatory decision making even under memory load challenges the assumption that information integration is effortful and depends on cognitive resources (see also Glöckner & Betsch, 2008).

Furthermore, a study with children (Mata, von Helversen, Rieskamp, 2011) showed that 9-10 year olds, but not older children, have difficulties to learn a TTB strategy in a decision environment where this strategy would be most successful (i.e., non-compensatory environment). The finding that the decision behavior of these children was more in line with compensatory strategies further suggests that compensatory strategies may not necessarily be more complex than TTB, which is consistent with the findings by Bröder (2003). This finding also shows that the adaptive learning of a TTB strategy in a non-compensatory environment seems to require cognitive capacities (see also Bröder, 2003), and these capacities may be less developed in younger than in older children. It should be noted, however,

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here because previous similar research also used this terminology (e.g., Rieskamp & Hoffrage, 2008; Scheibehenne & van Helversen, 2015) that these findings do not necessarily imply that the *execution* of TTB is more difficult than the execution of COMP[2]. What seems to be difficult is to figure out that TTB is more successful in a non-compensatory environment, that is, the adaptive learning or *selection* of a strategy (see Bröder & Newell, 2008, for a similar argument). [3] In sum, the aforementioned findings suggest that compensatory decision making may actually not be that effortful as commonly assumed and may thus be less dependent on cognitive resources. Nevertheless, there is also some support for the assumption that the execution of a TTB strategy (though not the learning of this strategy) could reduce effort and may thus be applied under ego-depletion.

In line with the latter reasoning, there is some initial support for our assumption that ego-depletion may foster participants' reliance on simple heuristics. Pohl, Erdfelder, Hilbig, Liebke, and Stahlberg (2013) examined the effects of ego-depletion on participants' use of the recognition heuristic (*RH*; Goldstein & Gigerenzer, 2002) Participants of their decision task made a series of binary choices (choosing the larger of two American cities); one group of participants were to perform an ego-depleting act prior to each decision whereas another group performed a non-depleting act. Compared with non-depleted participants, depleted participants were found to more frequently rely on the RH, that is, they chose the one of the two cities they recognized (irrespective of further knowledge). The finding suggests that states of ego-depletion may foster the reliance on simple decision heuristics such as RH when the decision immediately follows the depleting act. As discussed by the authors themselves, however, it remains unclear how long-lasting the effects of ego-depletion may be. Ego-depletion researchers generally assume the effects of ego-depletion to be relatively persistent. However, as participants of the study by Pohl et al. performed a depleting act prior to each decision, so that the depletion and the decision task were closely intertwined, it is not possible to disentangle the short-lived effects of the depleting intervention from its possible longer-lasting effects. Furthermore, it may be that cognitive load from switching between the decision task and the depletion task rather than actual ego-depletion caused these findings.

In the present research we sought to find evidence for longer-lasting effects of ego-depletion on choice behavior. To this end, an ego-depletion task was completed *prior to* an unrelated decision task. Furthermore, our decision task was specifically designed to examine participants' accordance with choices predicted by the TTB heuristic relative to their accordance with choices predicted by COMP (for a similar design, see Scheibehenne & von Helversen, 2015). To this end, participants were shown complete cue information about the decision options, and they were provided with cue validities. This task design differs from the task Pohl et al. (2013) used to investigate ego-depletion effects on RH usage. Participants of their task were required to retrieve cue information from memory

[2] Though implementing non-compensatory strategies like TTB in the ACT-R architecture revealed that the execution of such strategies may be less simple than commonly assumed (Marewski & Mehlhorn, 2011)

[3] Indeed, in the children study, those 9-10 year olds who had correctly learned to use a compensatory strategy in a compensatory environment suddenly showed a decision behavior more in line with TTB in the last block of the decision task. This strategy shift has been interpreted in terms of fatigue and might suggest therefore that TTB could be easier to apply.

and the options presented to them were the names of American cities which participants could or could not have known (making recognition a potential decision cue). One could assume that the finding by Pohl et al.—that ego-depletion increases participants' reliance on simple heuristics like RH—may be constraint to decision tasks involving the retrieval of cue information, because memory-based decisions are often considered as especially effortful (Bröder & Schiffer, 2003). Using a decision paradigm where cue information was visually presented during decision making, and considering another decision heuristic (TTB),[4] we aimed to generalize the effect of ego-depletion on heuristic decision making and to also find support for its persistency.

Method

Participants

Sixty-four Heidelberg University students participated in this study for either monetary compensation (6€) or partial course credit. Three participants were excluded from this sample due to extremely loud noise outside the laboratory during the experimental session. The final sample comprised 61 participants (10 male; $M_{\text{age}} = 23.20$).

Materials, Design and Procedure

Participants were tested in groups of up to six, but they worked individually on the tasks in partitioned cubicles. Participants first received instructions for the decision task. Their task was to choose from two unit funds the one that they expected to be more likely to have a higher return. Each fund was described by the recommendations of six financial experts (cues) who either recommended a fund (+) or not (-). The experts were said to vary in their validity, which was explained as the extent to which their recommendations were successful in predicting the more profitable fund. As in previous research using similar tasks (Rieskamp & Hoffrage, 2008; Scheibehenne & von Helversen, 2015), the term validity was thoroughly explained and example-illustrated. Participants then received information about the experts' validities: 0.87, 0.76, 0.67, 0.61, 0.57, and 0.54. They were informed that during the decision task, the validity rank of each expert would always be indicated right next to the corresponding expert's picture. After the decision-task instructions, participants were told that they would first perform an additional attention task for 7 minutes—the ego-depletion manipulation—before performing the decision task.

For the supposedly attention task, all participants received a neutral text about the history of a German city (Mannheim). Participants in the no-depletion group were instructed to just copy the text (hand-written). Participants in the ego-depletion group also were instructed to copy the text, but they received the additional instruction to skip the letters "e" and "n" when transcribing the text. This

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[4] Participants of our task had no prior knowledge about the choice options which were simply labeled A and B. Thus they could not apply a RH but had to rely on the cue information provided to them. Participants could either process the information in a straightforward TTB-manner or in a (more effortful) weighted-additive/equal-weight manner.

procedure, which requires participants to override their well-established writing habits, has proven effective in depleting participants' self-control strength (e.g., Bertrams, Baumeister, Englert, & Furley, 2015). Assignment to the two groups was determined randomly. After 7 minutes of transcribing the text, participants were signaled individually (by the computer) to stop. All participants then answered a four-item manipulation check, asking them about the self-control they exerted during the transcription task (e.g., *How effortful did you find the transcription task?*; Bertrams et al., 2015). Answers were given on scales from 1 (*not at all*) to 4 (*very*), where higher scores indicate stronger depletion.

Afterward, participants performed the decision task which comprised 50 trials. On each trial, they were shown a pair of different funds (labelled A and B) for each of which they were shown the recommendations (+ or -) of the six experts. The experts and their recommendations were presented in descending order of their validities (see Figure 1).

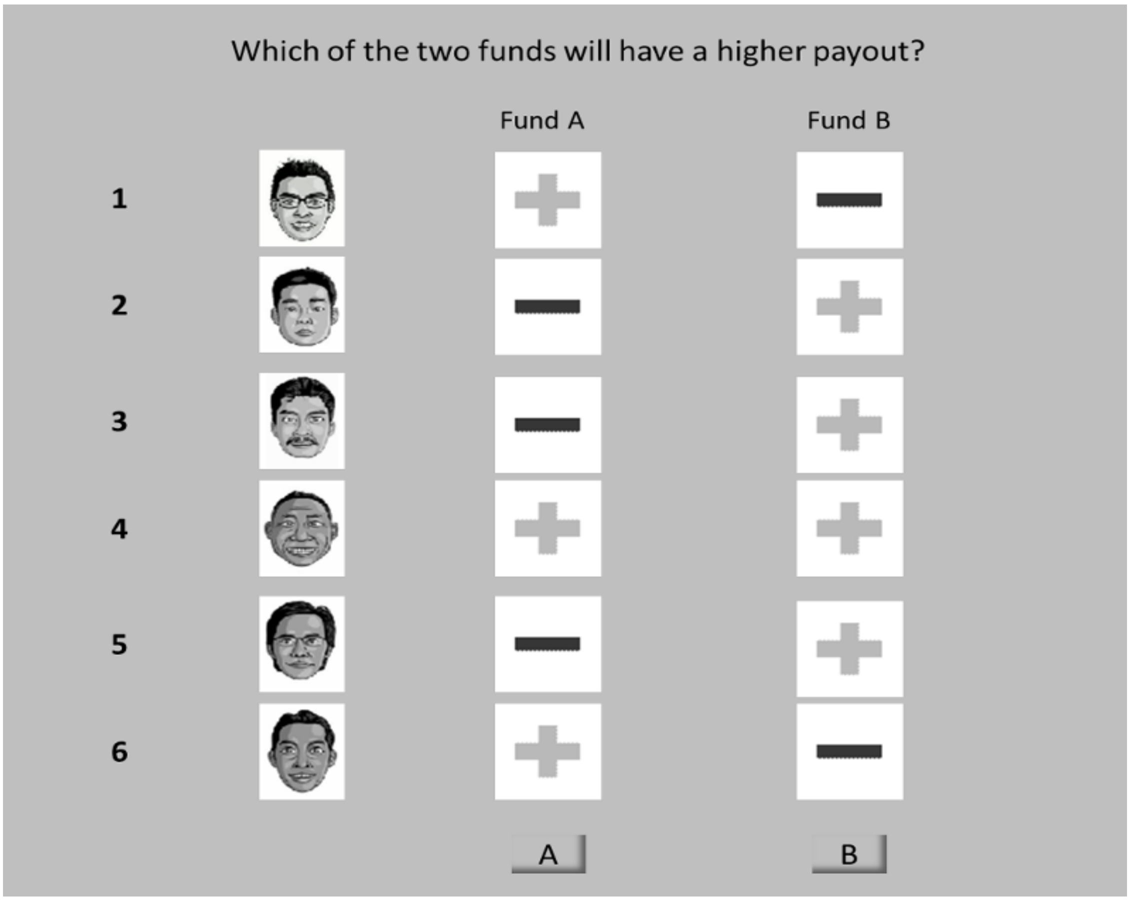

Figure 1. Example trial of the decision task. Participants had to choose the more profitable of two funds and were shown the recommendations from each of six experts, ranked by their validity. A plus sign indicates recommendation. In this example, take-the-best predicts the choice of Fund A, whereas compensatory strategies predict the choice of Fund B (Text has originally been shown in German).

For all participants, we used a set of 50 pairs for which TTB and COMP make opposing choice predictions (order of presentation was randomized). The provided validities (chance-corrected) implied a compensatory decision environment. However, we did not specify a 'correct' solution for the decision pairs and participants received no choice feedback and incentives. This also means that participants of this study were not required to learn a certain strategy; rather, we were interested in the choice behavior participants spontaneously show given their knowledge of the cue validities. With six cues and the validities mentioned, there were 95 pairs in total for which TTB and COMP predicted opposing choices. Of these 95 pairs we chose our final set of 50 pairs in a way that for 30 pairs the most-valid cue (0.87) was the best-discriminating cue—i.e., the cue on which TTB bases its choice; for 10 pairs the second-most valid cue (0.76) was the best-discriminating cue; and for another 10 pairs the third-most valid cue (0.67) was the best discriminating cue[5]. Thus, within subjects, the factor *validity rank of best discriminating cue* (expert) was varied. Varying the validity rank of the best cue was meant, among others, to counteract the possibility of a monotonous task routine which could have appeared when always the most valid cue was the best discriminating cue. Furthermore, we considered this factor in our analyses to test whether or how the validity rank of the best cue would affect participants' reliance on this cue. In a recent study (Dummel & Rummel, 2015), we found that decision makers who predominantly made choices in line with TTB showed less confidence in their decisions the lower the validity rank of the best cue was. One might expect therefore that decision makers may become less likely to follow the best cue (TTB) the lower the validity of this cue is (as a result of their being less confident of the less valid cues). The design of the present study was a 2 (ego-depletion: depletion vs. no-depletion) × 3 (validity rank of best discriminating cue: 1st, 2nd, 3rd) mixed-factorial design with the first factor manipulated between subjects and the second factor varied within subjects. Our dependent variable was the extent to which participants made choices in line with TTB.

Results

Manipulation check

Participants in the depletion condition had significantly higher scores on the manipulation-check measure (M = 2.71, SE = 0.12) than participants in the no-depletion condition (M = 1.91, SE = 0.09), indicating that the manipulation was successful, $F(1, 59) = 27.43$, $p < .001$.

Main Analysis

Individual choices were analyzed via a multilevel logistic regression. The multilevel approach is most appropriate for our data structure for two reasons. First, it takes into account dependence between different choices made by the same person and the nested structure due to the mixed design (cf. Hayes, 2006). Second, by using a logit link function to relate participants' choices to the predictors

[5] For clarification, the COMP sub-strategies equal-weight and weighted-additive made identical choice predictions for 40 out of the 50 pairs. For the remaining 10 pairs, equal-weight would have predicted a guess. We did not distinguish any further between weighted-additive and equal-weight on the basis of these 10 pairs, because modelling the guessing of the equal-weight strategy would have required an individual strategy-classification approach rather than considering overall adherence rates.

at hand, we account for the dichotomous nature of the outcome variable (i.e., a choice could have been either TTB-consistent or COMP-consistent). In the present case, using participants' single choices as the outcome variable is especially preferred over using aggregated choice proportions, because proportions are not normally distributed (Hox, 2010; for further arguments, see Jaeger, 2008). In fact, in both groups of our sample, choice proportions significantly deviated from a normal distribution according to the Shapiro-Wilks test ($ps < 0.05$). Being extensions of standard regression models, multilevel regression results can be interpreted in a similar way, that is, the coefficients estimated via multilevel regression can be interpreted like unstandardized beta weights in regression analyses. For multilevel analyses there is currently no common agreement on how to conduct power analyses. However, simulations by Maas and Hox (2005) suggest that a minimum of 50 level-2 and 7 level-1 observations are necessary to obtain parameter estimates of acceptable accuracy. Our design met these criteria as we had 61 level-2 (subjects across groups) and 50 level-1 (choices within subjects) observations.

In our model, the outcome variable choice (for which 1 indicated TTB-consistency and 0 indicated COMP-consistency) was regressed on the two dummy-coded factors ego-depletion manipulation (1 = depletion; 0 = no-depletion) and validity rank of best discriminating cue as well as their interaction. For ease of interpretation of coefficients, we recoded the three-levels factor validity rank in a way that we combined the second and third level of this factor into one single level (coded as 1) and contrasted this level to the first level of the factor (coded as 0). This way, only one contrast (1 0), comparing the first with the combined later levels, had to be included into the model as the predictor for the factor validity rank of best discriminating cue.[6] In line with recommendations by Barr, Levy, Scheepers, and Tily (2013) we attempted to maximize the random effects structure. Specifically, we included by-subjects random intercepts and slopes as well as by-item random intercepts. The multilevel analysis reported here was conducted in R using the glmer function of the package lme4 (Bates, Maechler, Bolker, Walker, 2015)

The coefficients estimated via multilevel logistic regression are depicted in Table 1. As shown there, the extent to which participants made choices in line with TTB (relative to COMP) was significantly predicted by both the ego-depletion manipulation and the validity rank of the best discriminating cue. The interaction was not significant. In line with our hypothesis, Figure 2 shows that the proportion of TTB-consistent choices was higher for depleted participants ($M = 0.42$, $SE = 0.04$) than for non-depleted participants ($M = 0.32$, $SE = 0.03$). Specifically, the odds of a TTB-consistent choice for depleted participants were 2.7 times higher than the odds for non-depleted

[6]Dummy-coding of a three-levels factor requires that one level be assigned as reference level against which each of the two remaining levels is then compared–each with a separate contrast. Thus, with a three-level factor two contrasts would enter the regression for this factor. We ran a model with the full three-levels validity-rank factor being dummy-coded, where we used the 1st rank as reference level. The results of this model were similar to the results of the model reported here: Depletion and validity rank (both contrasts) were significant predictors ($ps < 0.039$), whereas none of the interactions was significant ($ps > 0.117$). To facilitate interpretation of the coefficients, we decided to report the simpler model in our main analysis.

participants (see Table 1). Furthermore, the odds of a TTB-consistent choice for pairs with the second- or third-most valid cue as best discriminating cues (*M* = 0.44, *SE* = 0.03) were 3.18 times higher than the odds for pairs with the most valid cue as best discriminating cue (*M* = 0.30, *SE* = 0.03).

Table 1

Multilevel Logistic Regression Analysis Predicting Take-The-Best-Consistent Choices From Ego-Depletion Manipulation and Validity Rank of Best Discriminating Cue

Predictor	Coefficient	*SE*	Odds	95% CI	Wald *Z*	*p*	Bayes Factor
Ego-depletion manipulation	0.99	(0.48)	2.70	[0.04, 1.98]	2.06	0.039	BF_{10} = 1.2
Validity rank of best discriminating cue	1.16	(0.34)	3.18	[0.49, 1.84]	3.44	0.001	BF_{10} = 34.6
Ego-depletion manipulation × validity rank	-0.50	(0.38)	0.61	[-1.30, 0.27]	- 1.30	0.192	BF_{01} = 3.0

Note. SE = Standard Error; CI = Confidence Intervall; BF = Bayes Factor

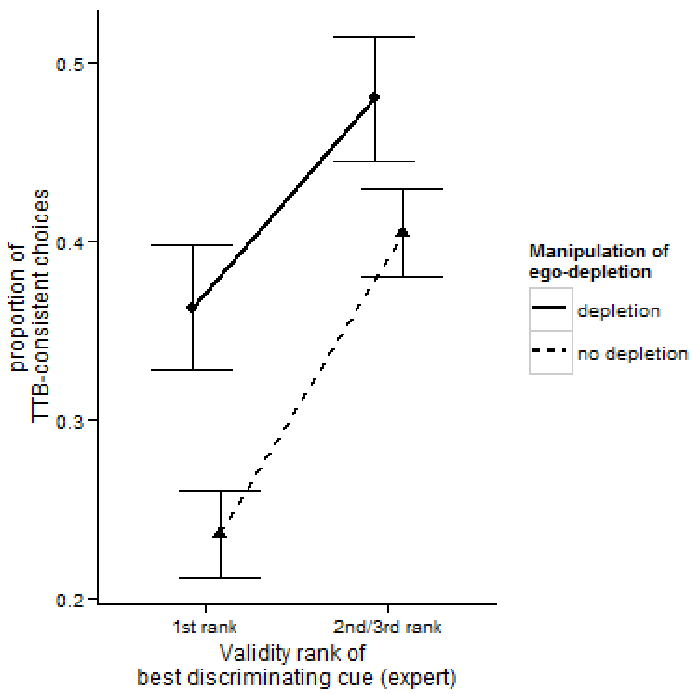

Figure 2. Mean proportions (± standard errors) of TTB-consistent choices as a function of the two manipulated factors ego-depletion manipulation and validity rank of best discriminating cue.

We also examined participants' decision times to check whether the groups differed in the amount of time they required to make their decisions. For the analysis of decision times, we removed individual outliers, which were defined as decision times smaller than 300ms and greater than individual mean plus 2.5 standard deviations (0.03%). Participants in the ego-depletion condition were slightly slower (M = 3.66, SE = 0.15) than participants in the no-depletion condition (M = 3.36, SE = 0.12), though this difference was not significant, $F(1, 59) = 0.69$, $p = 0.410$. We descriptively also analyzed decision times separately for those choices made in line with TTB and those choices made in line with COMP. Interestingly, participants of both groups were somewhat slower when making TTB-consistent choices as compared to when making COMP-consistent choices (depletion condition: $M_{\text{TTB-consistent}}$ = 3.76, SE = 0.22; $M_{\text{COMP-consistent}}$ = 3.55, SE = 0.20; no-depletion condition: $M_{\text{TTB-consistent}}$ = 3.44, SE = 0.18; $M_{\text{COMP-consistent}}$ = 3.28, SE = 0.16). We will discuss this issue in more detail in the Discussion section.

Discussion

Choices differ in the amount of information on which they are based and the present finding shows that decision makers who were ego-depleted prior to decision making were more likely to make choices in line with the TTB heuristic compared to participants who were not depleted. Basing one's choice on the best discriminating cue, a decision maker does not need to consider and integrate additional information, so TTB-consistent choices may reduce cognitive effort and may become preferable in a state of ego-depletion—a finding which is in line with the notion of an adaptive decision maker (Payne et al., 1988).

The effort-reducing function of TTB has previously been demonstrated in studies where decision makers' cognitive capacities were reduced at the time of decision making via time pressure (Rieskamp & Hoffrage, 1999; 2008). Our finding that TTB-consistent choices become more likely in a state of ego-depletion adds to this existing literature. Importantly, our research extends these findings by showing that the likelihood of making simplifying choices, such as TTB-consistent choices, is not only affected by features inherent to the decision situation itself (time pressure) or by individual differences variables (e.g., age; Mata, Schooler, & Rieskamp, 2007); but it is also affected by temporal states of ego-depletion which are due to events completely unrelated to the decision situations. That is, the completion of a task involving self-control strength but which had nothing to do with the subsequent decision task led to a greater reliance on the information provided by the best discriminating cue (TTB) than on the combined information of less valid cues (COMP).

This finding is well in line with the study by Pohl et al. (2013), who found greater reliance on the RH among depleted participants compared to non-depleted participants. In their study, however, participants performed a depleting act prior to each decision; it remained unclear therefore whether the effect of ego-depletion on strategy selection is of only short durability or whether it may persist over a longer period of time. The results of our study, where the depletion and the decision task were completely separated in time, provide support for the latter assumption—i.e., the effect of ego-depletion on decision making may be relatively persistent (see also Pocheptsova et al., 2009). Furthermore, using a decision paradigm where cue information was completely shown to participants (as is often the case, for example, in consumer magazines), we were able to show that the effect of ego-depletion on decision making is not restricted to the use of RH and to situations where cue information has to be retrieved from memory, but it also holds for the TTB heuristic and for situations where information search comes relatively easy.

Our hypothesis that a task involving self-control strength may subsequently lead to a higher rate of TTB-consistent choices was based on the assumption that both the self-control task and the decision task draw on a single, limited self-regulatory resource (Vohs et al., 2008). However, there is some debate on whether the effects of ego-depletion could not also be explained by factors other than ego-depletion (for an overview, see Hagger, Wood, Stiff, & Chatzisarantis, 2010). For instance, Job, Dweck, and Walton (2013) found typical depletion effects only for those people who believed that cognitive resources are limited; for those people who hold an unlimited resource theory, however, no, or even a reversed, depletion effect was found. This finding challenges the assumption that depletion effects stem from reduced cognitive resources, and they suggest that mechanisms other than limited resources may underlie depletion effects. In the present study, we did not assess participants' implicit theories about their cognitive resources, so we do not know whether our manipulation may only have worked for a subset of participants with a limited-resource theory. But the finding of a general depletion effect in this study, even without considering an additional moderator, suggests that our depletion manipulation did affect participants' choice behavior. The mechanisms underlying this effect, however, need to be addressed in future studies.

It is possible, for example, that the depletion task had a negative impact on participants' mood, as they may have perceived the task as irritating. Scheibehenne and von Helversen (2015) recently showed that, compared with a positive mood induction, a negative mood induction led to a higher proportion of TTB-consistent choices in a subsequent decision task. Negative mood has been suggested to narrow attentional focus and this may be conducive for TTB-consistent choices, as they require participants to focus on only one cue. Another explanation for our depletion effect could be that the depletion task reduced participants' motivation for the decision task. As a consequence, depleted participants may have considered information from a single cue as sufficient to make their choices (i.e., lower decision threshold). Such an account, however, would suggest that depleted participants would have made faster decisions on average than non-depleted participants. The decision times of both groups did not differ significantly from each other though. Descriptively, depleted participants were even somewhat slower than non-depleted participants. This observation is in line with a fatigue or a cognitive resources account of the depletion effect. That is, compared with non-depleted participants, depleted participants may have felt more tired, or their executive functions may temporarily have been impaired (e.g., Schmeichel, 2007), which may have generally slowed their subsequent decisions. As a result of their fatigue or their impaired executive functions, depleted participants may also have become more likely to make choices in line with TTB, because such TTB-choices may have simplified the decision process.

Note, however, that simplifying the decision process does not necessarily mean that decision makers ignored information when they made TTB-consistent choices (see Dummel, Rummel, & Voss, 2016, for example). That is, choice outcomes in line with TTB do not necessarily imply that decision makers actually used a TTB strategy. It is possible that decision makers in general processed cue information completely and, realizing that there is high conflict among cues, they may have tried to resolve the conflict by integrating the information in a compensatory manner, that is, by summing up the (validity-weighted) values. Depleted decision makers, however, might have perceived this integration process as more difficult than non-depleted decision makers, which is why the finally became more likely to choose the option favored by the best cue—as some kind of simplifying 'rule-of-thumb'.[7] Although speculative, the assumption that information may probably have not been ignored when choices were made in line with TTB receives some support when considering participants' decision times. Specifically, if for TTB-consistent choices information had been ignored one would at least have expected somewhat faster TTB-consistent than compensatory choices, but, as outlined in the Results section, the pattern was even reversed. An interesting avenue for future studies might be to systematically examine the decision processes underlying TTB-consistent choices and, in particular, how a depletion manipulation might affect these processes (i.e., whether it affects the amount of considered information or the way in which the considered information is processed).

Another interesting observation in this study was that participants generally relied more frequently on the best discriminating cue (TTB) when the cue's validity was lower rather than higher. At first glance, this finding seems paradoxical—why would a decision maker more frequently go with a third-rank cue than with a first-rank cue? A plausible explanation may be, however, that it is not only the validity rank of the best discriminating cue that matters, but also the amount and weight of those cues that could possibly contradict this cue. That is, when a first-rank cue points to one of the decision options, there are still five other cues that could point to the other option, and a decision maker may want to acquire information about these cues; if the lower-rank cues disagree with the first-rank cue, a decision maker may probably not want to go with the first-rank cue because of the amount and weight

[7] In the depletion condition, we observed a frequency of 42% TTB-consistent choices, which might also suggest that depletion increased guessing, as a choice could either have been consistent with TTB or with COMP. We thank an anonymous reviewer for this careful suggestion. It should be noted, however, that this indication of guessing (42%) is only at the group-level. To check whether ego-depletion indeed increased guessing at the individual-level, we ran the following analysis. In our task, a choice could either have been consistent with TTB or with COMP. If an individual was guessing in this task, a binomial test conducted on the 50 choices of this individual would have turned out non-significant. For each individual we therefore conducted a binomial test on the individual choice data. In the control condition the binomial test was non-significant (indicating a guessing pattern) for 7 out of 31 participants; in the depletion condition the binomial test was non-significant for 10 out of 30. Although descriptively slightly higher, the proportion of guessing individuals in the depletion condition did not differ significantly from the proportion of guessing individuals in the control condition, as indicated by a non-significant Chi square test, $p = .249$. Therefore, we suggest that the group-level frequency data (42% in the depletion condition) were not due to systematic guessing patterns at the individual level.

of the other cues. When the third-rank cue is the best discriminating cue, however, then there are only three remaining cues, which in addition are of relatively low validity. In this case, a decision maker may prefer a mental short-cut and rely on the third-rank cue without considering the remaining cues. Further research is necessary however to better understand how decision makers evaluate the utilities of different cues beyond the cues' validities.

In sum, the present research shows that the choice behavior of decision makers can be affected by tasks unrelated to the decision situation. When the decision-unrelated task is effortful, subsequent choices are more likely to be in line with a simplifying heuristic than when the unrelated task is less effortful.

References

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language, 68*(3), 255–278. doi: 10.1016/j.jml.2012.11.001

Bates, D., Maechler, M., Bolker, B., Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. doi:10.18637/jss.v067.i01.

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego depletion: Is the active self a limited resource? *Journal of Personality and Social Psychology*, *74*(5), 1252–1265. doi:10.1037/0022-3514.74.5.1252

Bertrams, A., Baumeister, R. F., Englert, C., & Furley, P. (2015). Ego depletion in color priming research: Self-control strength moderates the detrimental effect of red on cognitive test performance. *Personality and Social Psychology Bulletin*, *41*(3), 311–322. doi:10.1177/0146167214564968

Bröder, A. & Schiffer, S. (2003). Take the best versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology: General, 132*(2), 277–293

Bröder, A (2003). Decision making with the “adaptive toolbox”: Influence of environmental structure, intelligence, and working memory load. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 29*(4), 611–625.

Bröder, A., & Newell, B. R. (2008). Challenging some common beliefs: Empirical work within the adaptive toolbox metaphor. *Judgment and Decision Making, 3*(3), 205–214.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*, 451–482. doi:10.1146/annurev-psych-120709-145346

Dummel, S., & Rummel, J. (2015). Take-the-best and the influence of decision-inconsistent attributes on decision confidence and choices in memory-based decisions, *Memory,* advanced online publication. doi: 10.1080/09658211.2015.1117642

Dummel, S., Rummel, J., & Voss, A. (2016). Additional inforamtion is not ignored: New evidence for information integration and inhibition in take-the-best decisions, *Acta Psychologica,* advanced online publication. doi: 10.1016/j.actpsy.2015.12.001

Glöckner, A., & Betsch, T. (2008). Multiple reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning Memory, and Cognition, 34*(5), 1055–1075. doi: 10.1037/0278-7393.34.5.1055

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109*(1), 75–90. doi:10.1037/h0092846

Hagger, M. S., Wood, C., Stiff, C., & Chatzisarantis, N. L. D. (2010). Ego depletion and the strength model of self-control: A meta-analysis. *Psychological Bulletin*. doi:10.1037/a0019486

Hayes, A. F. (2006). A primer on multilevel modeling. *Human Communication Research*, *32*(4), 385–410. doi:10.1111/j.1468-2958.2006.00281.x

Hox, J. J. (2010). *Multilevel analysis: Techniques and applications*. New York: Routledge.

Inzlicht, M. & Schmeichel, B. J. (2012) What is ego depletion? Toward a mechanistic revision of the resource model of self-control. *Perspectives on Psychological Science, 7*(5), 450–463. doi: 10.1177/1745691612454134

Jaeger, T. F. (2008). Categorical data analysis: Away from ANOVAs (transformation or not) and towards logit mixed models. *Journal of Memory and Language, 59*(4), 434–446. doi: 10.1016/j.jml.2007.11.007

Job, V., Dweck, C. S., & Walton, G. M. (2013). Ego depletion—is it all in your head? Implicit theories about willpower affect self-regulation. *Psychological Science, 21*(11), 1686–1693. doi: 10.1177/0956797610384745

Lee, M. D., & Cummins, T. D. R. (2004). Evidence accumulation in decision making: Unifying the “take the best” and the “rational” models. *Psychonomic Bulletin & Review*, *11*(2), 343–352. doi:10.3758/BF03196581

Marewski, J. N., & Mehlhorn, K. (2011). Using the ACT-R architecture to specify 39 quantitative process models of decision making. *Judgment and Decision Making, 6*(6), 439–519.

Maas, C. J. M., & Hox, J. J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology, 1*(3), 86–92. doi: 10.1027/1614-1881.1.3.86

Mata, R., Schooler, L. J., & Rieskamp, J. (2007). The aging decision maker: Cognitive aging and the adaptive selection of decision strategies. *Psychology and Aging*, *22*(4), 796–810. doi:10.1037/0882-7974.22.4.796

Mata, R., von Helversen, B., & Rieskamp, J. (2011). When easy comes hard: the development of adaptive strategy selection. *Child Development, 82*(2), 687–200. doi: 10.1111/j.1467-8624.2010.01535.x

Muraven, M., & Slessareva, E. (2003). Mechanisms of self-control failure: Motivation and limited resources. *Personality and Social Psychology Bulletin, 29*(7), 894–906. doi: 10.1177/0146167203029007008Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(3), 534–552. doi:10.1037/0278-7393.14.3.534

Pocheptsova, A., Amir, O., Dhar, R., & Baumeister, R. F. (2009). Deciding without resources: Resource depletion and choice in context. *Journal of Marketing Research*, *46*(3), 344–355. doi:10.1509/jmkr.46.3.344

Pohl, R. F., Erdfelder, E., Hilbig, B. E., Liebke, L., & Stahlberg, D. (2013). Effort reduction after self-control depletion: The role of cognitive resources in use of simple heuristics. *Journal of Cognitive Psychology, 25*(3), 267–276. doi: 10.1080/20445911.2012.758101

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics, and how can we tell? In G. Gigerenzer, P. M. Todd, and the ABC Research Group (Eds.). *Simple Heuristics That Make Us Smart* (pp. 141–167). Oxford: Oxford University Press.

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276. doi:10.1016/j.actpsy.2007.05.004

Scheibehenne, B., & von Helversen, B. (2015). Selecting decision strategies: The differential role of affect. *Cognition & Emotion, 29*(1), 158–167. doi:10.1080/02699931.2014.896318

Schmeichel, B. J. (2007). Attention control, memory updating, and emotion regulation temporarily reduce the capacity for executive control. *Journal of Experimental Psychology: General, 136*(2), 241–255.

Vohs, K. D., Baumeister, R. F., Schmeichel, B. J., Twenge, J. M., Nelson, N. M., & Tice, D. M. (2008). Making choices impairs subsequent self-control: a limited-resource account of decision making, self-regulation, and active initiative. *Journal of Personality and Social Psychology*, *94*(5), 883–898. doi:10.1037/0022-3514.94.5.883

Erklärung gemäß § 8 Abs. 1 Buchst. c) und d) der Promotionsordnung der Fakultät für Verhaltens- und Empirische Kulturwissenschaften

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Doctoral Committee of the Faculty of Behavioural and Cultural Studies, of Heidelberg University

Erklärung gemäß § 8 (1) c) der Promotionsordnung der Universität Heidelberg für die Fakultät für Verhaltens- und Empirische Kulturwissenschaften
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