CONTRASTING FRAMEWORKS OF MULTI-ATTRIBUTE DECISION MAKING:

MULTIPLE STRATEGIES, CONNECTIONIST NETWORK, OR EVIDENCE ACCUMULATION?

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VORWORT

Diese Dissertation ist das Resultat meiner Forschung an der Universität Mannheim im Rahmen meines Promotionsstudiums am Center for Doctoral Studies in Social and Behavioral Sciences (CDSS) der Graduate School of Economics and Social Sciences (GESS).

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ZUSAMMENFASSUNG (GERMAN SUMMARY)

Täglich werden wir mit einer Vielzahl von unterschiedlichen Entscheidungsproblemen und -situationen konfrontiert. Die meisten Forscher im Bereich der Multi-Attribut-Entscheidungen stimmen darin überein, dass Entscheider ihr Verhalten an diese variierenden Umstände anpassen. Die Frage jedoch, *wie* diese Anpassung erreicht wird, wurde auf vollkommen unterschiedliche Weise beantwortet. So nimmt der multiple-Strategien-Ansatz an, dass Entscheider eine der vielen qualitativ unterschiedlichen Strategien auswählen, die in ihrer (mentalen) Werkzeugkiste enthalten sind. Uni-Prozess-Ansätze hingegen postulieren einen einzigen, uniformen Entscheidungsmechanismus, dessen Parameter jeweils angepasst werden. Dieser uniforme Mechanismus wird von unterschiedlichen Ansätzen jedoch unterschiedlich modelliert. Die vorliegende Arbeit vergleicht drei Ansätze für Multi-Attribut-Entscheidungen, um herauszufinden, welcher von ihnen Entscheidungen auf Basis dargebotener Informationen am besten beschreiben kann.

Das erste Projekt (Söllner, Bröder & Hilbig, 2013) konzentrierte sich auf das „parallel constraint satisfaction“-Modell (PCS, Glöckner & Betsch, 2008a) für Multi-Attribut-Entscheidungen, welches den konnektionistischen Netzwerk-Ansatz repräsentiert. Dieser Ansatz postuliert die parallele Integration aller passenden Informationen innerhalb einer neuronalen Netzwerkstruktur. Unter Einsatz verschiedener Formate für offene Informationspräsentation wurde PCS mit wichtigen Entscheidungsstrategien des multiple-Strategien-Ansatzes verglichen. Wenn sich die notwendige Informationssuche auf ein Minimum reduzierte, beschrieb PCS das individuelle Entscheidungsverhalten am besten. Sobald die Probanden jedoch aufgrund des eingesetzten Präsentationsformats Informationen suchen mussten, entsprach ihr Entscheidungsverhalten mehrheitlich nicht den PCS-Vorhersagen. Somit scheint die Eignung dieses Netzwerk-Modells zur Beschreibung von Entscheidungen auf Basis dargebotener Informationen erheblich von der sofortigen Verfügbarkeit aller Informationen abzuhängen.

Das zweite Projekt (Söllner, Bröder, Glöckner & Betsch, 2014) stellte dem multiple-Strategien-Ansatz den Evidenz-Akkumulations-Ansatz und den konnektionistischen Netzwerk-Ansatz gegenüber, die beide einen einzigen, uniformen Entscheidungsmechanismus postulieren. Das Projekt baute auf der Annahme des

multiple-Strategien-Ansatzes auf, dass Entscheider, die eine sparsame[1] Entscheidungsstrategie anwenden, Strategie-irrelevante Informationen ignorieren. Die Uni-Prozess-Ansätze hingegen nehmen an, dass alle relevanten Informationen in den postulierten Mechanismus eingespeist werden. Um diese konkurrierenden Vorhersagen zu testen, wurde das Informations-Intrusions-Paradigma entwickelt, das Probanden mit validen, aber Strategie-irrelevanten Informationen konfrontierte. Im Ergebnis ignorierten die Probanden diese zusätzlichen Informationen nicht, sondern passten ihr Entscheidungsverhalten (Wahlen, Informationssuche, Konfidenzurteile) konsistent an. Dieses Unvermögen Strategie-irrelevante Informationen zu ignorieren passt zu der Annahme eines uniformen Mechanismus, der alle passenden Informationen integriert.

Das dritte Projekt schließlich (Söllner & Bröder, 2014) beschäftigte sich mit dem Prozess der Informationssuche und insbesondere dem Stopp-Verhalten, wie es der multiple-Strategien-Ansatz und der Evidenz-Akkumulations-Ansatz vorhersagen. Dieser zweite Ansatz nimmt an, dass Entscheider Informationen sammeln bis die akkumulierte Evidenz zu Gunsten einer Option die individuelle Evidenz-Schwelle übersteigt und sie die entsprechende Option wählen. Mit Hilfe einer halb-offenen-halb-geschlossenen Darbietungsform wurden Probanden unterschiedliche Stufen von Evidenz zu Gunsten einer Option gezeigt und die anschließende Informationssuche wurde beobachtet. Die durchgeführten Analysen stützten übereinstimmend die Vorhersagen des Evidenz-Akkumulations-Ansatzes: Aggregierte Analysen zeigten, dass sich der Anteil des sofortigen Stoppens mit steigenden Stufen gegebener Evidenz erhöhte – ein Befund, der mit dem Evidenz-Akkumulations-Ansatz übereinstimmt, aber für die verwendeten Stimuli vom multiple-Strategien-Ansatz nicht vorhergesagt wird. Darüber hinaus ließ sich der Abbruch der Informationssuche auf individueller Ebene nicht gut durch den multiple-Strategien-Ansatz beschreiben, sondern entsprach der Annahme einer individuellen Evidenz-Schwelle.

Zusammengefasst belegen alle drei Projekte die Eignung der Uni-Prozess-Ansätze zur Beschreibung von Entscheidungen auf Basis dargebotener Informationen. Die vorliegenden Befunde zeigen Schwachstellen des weit verbreiteten multiple-Strategien-Ansatzes auf, verlangen jedoch gleichzeitig nach weiterer theoretischer Entwicklung seiner erfolgreichen Konkurrenten.

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[1] Der Begriff *sparsam*, auf eine Entscheidungsstrategie des multiple-Strategien-Ansatzes bezogen, bedeutet, dass die Strategie nur einen Teil der verfügbaren Informationen nutzt (Gigerenzer & Todd, 1999).

SUMMARY

Every day, decision makers are confronted with a multitude of different choice problems and situations. Most researchers in the field of multi-attribute decision making agree that decision makers adapt their behavior to these varying circumstances, but the question *how* this adaptation is achieved has been answered in fundamentally different ways. Whereas the multiple strategy framework assumes that decision makers select one of the multiple qualitatively different decision strategies contained in the decision makers' (mental) toolbox, single-process frameworks propose a single uniform mechanism for decision making. The nature of this mechanism, however, is modeled in different ways by different frameworks. The work presented in this thesis contrasted three frameworks of multi-attribute decision making to determine which one describes decision making from given information best.

The first project (Söllner, Bröder, & Hilbig, 2013) concentrated on the parallel constraint satisfaction (PCS, Glöckner & Betsch, 2008a) model for multi-attribute decision making, representing the connectionist network framework that assumes parallel integration of all applicable information within a neural network structure. Varying the format of openly presented information, PCS was contrasted with prominent decision strategies from the competing multiple strategy framework. PCS gave a superior account for individual decision behavior when information search was reduced to a minimum. However, as soon as the format of information presentation necessitated some extent of information search, individual decision behavior did not comply with PCS' predictions for the majority of participants. Thus, the adequacy of PCS to describe decision making from given information seems to crucially depend on the immediate accessibility of all relevant information.

The second project (Söllner, Bröder, Glöckner, & Betsch, 2014) contrasted the multiple strategy framework with the evidence accumulation framework and the connectionist network framework that both propose a single uniform mechanism for decision making. The project built on the multiple strategy framework's prediction that decision makers employing a frugal[2] decision strategy will ignore strategy-irrelevant information, whereas the single-process frameworks hold that all relevant information

[2] The term *frugal*, characterizing a decision strategy within the multiple strategy framework, means that the strategy makes use of only a subset of the available information (Gigerenzer & Todd, 1999).

will be fed into the proposed mechanism. To test these competing predictions, the *information intrusion paradigm* was developed that confronted participants with valid, but strategy-irrelevant information. As a result, participants did not ignore the additional information, but consistently adjusted their decision behavior (choices, information search, confidence judgments). The observed failure to ignore strategy-irrelevant information is in line with the assumption of a uniform mechanism that integrates all applicable information.

Finally, the third project (Söllner & Bröder, 2014) focused on the process of information search and, in particular, the stopping behavior as predicted by the multiple strategy framework and the evidence accumulation framework. The latter assumes that decision makers sample information until the accumulated evidence in favor of one option passes the individual evidence threshold and they choose the respective option. Participants were presented with varying levels of evidence in favor of one option within a half-open-half-closed information display and their subsequent information search was monitored. The conducted analyses unanimously supported the evidence accumulation framework's predictions: Analyses in the aggregate revealed that the percentage of immediate stopping increased with increasing levels of given evidence – a finding that is in line with the evidence accumulation framework, but not predicted by the multiple strategy framework for the employed stimuli. Moreover, on an individual level, the termination of information search was not well-captured by the different stopping rules (currently) contained in the multiple strategy framework, but confirmed the notion of an individual evidence threshold.

In sum, all three projects support the suitability of the single-process frameworks to describe decision making from given information. The reported evidence challenges the popular multiple strategy framework, but simultaneously demands further theoretical development of its successful competitors – the evidence accumulation framework as well as the connectionist network framework.

ARTICLES

This thesis is based on a set of three articles. The articles will be discussed in this thesis and are attached to it in the same order as they are listed below.

(1) Söllner, A., Bröder, A., & Hilbig, B. E. (2013). Deliberation versus automaticity in decision making: Which presentation format features facilitate automatic decision making? *Judgment and Decision Making*, *8*(3), 278–298.

(2) 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.

(3) Söllner, A. & Bröder, A. (2014). *Toolbox or adjustable spanner? A critical comparison of two metaphors for adaptive decision making*. Manuscript submitted for publication.

1 INTRODUCTION AND THEORETICAL BACKGROUND

When decision makers choose between options that differ on relevant attributes, they sometimes seem to rely on one good reason only, whereas sometimes many different reasons seem to be integrated into the final decision. The question, how this variability of decision behavior is generated, has been answered in fundamentally different ways. For example, multiple strategy models assume that decision makers select from a set of decision strategies the one that fits best to the specific situation. Other frameworks of multi-attribute decision making hold that, instead of choosing between qualitatively different strategies, decision makers employ the same uniform mechanism and merely adjust its parameters. The nature of this uniform mechanism, however, is modeled in different ways by different frameworks. The work presented in this thesis aims to empirically contrast the competing frameworks of multi-attribute decision making to determine, which one gives the best description of decisions from given information.

This introductory chapter is organized as follows: First I will give a brief introduction to multi-attribute decision making and the focus of my work within this research field. After that, the three frameworks relevant for this thesis will be introduced and discussed: the multiple strategy framework, the connectionist network framework, and the evidence accumulation framework. I will end this chapter by outlining the central aim of my work: contrasting the frameworks of multi-attribute decision making. The second chapter gives summaries of the articles this thesis is based on, including a discussion of each article in relation to the central aim of my work. In the concluding third chapter I will give a general discussion and an outlook to future research questions.

1.1 Multi-attribute decision making

The work reported in this thesis deals with multi-attribute decision making. Here, a decision maker chooses between two or more options (e.g., cities), each of which is characterized by varying, often binary values for the same set of attributes or cues (e.g., whether a city has an international airport, an opera house, an international fair, or a zoo). Typically, the cues differ in their relevance for the decision task (e.g., cue validity[3]). Figure 1 shows an exemplary multi-attribute decision task as employed in the

[3] A cue's validity is the rate at which the cue points to the correct (superior) option given that it discriminates between the options (Gigerenzer & Goldstein, 1996). However, cues can differ on further

first article of this thesis (Söllner, Bröder, & Hilbig, 2013). Here, the decision maker has to decide which city has more inhabitants (decision criterion) when the option "Garango" has a negative cue value for the most valid cue A and positive cue values for the less valid cues B, C, and D, whereas the alternative option "Bingo" has a positive cue value for cue A and negative cue values for cues B, C, and D.

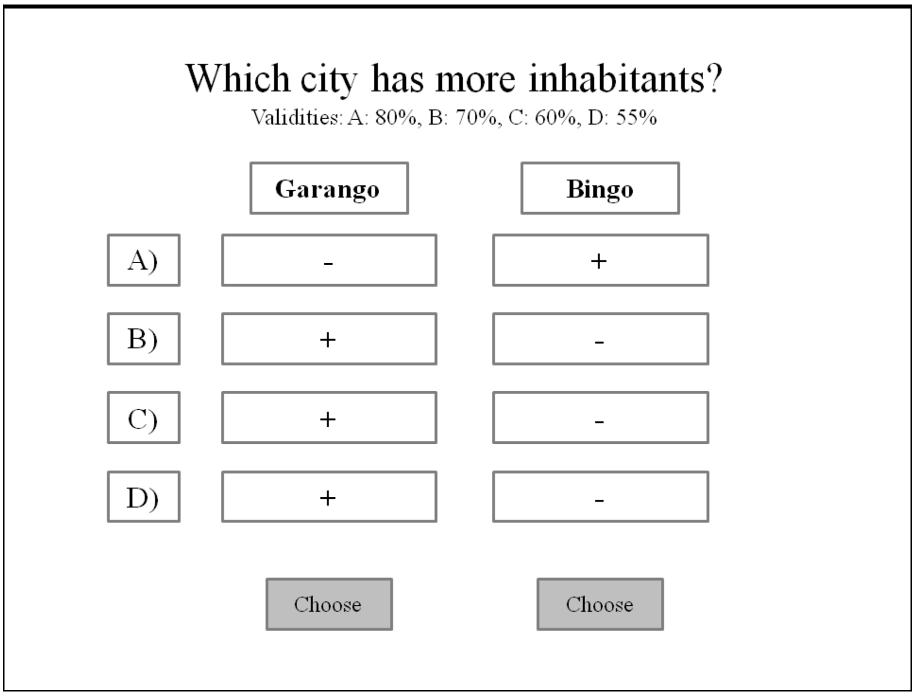

Figure 1: Exemplary multi-attribute decision task as employed in article 1 (Söllner et al., 2013).

If the decision criterion is a subjective one (e.g., personal preference for a day trip), the task is referred to as *preferential choice* task. A *probabilistic inference* task is characterized by an objective decision criterion (e.g., number of inhabitants, cf. Figure 1). As empirical similarities suggest similar cognitive processes in both domains (Bröder & Newell, 2008; Payne, Bettman, & Johnson, 1993; Todd, Gigerenzer, & ABC Research Group, 2012), approaches that were developed for preferential choice (e.g., Payne et al., 1993) as well as approaches for probabilistic inferences (e.g., Gigerenzer, Todd, & ABC Research Group, 1999) are in this thesis subsumed as applying to the more general term *multi-attribute decision* making. In order to zoom in on the research

dimensions, for example the discrimination rate (Gigerenzer & Goldstein, 1996). Thus, some authors argued to combine these two dimensions, for example, into a Bayesian validity (Bergert & Nosofsky, 2007; Lee & Cummins, 2004), success rate (Martignon & Hoffrage, 1999; B. R. Newell, Rakow, Weston, & Shanks, 2004), or usefulness rate (Hausmann-Thürig, 2004).

focus of my work, I will address two major classifications of research questions within this field in the following paragraphs.

1.1.1 Decisions from memory versus from given information

In multi-attribute decision making a major classification refers to where the necessary information for a decision comes from. Typically, decisions from memory are contrasted with decisions from given information (e.g., Gigerenzer & Goldstein, 1996; B. R. Newell, 2005). The former necessitate that the decision maker retrieves all task-relevant knowledge from memory, whereas the latter do not rely on the decision maker's long-term memory. Although research has mainly concentrated on decisions from given information, decisions from memory have received increasing attention in recent years (Bröder & Eichler, 2006; Bröder & Gaissmaier, 2007; Bröder, Newell, & Platzer, 2010; Bröder & Schiffer, 2003b, 2006b; Glöckner & Hodges, 2011; Khader, Pachur, & Jost, 2013; Persson & Rieskamp, 2009; Platzer & Bröder, 2012, 2013) as it has been argued that these two types of decision tasks trigger qualitatively different cognitive processes (Gigerenzer & Goldstein, 1996; see Platzer, 2013, for a detailed overview on multi-attribute decisions from memory).

The work I will present in this thesis employs decisions from given information. This type of decision tasks can be further subdivided into decision tasks necessitating external search and tasks that reduce information search to a minimum by "presenting all pieces of information simultaneously" (Gigerenzer, Dieckmann, & Gaissmaier, 2012, p. 244; see also Glöckner & Betsch, 2008b). This distinction becomes evident when one considers the two typical applications of the so-called *information board* (Payne, 1976): closed versus open information board. The closed information board (often referred to as *Mouselab*, Johnson, Payne, Bettman, & Schkade, 1989, a computer-based implementation) resembles the classic instantiation of this frequently employed, matrix-like way of presenting information (see Figure 1). In the closed information board, cue values are initially hidden from the decision maker and can be acquired in a sequential process, for example, by clicking on the respective box with the computer mouse. In contrast, the open information board displays all decision-relevant information openly to the decision maker. The work presented in this thesis comprises both kinds of decisions from given information: Article 1 employs an open information board, article 2 uses a closed information board, and in article 3 a half-open-half-closed information board is employed. Thus, in some experiments decision makers have to intentionally uncover initially hidden cue values, but they do not need to rely on long-term memory to assess the relevant information.

1.1.2 Prescriptive versus descriptive analyses

The second classification of research questions, that I would like to emphasize, refers to the purpose of analyses. Here, one can either aim to evaluate processes (prescription) or, alternatively, to understand and describe them. The former approach questions whether a process complies with a normative standard, for example, whether a specific decision strategy leads to a high percentage of correct decisions given a certain environmental structure (e.g., Czerlinski, Gigerenzer, & Goldstein, 1999; Gigerenzer & Brighton, 2009; Goldstein & Gigerenzer, 2002; Hogarth & Karelaia, 2006). However, instead of aiming to evaluate a certain process, one can raise the question whether empirical data is well accounted for by different models (description).

The work presented in this thesis focuses on such descriptive analyses of empirical data, for example choice outcomes, decision times, confidence judgments, and information search. More specifically, it concentrates on the question, which framework of multi-attribute decision making (from given information, see paragraph 1.1.1) *describes* decision behavior and its underlying processes best.

1.2 Frameworks of multi-attribute decision making

For multi-attribute decision making several frameworks (co)exist that make fundamentally different assumptions about the decision making process and how it is adapted to changing environments and different situations. In this section, I will outline three frameworks that apply to multi-attribute decision making[4]: the multiple strategy framework, the connectionist network framework, and the evidence accumulation framework.

1.2.1 Multiple strategies

The general idea of the models contained in the multiple strategy framework of multi-attribute decision making (Beach & Mitchell, 1978; Gigerenzer et al., 1999; Payne et

[4] As my work concentrates on decisions from given information, I will not address frameworks that primarily apply to decisions from memory as, for example, exemplar-based models (Juslin, Olsson, & Olsson, 2003; Juslin & Persson, 2002; Persson & Rieskamp, 2009).

al., 1993; Scheibehenne, Rieskamp, & Wagenmakers, 2013) is that decision makers can access a set of qualitatively different decision strategies – much like a mechanic owning a toolbox (e.g., the "adaptive toolbox," Gigerenzer & Todd, 1999) containing different instruments. A decision maker chooses adaptively among these strategies the one that fits best to the specific situation. This notion inevitably provokes the question, *how* decision makers select the appropriate strategy. Two different approaches to answer that question within the multiple strategy framework shall be introduced next.

Payne and colleagues (1993, see also Beach & Mitchell, 1978) posed that highly accurate decision strategies are (cognitively) more costly than less accurate ones and thus viewed strategy selection as a tradeoff between effort and accuracy. From this perspective, the *weighted additive rule* (*WADD*, Payne et al., 1993), that considers all cue values for all options and weighs them in accordance to the cue validities, represents the "maximum accuracy and maximum effort rule" (Payne et al., 1993, p. 92). Both Payne and colleagues as well as Beach and Mitchell (1978) addressed some task characteristics that should affect strategy selection, for example, time constraints. Adding to the testability of the cost-benefit-tradeoff idea, Payne and colleagues presented a measurement approach for the cognitive effort associated with a certain decision strategy: They suggested counting the number of "elementary information processes" (p. 76, see also A. Newell & Simon, 1972) necessary to execute the specific sequence of operations as proposed by the respective decision strategy for a particular decision problem.

Gigerenzer and colleagues (1999) built on this work, but questioned the aforementioned assumption that decision strategies implying less (cognitive) costs inevitably yield lower accuracy. Indeed, comprehensive analyses (e.g., Czerlinski et al., 1999; Gigerenzer & Goldstein, 1996; Hogarth & Karelaia, 2006; Martignon & Hoffrage, 1999) showed that fast (not involving much computation, Gigerenzer & Todd, 1999) and frugal decision strategies can be (at least) as accurate as more costly decision strategies – depending on environmental characteristics. Gigerenzer and colleagues (Gigerenzer et al., 1999; Todd et al., 2012) accordingly coined the term *ecological rationality*, implying that decision strategies are not per se (sub)optimal, but need to be scrutinized for their fit to environmental structures.

The multiple strategy framework, and in particular the adaptive toolbox, inspired a lot of subsequent research (see, e.g., Bröder & Newell, 2008, for a review on these authors' extensive empirical work). Especially the prominent decision strategy *take-the-best* (*TTB*, Gigerenzer & Goldstein, 1996) drew a lot of attention (e.g., Bergert & Nosofsky, 2007; Bröder, 2000, 2003; Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b; Hogarth & Karelaia, 2006; Khader et al., 2013; Lee & Cummins, 2004; B. R. Newell & Shanks, 2003; B. R. Newell, Weston, & Shanks, 2003). TTB poses that cues are inspected in descending order of validity (TTB's search rule) until a discriminating cue is found (TTB's stopping rule) and the option favored by this cue is chosen (TTB's decision rule). Thus, TTB involves *noncompensatory* information integration, meaning that a positive value on one cue cannot make up for a negative value on another one. In several empirical studies (e.g., Bergert & Nosofsky, 2007; Bröder, 2000, 2003; Hausmann & Läge, 2008; Lee & Cummins, 2004; B. R. Newell & Lee, 2009, 2011; B. R. Newell & Shanks, 2003; Rieskamp & Hoffrage, 1999; Rieskamp & Otto, 2006), this fast and frugal, noncompensatory decision strategy was contrasted with more costly *compensatory* decision strategies (allowing for tradeoffs between cues), for example, the *equal weight rule* (*EQW*, Dawes, 1979), that ignores relevance differences by giving unit weights to the cues, and the aforementioned WADD. From the numerous studies supporting the idea of adaptive decision strategy selection, only some shall be presented here: Rieskamp and Hoffrage (1999) showed that increased time pressure led to more frugal decision making (see also Payne et al., 1993), Rieskamp and Otto (2006) reported that choices consistent with TTB increased in a noncompensatory[5] environment as compared to a compensatory one (see also Bröder, 2003), and Bröder (2000) showed that increasing information costs led to more frequent choice behavior consistent with TTB (see also Bröder, 2003; B. R. Newell & Shanks, 2003; Rieskamp & Otto, 2006).

However, the multiple strategy framework also received some critical comments – based on (1) empirical findings as well as on (2) theoretical considerations. To begin with, critical empirical studies typically concentrated on specific decision strategies, most prominent the aforementioned TTB. For example, violations of TTB's search and stopping rule were repeatedly reported: Decision makers purchased more information than predicted by TTB's stopping rule despite high information costs (B. R. Newell & Shanks, 2003) and even when the additional cue was objectively useless (B. R. Newell et al., 2003). B. R. Newell and colleagues (2004) also reported violations of TTB's

[5] Referring to environments, the terms *noncompensatory* and *compensatory* relate to the environment's payoff structure - favoring noncompensatory or compensatory information integration respectively.

search rule (see also Rakow, Newell, Fayers, & Hersby, 2005). However, it is of importance to note that this critique applies to one specific decision strategy only and therefore does not affect the general idea of the multiple strategy framework.

Additionally, the multiple strategy framework faced some critique on a theoretical level. One important critique refers to the aforementioned strategy selection problem: Although different approaches were made, for example, focusing on the role of cognitive niches (Marewski & Schooler, 2011), learning (Rieskamp & Otto, 2006), and environmental characteristics (e.g., Bröder, 2003; Rieskamp & Otto, 2006), the multiple strategy framework has not yet comprehensively explained how the different decision strategies are selected (Glöckner, Betsch, & Schindler, 2010; B. R. Newell & Bröder, 2008). Another fundamental challenge to the multiple strategy framework is the question, how the set of decision strategies is theoretically limited (Glöckner et al., 2010; B. R. Newell & Lee, 2011, but see Marewski, 2010).

1.2.2 Connectionist networks

The connectionist network (sometimes also referred to as *neural network* or *parallel distributed processing*) framework models cognitive processes as passage of activation among neuron-like units. Importantly, the connectionist network framework does not focus on neural modeling, but is neurally inspired (Rumelhart & McClelland, 1986). The most important components of a connectionist network model are the nodes (or units) that are interlinked by weighted connections. As activation spreads in parallel through the network, the activation value associated with each node is updated. One major distinction between different connectionist models refers to the patterns of connectivity (Bechtel & Abrahamsen, 1991): Feedforward networks have unidirectional connections, whereas interactive networks have at least some bidirectional connections, leading to parallel forward and backward processing across a large number of cycles. Most connectionist models count as interactive models (Rumelhart, Hinton, & McClelland, 1986) and have gained a lot of interest as they consider multiple constraints in parallel (Read, Vanman, & Miller, 1997) and settle after a certain number of iterations on optimal solutions (Rumelhart, Smolensky, McClelland, & Hinton, 1986)[6]. Among these constraint satisfaction models (e.g., Holyoak & Simon, 1999; Read et al., 1997; Simon & Holyoak, 2002) one is of vital interest for the work presented herein as it was developed for the purpose of describing multi-attribute decision making: the parallel constraint satisfaction (PCS) model for probabilistic inferences (Glöckner & Betsch, 2008a).

The PCS model for probabilistic inferences (Glöckner & Betsch, 2008a) assumes that multi-attribute decision tasks can be represented in a connectionist network structure. In the PCS model, options and cues are represented as nodes. These nodes are interconnected by bidirectional links that represent the logical relations of the decision problem. For example, a positive cue value will be represented as an excitatory link between the cue and the respective option. The option nodes are interlinked by an inhibitory connection, reflecting the commonly given instruction to choose exactly one of the presented options. The network is activated by a general validity node that is linked to all cue nodes. These links represent the validity of the cues. Activation spreads in parallel through the network which will settle after a certain number of iterations to a state of maximized consistency. In this state, one option will be highly (positively) activated and therefore chosen by the decision maker (Glöckner & Betsch, 2008a).

Glöckner, Betsch, and colleagues (e.g., Glöckner & Betsch, 2008b, 2012; Glöckner et al., 2010; Glöckner & Bröder, 2011; Glöckner & Hodges, 2011) reported several findings supporting the PCS model. For example, Glöckner and Betsch (2012) showed that adding information in a multi-attribute decision task can decrease decision times when the additional information increases the coherence[7] in the information pattern. This finding was predicted by Glöckner and Betsch's (2008a) model, but contradicts the multiple strategy framework's prediction that more information necessitates longer decision times as more elementary information processes (see paragraph 1.2.1) are involved in the process of decision making. The probably most

[6] As Bechtel & Abrahamsen (1991) point out, this settling to an optimal solution is no necessity to interactive models. Also, these models sometimes settle on local optima instead of the global optimum (Bechtel & Abrahamsen, 1991).

[7] The term *coherence* refers to the degree of compatibility of the information given by different cues. High coherence is achieved when all cues favor one option and speak against the alternative. In contrast, if some cues favor one option, but others the alternative one, the information pattern has low coherence (see, e.g., Betsch & Glöckner, 2010).

intriguing finding supporting the connectionist network framework, however, was the demonstration of so-called *coherence shifts* (e.g., Glöckner et al., 2010; Holyoak & Simon, 1999; Russo, Carlson, Meloy, & Yong, 2008; Simon, Pham, Le, & Holyoak, 2001) – confirming a theoretical prediction derived from the assumed bidirectional links in the interactive connectionist network. For multi-attribute decision tasks, the coherence shift prediction refers to the posterior subjective cue weights: As cue and option nodes are bidirectionally linked, activation flows from cue nodes to option nodes, but also from option nodes back to cue nodes. Thus, in the course of consistency maximization a cue supporting the superior option will be positively activated, whereas a conflicting cue will be negatively activated – leading to an increased subjective cue weight for the supporting cue, but a decreased subjective cue weight for the conflicting cue. Glöckner and colleagues (2010) reported such a coherence shift: In their studies, participants' subjective (self-reported) initial cue weights were not stable, but adjusted to support the favored option.

However, the connectionist network framework also received some critical comments. For the sake of brevity, I will concentrate on two issues that are of particular importance for the research on multi-attribute decision making (see, e.g., Bechtel & Abrahamsen, 1991; Rumelhart & McClelland, 1986, for a broader discussion). To begin with, the connectionist network framework avoids the aforementioned multiple strategy framework's strategy selection problem by assuming that the same uniform mechanism is employed across different problems and situations. However, to account for individual differences, model parameters have to be adapted. The question how the parameter values are selected constitutes a structurally similar problem to the strategy selection problem and has not yet been addressed satisfactorily (Marewski, 2010). The second issue of importance is PCS' concentration on the process of information integration; Glöckner and Betsch's (2008a) model does (so far) not specifically address the process of information search. Instead, Betsch and Glöckner (2010) put forward a component approach proposing that decision makers employ different strategies for information search, but a uniform mechanism (i.e., PCS) for information integration (see Betsch & Glöckner, 2010; Glöckner & Betsch, 2008a; Glöckner & Herbold, 2011, for general predictions concerning the interplay of the two components). This approach, however, raises the questions (1) what information search strategies are incorporated and how they are selected (Marewski, 2010) as well as (2) how this component approach can be put to the test (but see Betsch & Glöckner, 2010, for some suggestions).

1.2.3 Evidence accumulation

The evidence accumulation (sometimes also referred to as *sequential sampling* or *evidence accrual*) framework models cognitive processes as sequential sampling processes that terminate as soon as the accumulated evidence passes an evidence threshold. One major differentiation of model classes within this framework refers to the number of accumulators assumed: Diffusion models or random walk models (e.g., Busemeyer & Townsend, 1993; Diederich & Busemeyer, 2003; Ratcliff, 1978; Ratcliff & Smith, 2004) assume a single accumulator where positive evidence for one option simultaneously means negative evidence for the alternative option. In contrast, accumulator models or counter models (e.g., Ratcliff & Smith, 2004; Usher & McClelland, 2001; Vickers, 1970) assume single accumulators or diffusion processes for each option (see, e.g., Ratcliff & Smith, 2004, for an overview). However, for the work presented in this thesis, another distinctive feature of the different models is of vital interest: The step-size of the models and therefore the (current) field of application.

The most prominent evidence accumulation models for decision making (e.g., Busemeyer & Townsend, 1993; Diederich & Busemeyer, 2003; Ratcliff & McKoon, 2008; Roe, Busemeyer, & Townsend, 2001; Usher & McClelland, 2001; Vickers, 1970) apply to rapid one-process decisions (e.g., lexical word-nonword-decisions, see Ratcliff & Smith, 2004). They share the assumption that the representation of stimuli is inherently noisy and to make a decision about a stimulus, a decision maker will accumulate successive samples of this noisy stimulus representation until enough evidence is obtained to reach the evidence threshold.[8] The height of this evidence threshold can be adjusted, for example, to account for the importance of a decision and the costs associated with sampling additional information (Busemeyer & Townsend, 1993).

[8] Interestingly, some of these models (e.g., Roe, Busemeyer, & Townsend, 2001; Tsetsos, Usher, & Chater, 2010) have been re-interpreted as connectionist feedforward network models with unidirectional links. However, within this thesis the term *connectionist network* (cf. paragraph 1.2.2) refers to the more common interactive, parallel constraint satisfaction networks that reach a stable state after a certain number of iterations.

As multi-attribute decision making from information given[9] in a closed information board constitutes itself a sequence of simple choice tasks (see, e.g., Busemeyer & Rapoport, 1988), evidence accumulation models applying to this whole sequence have adapted the step-size of the accumulation process (Hausmann & Läge, 2008; Lee & Cummins, 2004; B. R. Newell, 2005). In these models, each cue-acquisition constitutes one step in the proposed sequential sampling process and the simple choices themselves – whether or not to search for more information – are *not* subject to the evidence accumulation modeling. Accordingly, the process of cue-wise information search terminates as soon as one option gained enough positive evidence to overshoot the evidence threshold and is thus chosen. If the threshold is not passed, further cue information is acquired until either the threshold is reached or no more information is available (and the option with the highest positive evidence is chosen). Again, the height of the evidence threshold can be adjusted, for example, to account for varying costs associated with the information search (Hausmann-Thürig, 2004; B. R. Newell & Lee, 2009).

The adequacy of the evidence accumulation framework to describe multi-attribute decision making was documented by several empirical studies (Hausmann & Läge, 2008; Hausmann-Thürig, 2004; Jekel, 2012; Lee & Cummins, 2004; B. R. Newell, Collins, & Lee, 2007; B. R. Newell & Lee, 2009, 2011). For example, investigating the process of information search, Hausmann and Läge (2008) reported that decision makers' stopping behavior was well predicted by the individually estimated evidence thresholds and did not correspond to the stopping rules incorporated in the multiple strategy framework. This finding is in line with other studies reporting information search and stopping behavior inconsistent with decision strategies' rules (B. R. Newell & Lee, 2009, 2011; B. R. Newell & Shanks, 2003). But also studies concentrating on choice outcomes as dependent variable found support for the evidence accumulation framework. For example, B. R. Newell and Lee (2011) reported that Lee and Cummins' (2004) evidence accumulation model fared best in a model comparison including several alternative models derived from the multiple strategy framework.

However, the (current) evidence accumulation framework to describe multi-attribute decision making faces some critical issues as well: (1) Just as the multiple

[9] For an evidence accumulation model describing multi-attribute decision making from memory see Diederich (1997).

strategy framework needs to specify how the different decision strategies are selected, the evidence accumulation framework needs to explain how the model parameters are adapted (e.g., B. R. Newell, 2005). This problem most obviously applies to the threshold parameter, but concerns other model parameters as well (e.g., how the cue validities are transferred to the evidence scale, see Lee & Cummins, 2004, for one suggestion). (2) Related to the first issue, one might criticize that the assumptions concerning, for example, information search vary considerably between different models within the evidence accumulation framework. For example, Busemeyer and Townsend (1993, see also Bergert & Nosofsky, 2007) propose a probabilistic search order, whereas Lee and Cummins' (2004) model employs a deterministic search order. Thus, the evidence accumulation framework as a whole is rather flexible and makes few strong predictions that can be put to the test.

1.3 Contrasting the frameworks of multi-attribute decision making

The aforementioned frameworks maintain a (more or less) peaceful coexistence, in my view, mainly for two reasons: (1) Research was often conducted within one of the frameworks rather than contrasting them (but see, e.g., Glöckner et al., 2010; Hausmann & Läge, 2008; B. R. Newell & Lee, 2011) and (2) the frameworks closely mimic each other. For example, PCS can mimic choices in line with TTB, WADD, and EQW respectively by adjusting the cue weights in the proposed network (Glöckner, 2009; Glöckner, Hilbig, & Jekel, 2014). Evidence accumulation models, to give another example, can mimic the limited information search predicted by TTB as well as exhaustive search as predicted by compensatory decision strategies by adjusting the proposed evidence threshold (e.g., Hausmann & Läge, 2008).

Due to this mimicking relationship, the different frameworks can often equally well account for empirical data and disentangling them poses an "empirical challenge" (B. R. Newell, 2005, p. 13). Notwithstanding the complexity of this task (B. R. Newell & Bröder, 2008), disentangling the frameworks has repeatedly been advocated (Glöckner & Betsch, 2011; B. R. Newell, 2005; B. R. Newell & Bröder, 2008) as "'theory' accumulation is not a proof for progress" (Glöckner & Betsch, 2011, p. 718) and the frameworks do, in fact, "comprise at least partly incompatible assumptions" (B. R. Newell & Bröder, 2008, p. 200).

Therefore, the central aim of my work is to contrast the aforementioned frameworks of multi-attribute decision making and empirically determine which one describes human decision behavior best. The aforementioned empirical challenge was tackled in different ways, each relying on competing predictions derived from either specific model instantiations of the frameworks (Söllner et al., 2013) or the frameworks themselves (Söllner, Bröder, Glöckner, & Betsch, 2014, and Söllner & Bröder, 2014).

Of course, previous attempts have been made to contrast the frameworks (see also paragraphs 1.2.2 and 1.2.3), but the question which one describes decision making best, has not yet been answered satisfactorily. For example, Glöckner and colleagues (Glöckner & Betsch, 2008b; Glöckner & Bröder, 2011; Horstmann, Ahlgrimm, & Glöckner, 2009) found support for the connectionist network model PCS (Glöckner & Betsch, 2008a) by complementing choice outcome analyses with either decision times and confidence ratings or eye-tracking data. As the quoted studies unanimously employed the matrix-like presentation format of the open information board, the aim of the first article (Söllner et al., 2013) was to test whether this reported dominance might crucially depend on this specific format of information presentation. For articles 2 and 3, previous work was reviewed in a similar, critical vein. For the sake of brevity, I do not give a comprehensive review on all the previous work here, but include a brief summary of the main critique concerning relevant previous attempts and the implemented approach for improvement in the next chapter for each article separately.

2 SUMMARIES OF ARTICLES

In the following sections I will provide summaries of the three articles this thesis is based on. For the sake of brevity, I will focus on the main statements of each of the articles, as more detailed information can be found in each of the respective articles. In excess of the general discussion given in each of the articles, I will discuss how the results contribute to the central aim of my work, namely, contrasting the three frameworks, and address potential critical issues more comprehensively. An additional, general discussion will be given in the next chapter.

2.1 Contrasting a connectionist network model with decision strategy models

Söllner, A., Bröder, A., & Hilbig, B. E. (2013). Deliberation versus automaticity in decision making: Which presentation format features facilitate automatic decision making? *Judgment and Decision Making*, *8*(3), 278–298.

In this article, we aimed to contrast the connectionist network model PCS (Glöckner & Betsch, 2008a) with three decision strategies routinely investigated within the multiple strategy framework: TTB, EQW, and WADD. The rationale for this endeavor was the observation that studies reporting a dominance of PCS-consistent behavior (e.g., Glöckner & Betsch, 2008b; Glöckner & Bröder, 2011; Horstmann et al., 2009) predominantly employed an open information board. As Glöckner and Betsch (2008b) already concluded that sequential information search as induced by a closed information board seems to impede the applicability of PCS, we wondered whether behavior in line with PCS' predictions might be even more restricted than that. In particular, we hypothesized that PCS-consistent decision behavior crucially depends on the format in which the decision-relevant information is (openly) presented.

As PCS can, in general, mimic the choice outcome predictions of each of the considered decision strategies (Glöckner, 2009; Glöckner et al., 2014) and produces for the environments employed in this article the exact same choice outcome predictions as WADD, the PCS model cannot be distinguished from the decision strategies based on choice outcomes alone. However, Glöckner (2009) developed a Multiple-Measure Maximum Likelihood (MM-ML) method that estimates a single maximum likelihood[10]

[10] As the models entail a different number of free parameters, the Bayesian Information Criterion (BIC, Schwarz, 1978) is employed within MM-ML to control for model complexity (Glöckner, 2009).

for each of the considered models based on their predictions concerning choice outcomes, decision times, and confidence judgments. For example, WADD predicts equal decision times for decision tasks that entail the same number of options and cues (and, therefore, cue values) based on the constant number of elementary information processes involved – irrespective of the characteristic cue values given in the specific tasks. PCS, in contrast, predicts longer decision times with decreasing distance of the options on the decision criterion value (Glöckner & Betsch, 2012, see Glöckner, 2009, for a detailed overview of the specific predictions). In line with previous work (e.g., Glöckner & Bröder, 2011), we used this classification method to contrast PCS and the aforementioned strategies in order to test our presentation format hypothesis.

All three experiments employed the well-known City-Size task (Gigerenzer, Hoffrage, & Kleinbölting, 1991), presenting it in the matrix-like presentation format of the open information board, a newly created map presentation format (conceptually following the example of a common city map), and additional variations of both presentation formats. Across all three experiments a presentation format effect emerged: In the matrix presentation format PCS was the best fitting model, whereas decision strategies accounted best for participants' behavior in the map presentation format. Varying the extent of information search within both presentation formats, we observed that PCS' dominance was constrained to the original matrix presentation format – the only presentation format that completely eliminated information search (by presenting the cues in a fixed order across all trials of the respective experiment).[11]

Our results indicate that PCS-consistent behavior is dominant when all decision-relevant information is highly accessible. As soon as some information search is required (as little as it might be), a majority of participants does not comply with PCS' predictions. One possible interpretation of this result is given in the article: The perception-like, automatic integration process as proposed by PCS applies only to

[11] The original map presentation format necessitated some information search as the relevant cue information was distributed randomly across the city area. Varying (i.e., reducing) the extent of information search in this presentation format, we restricted the area where each cue could be displayed, for example, the most valid cue was only displayed in the upper left quarter of the city area. However, this reduced extent of information search in the map presentation format did *not* eliminate information search to the extent that it is achieved in the (original) matrix presentation format. Dominance of PCS-consistent behavior was neither observed in the original maps nor in the maps with reduced information search (nor in the matrices with increased information search).

choice situations that conveniently lie out all necessary information to the decision maker. If this automatic process cannot come into play, decision makers will resort to one of the decision strategies also applicable in this situation.

In regard to the central aim of this thesis, I would like to discuss two critical issues of the reported work: (1) the decision time predictions within the MM-ML method and (2) the general approach employed to contrast the frameworks. The first critical issue relates to the predictions for the dependent variables by the different models in general and the adequacy of the decision time predictions in particular. In general, the MM-ML method – as any model fit comparison – necessitates explicit model specifications that are, of course, debatable. For example, critics might argue that TTB users[12] might not base their confidence judgments on the validity of the first discriminating cue exclusively (cf. Glöckner, 2009) when further information is openly displayed. However, the most severe problem with the predictions employed – also for our analyses – concerns the decision time predictions for PCS. These predictions cover the process of information integration only, whereas the time necessitated for information search is neglected (due to the missing formal model, see paragraph 1.2.2). As soon as information search is not limited to a minimum, it adds noise to the process of interest (i.e., information integration), making differences – as predicted by PCS – harder to detect. Therefore, one could argue that mere noise accounts for the presentation format effect reported in this article, as WADD (representing the multiple strategy framework) gives the same choice outcome predictions and similar confidence judgment predictions as PCS, but does not predict any decision time differences between trials. Although we give conclusive arguments in the general discussion of the article that this noise interpretation cannot (alone) account for our findings, the issue raised is fundamental in respect to contrasting the connectionist network framework with other frameworks: Whereas the multiple strategy framework and the evidence accumulation framework consider information search and integration, the connectionist network framework (mainly) regards the process of information integration. These different foci have to be taken into account when contrasting the different frameworks.

[12] The notion that a person "uses" a certain decision strategy is a simplification that is employed to improve the readability of the text. What it means, essentially, is that the observed behavior of a person is best accounted for by the predictions of the respective strategy.

The second issue, I would like to address, concerns the general approach to contrasting the frameworks. In line with Glöckner and colleagues (Glöckner & Betsch, 2012; Glöckner & Bröder, 2011, 2014; Glöckner et al., 2014) we employed the MM-ML method to contrast PCS and several prominent decision strategies routinely investigated within the multiple strategy framework. More generally, we contrasted one specific model instantiation from the connectionist model framework with other specific model instantiations from the multiple strategy framework. One advantage of this approach is that it asks for explicit model specifications, but one potential drawback is that conclusions may be restricted to the considered instantiations of the model classes and may therefore not generalize to the framework level. The following articles addressed both issues.

2.2 Contrasting frameworks I: Multiple strategies versus connectionist network and evidence accumulation

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.

In this article, we included all three frameworks of multi-attribute decision making: The multiple strategy framework, that proposes the existence of several distinct decision strategies, was contrasted with the connectionist network framework and the evidence accumulation framework, that both pose a single uniform mechanism to describe decision making. Previous work yielding positive evidence in favor of the single-process frameworks (e.g., Glöckner & Betsch, 2008b; Glöckner & Bröder, 2011; Horstmann et al., 2009; Lee & Cummins, 2004; B. R. Newell et al., 2007; B. R. Newell & Lee, 2011) has, just like the work reported in the previous article (Söllner et al., 2013), regularly concentrated on comparing specific models from the different frameworks. We argue that when employing this approach, conclusions may be restricted to the considered model instantiations, and therefore advocate testing basic assumptions shared by all models within one framework instead. Moreover, analyses in some previous work were limited to one specific dependent variable alone (e.g., Hausmann & Läge, 2008; Lee & Cummins, 2004; B. R. Newell et al., 2007). To gain a broader empirical basis for the framework comparison, we did not restrict our considerations to either information search[13] or choice outcomes, but included both (and more) dependent variables.

The basic idea of this article was to test predictions derived from the most prominent frugal decision strategy TTB against general predictions derived from the single-process frameworks. In particular, we aimed to test whether participants seemingly using TTB would actually ignore strategy-irrelevant information as predicted by TTB's famous algorithm: "take the best, ignore the rest" (Gigerenzer & Goldstein, 1996, p. 653). As TTB-irrelevant information is not necessarily irrelevant for the decision task per se, but only for this frugal decision strategy, single-process frameworks predict that this valid information is not ignored. Instead, decision behavior should vary contingent on the content of this additional information.

To test these predictions, we developed an information intrusion paradigm. Here, participants had to purchase cue value information in a closed information board, but as soon as the first cue value information was intentionally acquired by the participant, additional information intruded – boxes opened for free without being clicked on. We manipulated the content of the additional, TTB-irrelevant information as being either compatible with the option predicted by TTB's decision rule or speaking against the option favored by TTB (incompatible information). As our hypotheses relied on (apparent) TTB use, we employed a decision strategy induction procedure (bottom-up via choice feedback alone or, alternatively, bottom-up plus top-down via instruction) and limited our analyses to (the vast majority of) participants whose behavior during the induction phase was best accounted for by TTB.

The results of both experiments supported the single-process frameworks' prediction that task-relevant information is not ignored, but influences all of the investigated dependent variables. In particular, decision makers (seemingly) using TTB searched for more information when the TTB-irrelevant intrusions were incompatible than when they were compatible with the option predicted by TTB's decision rule. They also refrained more frequently from choosing the TTB option when incompatible TTB-irrelevant information intruded and were less confident when choosing it.

[13] However, as has been argued before, the connectionist network framework (mainly) focusses on the process of information integration. Thus, our single-process framework predictions concerning information search were primarily derived from the evidence accumulation framework.

We concluded that participants seemingly using TTB did not ignore strategy-irrelevant information, but systematically varied their information search behavior, their choices, and their confidence judgments contingent on the content of this “irrelevant” information. These unanimous findings on diverse dependent variables support the single-process view that applicable information cannot be ignored, but will be fed into the proposed uniform decision making mechanism.

In the article, we discussed two potential objections to the conclusions drawn: (1) Participants might have switched strategies between induction and test phase contingent on the environmental change (since, on average, the nature of the intruding information changed). We believe this interpretation implausible as there was no recognizable change in the task structure and appearance, no change in payoffs, a consequent reinforcement of using TTB, and some strategy-irrelevant information intrusions were incorporated in the induction phase already. Thus, the two phases were as similar to each other as possible. (2) Strategy selection was circumvented in our paradigm. We answer this objection in two ways: In our approach, the induction phase was meant to select an appropriate decision strategy (multiple strategy framework interpretation) and our predictions concerned processing after this initial calibration. Most participants (seemingly) selected the in terms of payoff successful TTB, but some participants apparently selected other strategies. Thus, strategy selection was not obviated, but systematically influenced by our manipulation. Additionally, we analyzed data separately for the subset of participants that was not additionally instructed to adhere to TTB, but learned it bottom-up exclusively. The pattern of results was identical for this more natural strategy selection situation.

In regard to the central aim of this thesis, I believe two further issues should be addressed at that point: (1) Although strategy selection was not circumvented in this work, our predictions for the multiple strategy framework were only valid for users of the induced decision strategy TTB and the experimental logic can only be applied to strategies that ignore information. Thus, the framework comparison still rested on one specific model instantiation (at least for the multiple strategy framework). As pointed out earlier, contrasting basic assumptions of the frameworks without referring to specific models might further increase the generalizability of the conclusions drawn. (2) Critics might further argue that the intruding information in our paradigm provoked demand effects as strategy-irrelevant information was forced upon participants by openly displaying it to them. Of course, information intruded right in the beginning of each trial and deviating from the induced strategy was maladaptive in terms of payoff, but the reported evidence should be supplemented by findings that do not build on participants' willingness to ignore information given to them by the experimenter. The following article addressed both issues.

2.3 Contrasting frameworks II: Multiple strategies versus evidence accumulation

Söllner, A. & Bröder, A. (2014). *Toolbox or adjustable spanner? A critical comparison of two metaphors for adaptive decision making*. Manuscript submitted for publication.

In this article, we contrasted the multiple strategy framework and the evidence accumulation framework by concentrating on the process of information search and, in particular, the stopping behavior as predicted by the two frameworks. Previous work (Hausmann & Läge, 2008; Hausmann-Thürig, 2004; Jekel, 2012; B. R. Newell & Lee, 2009, 2011; Söllner et al., 2014) reported evidence for the adequacy of evidence accumulation models to describe information search behavior, but we deemed several shortcomings worth tackling in order to conclusively disentangle the two frameworks: (1) In contrast to Hausmann and Läge's (2008) approach (see also Jekel, 2012) that only compared single cue validities to thresholds, we deemed it crucial to also consider combinations of cues as essential part of the evidence *accumulation* framework. (2) In line with Hausmann and Läge, we aimed to estimate an individual evidence threshold for each participant. Consequently, the frameworks' predictions were contrasted in the aggregate (B. R. Newell & Lee, 2011; Söllner et al., 2014) as well as on the individual level (Hausmann & Läge, 2008). (3) Finally, most of the cited work (Hausmann & Läge, 2008; Hausmann-Thürig, 2004; Jekel, 2012; B. R. Newell & Lee, 2009, 2011) compared specific evidence accumulation models to specific decision strategy models. As discussed before, conclusions based on this approach are in principle only valid for the specific models considered. Thus, we aimed to contrast basic assumptions of the superordinate frameworks to provide more general conclusions.

The basic idea of this article was to present decision makers with half-open-half-closed information boards, openly conveying different levels of given evidence in favor of one option. The rationale was that the frameworks differ in their assumptions about the termination of information search: According to the multiple strategy framework, stopping behavior should comply with the decision strategies' stopping rules, thus predicting distinct patterns of stopping behavior. In contrast, the evidence accumulation framework predicts stopping behavior to be contingent on the extent of (acccumulated) evidence and in accordance to the proposed individual evidence threshold. To contrast these predictions, we constructed stimuli in such a way that decision strategies' stopping rules would predict the same stopping behavior for each of the investigated levels of given evidence – either immediate stopping or continued information search for each level. The evidence accumulation framework, however, would predict that participants terminate information search contingent on the level of given evidence. In particular, the frequency of immediate stopping should increase with increasing levels of given evidence.

We ran three experiments that consisted of calibration phases, that were meant to select a decision strategy (or adjust the evidence threshold respectively) based on the outcome feedback provided, and test phases that employed the levels of given evidence paradigm. Here, we manipulated within subject, how much evidence in favor of one option was provided by the openly displayed cues, and monitored the subsequent information acquisition behavior. In line with the evidence accumulation framework prediction, we found that the percentage of immediate stopping increased with increasing levels of evidence – on the aggregate level across all participants as well as when running separate analyses for TTB users and compensatory strategy users (strategy classification based on calibration phase data). On the individual level, we found that for the vast majority of participants (mean percentage across all three experiments: 71.5 %) the stopping behavior was best accounted for by assuming a noisy individual evidence threshold.

We concluded that the evidence accumulation framework accounted better for the observed stopping behavior than the multiple strategy framework did. It seemed that participants applied a much wider range of termination points than implied by the different stopping rules incorporated in the multiple strategy framework. Hence, the more continuous evidence accumulation account offered a superior description in the aggregate as well as on the individual level.

Anticipating potential critique, we discussed (1) the reasonableness of our assumptions and (2) the generalizability of our conclusions, especially to the multiple strategy framework. The first issue referred to the crucial assumptions that participants did neither switch strategies between calibration and test phases nor, even more critical, within the test phases. To briefly reiterate our discussion of the latter assumption, we deemed it reasonable as (1) previous work within the multiple strategy framework reported routine effects in decision strategy use (cf. Bröder & Schiffer, 2006a; Rieskamp, 2006) and (2) established decision strategy classification methods routinely rely on this assumption (e.g., Bröder & Schiffer, 2003b; Glöckner, 2009; Payne et al., 1993). On a more theoretical level, we argued that the notion of a scanning mechanism that evaluates for each information pattern whether a certain decision strategy's selection seems worthwhile contradicts the basic idea of a decision strategy as an ordered set of processes to solve a task.

The question whether our conclusions actually generalize to the multiple strategy framework arose from the fact that our stimuli were constructed considering only some decision strategies (i.e., the most frequently investigated ones: TTB and compensatory strategies) and their respective deterministic stopping rules. Extending these strategies' deterministic stopping rules by allowing for random errors to occur did not invalidate our conclusions. However, one could argue that the multiple strategy framework comprises more decision strategies and stopping rules than considered in our paradigm. In the article's general discussion, we comprehensively addressed the two general stopping rules discussed by Gigerenzer and colleagues (2012) and, in particular, the "Take Two" heuristic (Dieckmann & Rieskamp, 2007) that indeed predicts continued information search for some lower levels and immediate stopping for the higher levels of given information in our paradigm. However, extending our considerations to these alternative accounts did not invalidate our findings. We are not aware of further stopping rules or decision strategies currently contained in the multiple strategy framework that could account for our results.

However, I would like to extend this discussion to two further issues that relate to the central aim of this thesis as well: (1) this article's focus on information search only and (2) the flexibility of the different frameworks. In regard to the first issue, one could argue that concentrating on information search predictions alone does not yield the desirable broad empirical basis to disentangle the frameworks (see also section 2.2 for a similar argument). However, I deem the reported concentration on the frameworks' stopping behavior predictions valuable for two reasons. On the one hand, evidence accumulation models are basically characterized by the proposition of an (individual) evidence threshold. Investigating the adequacy of this essential component to account for empirical findings, especially on the eligible individual level (e.g., Cohen, Sanborn, & Shiffrin, 2008; Gigerenzer & Gaissmaier, 2011; Pachur, Bröder, &

Marewski, 2008), constitutes an important step towards the aim to disentangle this framework from the multiple strategy framework. On the other hand, the reported studies complemented our previous work employing an information intrusion paradigm (Söllner et al., 2014) by tackling two critical issues thereof (see section 2.2). In particular, (1) demand effects due to (incompatible) information provided by the experimenter were excluded by not providing any incompatible information for free and (2) the concentration on the frugal decision strategy TTB became dispensable by also including compensatory strategies in our considerations. The compatibility analysis (not reported so far within this thesis) following our previous reasoning (Söllner et al., 2014) showed that participants' subsequent search behavior was systematically influenced by the compatibility of additional information with prior evidence – not only when it intruded for free (Söllner et al., 2014), but also when intentionally purchased by the participant. These findings were in line with the evidence accumulation framework, but not predicted by the multiple strategy framework.

The second issue, I would like to discuss, relates to the complexity[14] (flexibility) of the considered frameworks. One might argue that the reported superiority of the evidence accumulation framework was due to this framework's higher complexity, allowing for more possible patterns of stopping behavior. Of course, TTB's stopping rule, the compensatory strategy's stopping rule, and further stopping rules contained in the multiple strategy framework are nested within the evidence accumulation framework's stopping behavior predictions for our paradigm. Thus, there are data patterns that would contradict the evidence accumulation framework's stopping behavior predictions (e.g., decreasing percentage of immediate stopping with increasing levels of given evidence as observed for two participants), but these couldn't be accounted for by the multiple strategy framework either. In my view, this issue certainly

[14] A model's *complexity* is defined as "the property of a model that enables it to fit diverse patterns of data; it is the flexibility of a model" (Pitt & Myung, 2002, p. 422) and constitutes "a key property of a model that must be considered by any selection method" (Pitt, Myung, & Zhang, 2002, p. 473). The reason for that request is that the "appeal of an excellent fit to the data (i.e., high descriptive adequacy) needs to be tempered to the extent that the fit was achieved with a highly complex and powerful model (i.e., low parsimony)" (Vandekerckhove et al., in press). This principle is also known as *Occam's razor*: "Occam's metaphorical razor symbolizes the principle of parsimony: by cutting away needless complexity, the razor leaves only theories, models, and hypotheses that are as simple as possible without being false." (Vandekerckhove et al., in press).

is of high relevance (cf. the various approaches to counterbalance goodness of fit and simplicity in model selection, e.g., Forster, 2000; Pitt, Myung, & Zhang, 2002; Vandekerckhove, Matzke, & Wagenmakers, in press) and necessitates careful consideration. In regard to the work presented here, I would like to answer this critique based on three arguments: (1) Arguing on a theoretical level, higher complexity in a model (or framework) is not disadvantageous per se, but might sometimes be warranted (e.g., Scheibehenne et al., 2013). If a simpler model cannot account for highly systematic findings, more complexity might yield distinctly improved description (goodness of fit). The work reported in this article shows that the stopping behavior of a majority of participants is not well described by assuming some distinct stopping rules, but better accounted for by the evidence accumulation framework. (2) For the sake of generalizability, we contrasted basic framework assumptions instead of engaging in a model fit comparison, accepting the drawback of our approach that the complexity of the superordinate frameworks cannot (easily) be assessed (cf. Scheibehenne et al., 2013; Thagard, 1988). However, within the field of multi-attribute decision making, several approaches to model selection, taking into account the complexity of the tested models, have been employed (e.g., Glöckner, 2009; B. R. Newell & Lee, 2011; Scheibehenne et al., 2013). In line with our conclusions, several studies following such an approach found support for evidence accumulation models (Lee & Cummins, 2004; B. R. Newell et al., 2007; B. R. Newell & Lee, 2011) – despite punishing these models for their higher complexity in comparison to models derived from the multiple strategy framework. (3) Arguing about the flexibility of the evidence accumulation framework and the multiple strategy framework, it is further of importance to consider that in our paradigm the multiple strategy framework's stopping behavior predictions were constrained by design, on purpose. For this paradigm, the multiple strategy framework predictions were nested within the evidence accumulation framework predictions, leading to the impression that the evidence accumulation framework is – in general – more flexible than the multiple strategy framework. However, this relationship is not universal. As I have argued before, the complexity of the superordinate frameworks cannot easily be assessed (cf. Scheibehenne et al., 2013; Thagard, 1988). But even when exclusively concentrating on the frameworks' predictions concerning the termination of information search, assessing the frameworks' complexity is far from trivial. For example, stopping rules relying on a fixed number of cues (Gigerenzer et al., 2012) are not nested within the stopping behavior predictions of the evidence accumulation framework. Thus, observing stopping patterns consistent with these stopping rules (in a different paradigm, of course) would support the multiple strategy framework and would not easily be accounted for by the evidence accumulation framework.

3 GENERAL DISCUSSION AND OUTLOOK

In this concluding chapter of the thesis, I will first give a brief summary of the work reported in detail in the previous chapter, before discussing some vital issues arising from that work. I will end this first section with a summary of the main conclusions – based on the work presented and the subsequent discussion of it. The last section of this chapter will give an outlook to future research questions that emerge from the work presented in the thesis.

3.1 General discussion

The work reported herein is concerned with the question which framework describes multi-attribute decision making best. The three articles outlined in this thesis each took a different approach to address this question.

The first article contrasted the connectionist network model PCS with prominent decision strategies, aiming at boundary conditions for PCS (Glöckner & Betsch, 2008a). We observed individual behavior (choice outcomes, decision times, and confidence judgments) to be in line with PCS' predictions when information was highly accessible, but more in line with the decision strategies when information accessibility decreased. Thus, we concluded that decision behavior consistent with PCS necessitates highly accessible information to allow for the proposed holistic processing in a perception-like manner.

In the second article we aimed to contrast the multiple strategy framework with the single-process frameworks (connectionist network and evidence accumulation framework) based on several dependent variables (most importantly, choice outcomes and information search). Employing an information intrusion paradigm, we found that participants seemingly using a frugal decision strategy did not ignore intruding strategy-irrelevant information, but varied their choices and information search behavior in accordance with the additional information. These findings were in line with the single-process frameworks assuming that applicable information cannot be ignored, but will automatically be fed into the uniform decision mechanism.

Finally, the third article contrasted the multiple strategy framework and the evidence accumulation framework, based on predictions concerning the termination of information search. Employing a half-open-half-closed information board, we presented participants with different levels of evidence in favor of one option and found that the stopping behavior (aggregate and individual) was systematically influenced by the given evidence – as predicted by the evidence accumulation framework, but not the multiple strategy framework for our stimuli. We concluded, that the stopping rules incorporated in the multiple strategy framework do not account well for the stopping behavior observed in our experiments, whereas our findings comprehensively comply with the evidence accumulation framework.

For each of the three articles, some critical issues were discussed in the respective sections of the previous chapter. The present section therefore concentrates on an additional cross-article discussion before summarizing the main conclusions of the work presented.

The first issue I would like to address refers to the status of PCS: Does PCS replace or complement the multiple strategy framework? In the first article (Söllner et al., 2013) we argued that automatic decision making as proposed by PCS may be limited to specific situations – that is, when information is highly accessible, enabling a perception-like, automatic processing of the whole information pattern (see also Gigerenzer et al., 2012). If the proposed connectionist network cannot immediately be set up, decision makers have to employ (other) decision strategies. This interpretation of PCS as an automatic decision strategy complementing the multiple strategy framework[15], however, is not in line with Glöckner and Betsch's (Betsch & Glöckner, 2010; Glöckner & Betsch, 2008a; Glöckner et al., 2010) conception of PCS as constituting a single-process model aiming to replace the multiple strategy framework. However, for PCS (or the component model, Betsch & Glöckner, 2010, see also paragraph 1.2.2) to replace the multiple strategy framework, the process of information search has to be formally modeled in addition to the present model of information integration. Whether such a comprehensive model could account for the empirical

[15] As we have argued in the first article (Söllner et al., 2013), this interpretation is actually implied by employing the MM-ML classification method developed by Glöckner (2009; Jekel, Nicklisch, & Glöckner, 2010): PCS is *not* contrasted with the multiple strategy framework as a whole, but added as alternative model in a strategy classification method that is based on work within the multiple strategy framework (Bröder & Schiffer, 2003a). The result of this method necessarily entails a certain percentage of participants classified as most probably adhering to some of the prominent decision strategies and a certain percentage of participants whose behavior is best accounted for by PCS. Thus, some decision makers seem to rely on automatic decision making whereas others select one of the *other* decision strategies.

findings reported in the first article (Söllner et al., 2013) currently remains, unfortunately, an open question. For the second article (Söllner et al., 2014), we derived basic predictions from the connectionist network framework (based on the information integration process formally modeled), thus interpreting PCS as the single-process model it was originally proposed to be.

The second central issue I would like to discuss emerges from the work presented in the second article (Söllner et al., 2014): What does it mean if decision makers do not ignore “irrelevant” information? Employing an information intrusion paradigm in the second article, we found that decision makers seemingly employing a frugal decision strategy did not ignore strategy-irrelevant information that was given to them for free and without being intentionally acquired. The finding that when encountering incompatible irrelevant information decision makers invest more resources (in terms of information costs) even though that purchase does not pay overall (the frugal decision strategy yielded the highest payoff) is intriguing. Moreover, the work reported in the third article (Söllner & Bröder, 2014) demonstrates that this failure to ignore additional information is not limited to the case of intruding information that might be criticized for evoking demand effects (see section 2.2), but holds for intentionally acquired information as well. These findings support the notion of a single uniform mechanism for decision making that incorporates all applicable information – as assumed by the connectionist network framework as well as the evidence accumulation framework. This conclusion concurs with Bröder and Newell’s (2008) conclusion that the *integration* of information does not seem to be as costly as assumed by the multiple strategy framework. In line with our findings, recent studies have gathered further support for the idea of automatic information integration within a uniform mechanism (Betsch, Lang, Lehmann, & Axmann, 2014; Dorrough, Glöckner, Betsch, & Wille, 2014).

Before giving an outlook to future research questions, I would like to summarize my main conclusions drawn from the work presented herein: (1) Automatic (compensatory) information integration can be observed for multi-attribute decisions from given information, when information search is reduced to a minimum (Söllner et al., 2013). This conclusion concurs with Gigerenzer and colleagues’ (2012) conjecture that “If an experiment eliminates search by presenting all pieces of information simultaneously, participants may readily perform some cognitive integration of all or most of the cues presented” (p. 244). Interestingly, according to our results, simultaneous presentation of information (as also assumed by Glöckner & Betsch, 2008b) is not sufficient: Information search has to be reduced to a minimum. The question, however, which framework accounts best for decisions from given information that necessitate information search, was not central to this investigation (Söllner et al., 2013) and cannot be answered based on the data collected. In the article we argued in favor of the multiple strategy framework, but the data patterns might equally well be accounted for by a further specified component model (Betsch & Glöckner, 2010) or by an evidence accumulation account respectively. (2) Decision makers do not ignore additional information, but seem to automatically integrate it as they vary their behavior (choice outcomes, information search, confidence judgments) in accordance to its content. This finding does not comply with the notion of selecting a certain decision strategy to be continuously employed for a specific task (multiple strategy framework), but supports the idea of a single uniform mechanism as proposed by the connectionist network framework[16] and the evidence accumulation framework. (3) Stopping behavior is dependent on the level of evidence given and inter-individually diverse – much more than predicted by the stopping rules (currently) incorporated in the multiple strategy framework. This finding lends further support to the adequacy of the evidence accumulation framework to describe multi-attribute decision making.

3.2 Outlook

I would like to conclude this thesis with an outlook to future research questions. The first suggestions are most directly related to the work presented herein, concentrating on the adequacy of the different frameworks to describe multi-attribute decision making from given information. The concluding ones broaden the focus to briefly address the initially excluded adjacent research areas in multi-attribute decision making: decisions from memory and prescriptive analyses.

Especially the articles contrasting the different frameworks of multi-attribute decision making (Söllner et al., 2014, and Söllner & Bröder, 2014) suggest that the multiple strategy framework cannot (easily) account for some empirical findings and might therefore offer a too simple description of human decision making. However, the alternative frameworks superiorly accounting for the empirical data necessitate

[16] Note, however, that information search predictions are rather difficult to derive for the connectionist network framework as the process of information search is not formally modeled.

theoretical development in (at least) two directions: (1) The process of information search is not formally modeled within PCS – the model representing the connectionist network framework of multi-attribute decision making. I believe that extending PCS to formally model the links between the information integration connectionist network and the deliberate information search strategies (as assumed by the component model, Betsch & Glöckner, 2010) constitutes an essential next step to further disentangle the different frameworks. (2) The evidence accumulation framework accounted very well for the empirical data presented herein. An essential next step within this framework mirrors the strategy selection problem discussed for the multiple strategy framework: The question, how the parameter values are adapted, has to be answered. Of course, some work in this direction has been done already (e.g., Hausmann-Thürig, 2004; B. R. Newell & Lee, 2009) and some ideas developed within the multiple strategy framework can probably be transferred to the evidence accumulation framework (e.g., concerning the role of learning, Rieskamp & Otto, 2006). Nonetheless, further research is needed to comprehensively address this current shortcoming. Furthermore, it will be important to also disentangle the connectionist network framework and the evidence accumulation framework (see, e.g., Glöckner, Heinen, Johnson, & Raab, 2012; Tsetsos, Usher, & Chater, 2010) – as in the work presented in this thesis the multiple strategy framework constituted the comparison standard for each of the alternative frameworks.

In a broader sense, one might consider two further vital research areas within multi-attribute decision making (see paragraphs 1.1.1 and 1.1.2) as potentially promising for future investigations: decisions from memory and prescriptive analyses. Multi-attribute decisions from memory have, for example, recently been addressed by Platzer (2013), concentrating on the multiple strategy framework and exemplar-based models (Juslin, Olsson, & Olsson, 2003; Juslin & Persson, 2002; Persson & Rieskamp, 2009). In her work, however, Platzer complemented the multiple strategy framework with exemplar-based decision making (cf. the discussion on PCS' status in relation to the multiple strategy framework, section 3.1). Shifting the focus to a framework comparison and broadening it to also include connectionist network models (Glöckner & Bröder, 2014; Glöckner & Hodges, 2011) and evidence accumulation models (e.g., Diederich, 1997) constitutes an important research topic that has not been addressed so far. One reason for this shortcoming is evident: The empirical challenge encountered when aiming to disentangle the frameworks for decisions from given information might seem negligible when switching to decisions from memory. Still, maybe novel approaches to trace information search in memory (e.g., Khader et al., 2013; Renkewitz & Jahn, 2012, but see also Bröder & Gaissmaier, 2007) or clever research paradigms (as I hope to have presented in this thesis) will contribute to successfully tackle this immense empirical challenge in the future.

Interestingly, the prescriptive aspect of multi-attribute decision making, in my view, does not need extensive additional work in regard to the introduced frameworks. Within the multiple strategy framework, the adaptive toolbox approach (Gigerenzer & Todd, 1999) constituted a vital development by arguing (and showing) that simple heuristics can be (at least) as accurate as more complex decision strategies (e.g., Czerlinski et al., 1999; Gigerenzer & Brighton, 2009; Gigerenzer & Goldstein, 1996; Hogarth & Karelaia, 2006; Martignon & Hoffrage, 1999). The underlying idea of adaptation to environmental characteristics, however, is not universal to the multiple strategy framework, but (potentially) also part of connectionist network models and evidence accumulation models (see, e.g., Glöckner et al., 2014) that can adjust their parameters adaptively. As has been argued before, the question *how* these parameters are adjusted constitutes a theoretical challenge for the single-process frameworks just as the strategy selection problem continues to challenge the multiple strategy framework.

In sum, the work presented in this thesis aimed to contrast different frameworks of multi-attribute decision making from given information. The empirical challenge emerging from the mimicking relationship between the multiple strategy framework and the single-process frameworks was tackled in different ways in this thesis' three articles. The reported superiority of the single-process frameworks to describe decision behavior in multi-attribute decision tasks challenges the popular multiple strategy view, but at the same time demands further theoretical development of the single-process frameworks.

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APPENDIX: COPIES OF ARTICLES

(1) Söllner, A., Bröder, A., & Hilbig, B. E. (2013). Deliberation versus automaticity in decision making: Which presentation format features facilitate automatic decision making? *Judgment and Decision Making*, *8*(3), 278–298.

(2) 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.

(3) Söllner, A. & Bröder, A. (2014). *Toolbox or adjustable spanner? A critical comparison of two metaphors for adaptive decision making*. Manuscript submitted for publication.

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Deliberation versus automaticity in decision making: Which presentation format features facilitate automatic decision making?

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Abstract

The idea of automatic decision making approximating normatively optimal decisions without necessitating much cognitive effort is intriguing. Whereas recent findings support the notion that such fast, automatic processes explain empirical data well, little is known about the conditions under which such processes are selected rather than more deliberate stepwise strategies. We investigate the role of the format of information presentation, focusing explicitly on the ease of information acquisition and its influence on information integration processes. In a probabilistic inference task, the standard matrix employed in prior research was contrasted with a newly created map presentation format and additional variations of both presentation formats. Across three experiments, a robust presentation format effect emerged: Automatic decision making was more prevalent in the matrix (with high information accessibility), whereas sequential decision strategies prevailed when the presentation format demanded more information acquisition effort. Further scrutiny of the effect showed that it is not driven by the presentation format as such, but rather by the extent of information search induced by a format. Thus, if information is accessible with minimal need for information search, information integration is likely to proceed in a perception-like, holistic manner. In turn, a moderate demand for information search decreases the likelihood of behavior consistent with the assumptions of automatic decision making.

Keywords: decision strategy, information search, parallel constraint satisfaction, strategy selection.

1 Introduction

Making good decisions can be a challenge—it is often subjectively effortful, time-consuming, and appears to nudge us to the limits of our cognitive capacity. Typically, it is taken for granted that the normative standard of decision making—the weighing and adding of all available information—may be the most accurate way forward, but that it also bears the largest costs in terms of time and effort (Payne, Bettman, & Johnson, 1993). Therefore, some have deemed the actual application of such a complex strategy by default rather unlikely and argued for shortcut strategies (*heuristics*, Gigerenzer, Todd, & the ABC Research Group, 1999). However, the necessity of resorting to simplifying strategies hinges on the assumption of effortful, serial, and deliberate information processing—an assumption that may well be limited to certain circumstances. Under other conditions, one might expect largely automatic and thus mostly effortless information processing which, in turn, would allow for relying on complex strategies without imposing severe costs.

In the present work, we focus on the format of information presentation as one possible key determinant of more or less automatic—as opposed to effortful stepwise—decision making. As such, we intend to provide evidence for automatic decision making, thus broadening the focus of traditional research by considering automatic processes as a plausible further strategy in the well-established multiple strategy approach. More importantly, we aim to specify the strategy selection conditions of automatic decision making, that is, the presentation format features that elicit it. More generally, the current work investigates aspects of the task environment that facilitate automatic decision making. Thus, if real-world environments can be structured correspondingly, it might be possible to achieve a high prevalence of normatively optimal decisions without necessitating too much time and effort.

In this paper, we report three experiments that contrast the classic *matrix* with an alternative presentation format. While the first experiment concentrates on this comparison only, the second experiment examines two main features of the respective presentation formats for their influence on strategy selection. The final third experiment investigates one of these features—the extent of information search—more closely within the matrix presentation format.

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1.1 Multi-attribute decision tasks

In multi-attribute decision tasks, decision makers choose from a set of options, each of which is described by values of the same set of attributes. The decision is made with respect to a certain criterion that can either be a subjective one (like personal preference) or an objective criterion (like e.g., size of cities or turnover of enterprises). When the available attributes are predictive of a categorical criterion to some (imperfect) degree, the latter type of multi-attribute decision task is called a *probabilistic inference task*.

With regard to their content, probabilistic inference tasks can vary remarkably (Czerlinski, Gigerenzer, & Goldstein, 1999). In previous research, the City-Size task (Gigerenzer, Hoffrage & Kleinbölting, 1991) has frequently been employed (e.g., Bröder & Eichler, 2006; Gigerenzer & Goldstein, 1996; Glöckner & Bröder, 2011; Horstmann, Ahlgrimm, & Glöckner, 2009). Here, a decision maker typically is faced with the task to infer which of two cities (options) has more inhabitants (decision criterion). Given no prior knowledge about options, the decision maker is informed about the presence versus absence (value) of different cues (attributes). These cues could be whether a city has an international airport, an opera house, an international fair, or a zoo. Additionally, the decision maker is informed about (or learns) the validity of the different cues, that is, how well each can predict the criterion.

1.2 Two approaches to describe decision making

To explain how decision makers solve these probabilistic inference problems, different approaches have been proposed. One obvious way to address these tasks would be to deliberately perform a sequence of elementary information processes (EIPs) as proposed by Payne et al. (1993). Different combinations and sequences of these EIPs are called *decision strategies*. Though these different decision strategies differ in several aspects, they all share the basic assumption of decision making as a sequential, stepwise process.

1.2.1 Multiple strategy approach

Research on probabilistic inferences (e.g., Bröder & Schiffer, 2003b; Gigerenzer & Goldstein, 1996; Glöckner, 2009) has often focused on three prototypical EIP-based decision strategies: the "Weighted Additive Rule" (WADD), the "Equal Weight Rule" (EQW, Dawes, 1979), and the "Take-The-Best"-heuristic (TTB, Gigerenzer & Goldstein, 1996). While a decision maker using WADD considers and integrates all available information (cue values and validities) in a weighted-additive manner, an EQW user ignores the validities by weighing all cues equally. For both strategies, the absence of a cue can be compensated by the presence of others. This is not the case for TTB which considers the information cue by cue in decreasing order of validity. As soon as a cue discriminates between options, the decision maker stops the information search and chooses the option that is favored by the most valid discriminating cue—ignoring all other information.

Although the sequence and amount of EIPs differs considerably between the introduced strategies (WADD, EQW, and TTB), all three of them rest upon the notion of stepwise, sequential information processing. Though these processes are often interpreted as being deliberate (e.g., Gigerenzer & Todd, 1999), that is no necessary presumption (Gigerenzer, 2007; 2008).

1.2.2 Parallel Constraint Satisfaction (PCS)

The basic assumption of effortful, sequential decision making shared by EQW, TTB, and WADD is not part of all models that apply for multi-attribute decision tasks (for overviews see Evans, 2008; Gilovich, Griffin, & Kahneman, 2002; Glöckner & Witteman, 2010). The parallel constraint satisfaction (PCS) model for probabilistic inferences (Glöckner & Betsch, 2008a), which conceptualizes decision making as an automatic, parallel process, is one of these alternative models. Information integration in the PCS network model is not limited by the cognitive costs assumption made by the multiple strategy approach. Instead, Glöckner and Betsch (2008a, 2012) postulate that automatic processing in the PCS network requires only a minimum of cognitive resources for mimicking a fast weighted addition of all available information (Glöckner, 2010).

The basis of the PCS model is a network of cue- and option-nodes that are interlinked. Through an iterative, parallel process (spreading of activation) the network maximizes consistency under parallel consideration of all constraints. As soon as the network passes a certain consistency threshold, the iterative process terminates and the option with the highest positive activation level is chosen.

According to Glöckner and Betsch (2008a), decision makers create the aforementioned network spontaneously and automatically when confronted with a decision problem. In this network, all available and applicable pieces of information are incorporated. Here, the authors draw a parallel to the basic idea of Gestalt psychology (e.g., Köhler, 1947) that the mental system automatically strives to maximize consistency by forming mental representations ("Gestalten") in a holistic process. Glöckner and colleagues (Glöckner & Betsch, 2012; Glöckner & Hodges, 2011) describe this process, that automatically captures the initial constellation of information, to be comparable to processes of perception.

1.3 Strategy selection

Adopting the view of the multiple strategy approach that people are equipped with a repertoire of different decision strategies, the strategy selection problem arises: How does the decision maker determine which strategy to choose? Payne et al. (1993, see also Beach & Mitchell, 1978) argued that strategy selection can be viewed as a tradeoff between (cognitive) effort and accuracy. This approach has been criticized for several reasons, the main concerns being (1) the necessity of a meta-calculus deciding how to decide (Glöckner & Betsch, 2008a; Rieskamp & Otto, 2006) and (2) the assumption that high accuracy is inevitably associated with increased effort (Gigerenzer & Goldstein, 1999; Gigerenzer & Gaissmaier, 2011). Subsequently, some authors (e.g., Bröder & Schiffer, 2006a; Rieskamp & Otto, 2006) investigated the central role of learning in strategy selection, whereas other investigations concentrated on monitoring the influence of different task features on strategy selection (e.g., time pressure, Rieskamp & Hoffrage, 1999; working memory capacity, Bröder & Schiffer, 2003a; salience of cue information, Platzer & Bröder, 2012). Marewski and Schooler (2011) observed that the strategy selection problem is frequently resolved by the fact that sometimes only one specific strategy (or at most a small set of strategies) is applicable or afforded. In their *cognitive niche framework* Marewski and Schooler (2011) assume that strategy selection follows a cost-benefit-tradeoff only if more than one strategy can be applied. Hence, according to this framework, the task environment already constrains the set of applicable strategies, thus facilitating cost-benefit selection between the remaining ones.

Glöckner and Betsch (2008a) avoid the strategy selection problem by assuming only one uniform mechanism (namely, PCS) instead of a repertoire of different strategies (see also Lee & Cummins, 2004, for an alternative unifying model). However, we deem it sensible to treat the PCS model as if it belongs to the humane repertoire of decision strategies for several reasons: (1) Proponents of the PCS model repeatedly treated it themselves as if it was one of several applicable strategies by contrasting it with the different decision strategies instead of the multiple strategy approach as a whole (e.g., Glöckner & Betsch, 2008b; Glöckner & Hodges, 2011; Horstmann et al., 2009). (2) Some evidence from these investigations suggests that the PCS model cannot successfully account for decision making under certain constraints (i.e., inferences from memory, Glöckner and Hodges, 2011; forced sequential information search, Glöckner & Betsch, 2008b). (3) Despite PCS's notion of parallel information integration, Bröder and Gaissmaier (2007) found evidence that people sometimes actually employ TTB in a serial manner—a finding, PCS cannot easily account for. Finally (4), even a unifying model can account for differences only by assuming different parameter values. How these are determined is a structurally similar problem to strategy selection in a multiple strategies framework.

1.4 Presentation format and strategy selection

In the course of monitoring, how different task features influence people's strategy selection (within the multiple strategy approach), the presentation format has been addressed by several authors. Bröder and Schiffer (2003b; 2006b) found that in memory-based choices, their participants seemed to employ a compensatory decision strategy (i.e., EQW or WADD) in a pictorial presentation format more often than when verbal information was presented in a matrix-like format. Here, TTB seemed to be more frequently employed. In contrast to these results, Bergert and Nosofsky (2007) observed a frequent use of TTB when information was presented in a pictorial format, whereas Newell, Collins and Lee (2007) did not find any effect of whether information was presented verbally or pictorially. As only Bröder and Schiffer's (2003b; 2006b) experiments induced considerable memory retrieval costs, Bröder and Newell (2008) conclude that the format of the stimulus material seems to have little effect as long as solving the decision problem does not burden working memory too much. Platzer and Bröder (2012) raised additional doubts concerning the importance of the format of information presentation on decision strategies: When controlling for salience in the pictorial condition, the format effect reported by Bröder and Schiffer (2003b; 2006b) disappeared. These findings suggest that not the presentation format *per se*, but the *accessibility of information*, as determined by the presentation format, influences which strategies decision makers employ.[1]

To our knowledge, it remains unclear whether the format of information presentation influences the application of PCS. In their investigations, proponents of the PCS network model have predominantly employed the matrix-like presentation format of the open information board (Glöckner & Betsch, 2008b; Glöckner & Bröder, 2011; Horstmann et al., 2009) which demands particularly little information search.[2] Here, a remarkable dominance of PCS-consistent behavior has repeatedly been

[1] In the aforementioned investigations, "automatic" decision making (PCS), was not considered. However, findings that support compensatory information integration (i.e., WADD) are also in line with PCS. The nature of the compensatory information integration process can only be assessed when further measures are taken into account.

[2] Note that the information board (Payne, 1976) is a very popular

shown. In turn, one might question whether presenting information in an open, matrix-like format is actually a necessity for PCS. Indeed, this is plausible given that one crucial pre-condition for "automatic" decision making (in line with PCS) was mentioned by Glöckner and Betsch (2008b): Sequential information search seems to impede the reliance on PCS. The authors contrasted the *open* and the *closed* (cue values are initially hidden and have to be looked up by the participant) information board and found a considerable difference in decision strategy use between the two experimental procedures (see also Lohse & Johnson, 1996). Stated briefly, sequential information search as induced by the closed information board appeared to keep participants from PCS-consistent information integration.

Combining this finding with Marewski and Schooler's (2011) cognitive niche framework, we hypothesize that PCS's applicability might be limited by the accessibility of information. When information is highly accessible, different decision strategies as well as PCS-consistent information integration are applicable. From a cost-benefit-view, the dominance of PCS-consistent behavior shown in previous studies makes perfect sense, as PCS combines high accuracy with low cognitive effort. If high information accessibility is a pre-condition for PCS-consistent behavior, task environments featuring lower information accessibility might constitute situations where the PCS model simply is not contained in the set of applicable strategies, thus leading to information integration as proposed by the multiple strategy approach instead.

1.4.1 The presentation formats of the present investigation

In the present investigation, the standard presentation format of the information board (matrix) is contrasted with an alternative presentation format. Employing the aforementioned City-Size task, this alternative presentation format should resemble the way that information about cities is often displayed to people. Thus, we decided to create a presentation format that conceptually follows the example of a common city map, where pictograms indicating the presence of certain facilities are distributed according to the geographic conditions of the respective city. In order to maximize the experimental control and minimize unintended noise (e.g., effects of salience as reported by Platzer & Bröder, 2012), the background of the map presentation format was uniform grey (instead of comprising actual buildings, streets, etc.) and the symbols representing cues present in the respective city were symbolized by letters (instead of the usual pictograms). Hence, our "map" representation is rather stylized for reasons of experimental control, but it maintains the need to search relevant cues, which is also a feature of actual maps.

Both presentation formats (*matrix* and *map*) are varied in several details across experiments in order to identify critical presentation format features that are responsible for differences in information integration processes. According to our working hypothesis, presentation formats that enable a quick and easy encoding of cue information should foster PCS-consistent processing.

1.5 Model classification with the Multiple Measure Maximum Likelihood method

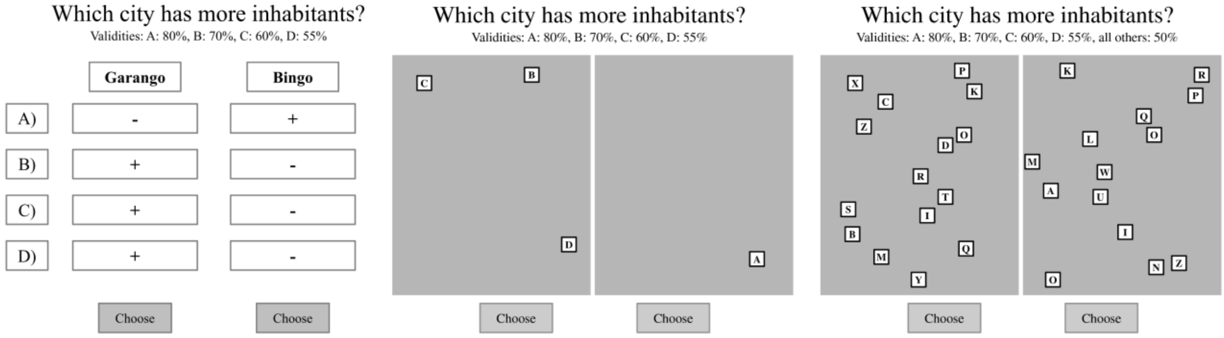
In order to investigate which decision strategy is employed by a decision maker, the observed data pattern can be compared to the predictions of the different models. The participant is classified as in favor of the model that explains the observed data pattern best. If the models differ in their predictions regarding participants' choices, the outcome-based strategy classification method (Bröder & Schiffer, 2003a; Bröder, 2010) offers one well-established and frequently employed possibility for model classification (e.g., Ayal & Hochmann, 2009; Bröder & Gaissmaier, 2007; Bröder, Newell, & Platzer, 2010; Glöckner & Betsch, 2008a). However, if two models predict exactly the same choice patterns—as WADD and PCS do for our experiments—the outcome-based classification method cannot distinguish between these models. Building on this method, Glöckner (2009; 2010; Jekel, Nicklisch & Glöckner, 2011) therefore introduced an approach that integrates choices, decision times, and confidence judgments in order to make specific predictions that are unique for each of the models. This Multiple Measure Maximum Likelihood (MM-ML) method allows to distinguish between the sequential decision strategies EQW, TTB, and WADD and the PCS model by computing a single maximum likelihood for each of the considered models (Appendix A). To control for parsimony, the Bayesian Information Criterion (BIC, Schwarz, 1978; Appendix B) is computed and used as indicator for the best fitting model.

2 Experiment 1: Examining the influence of the presentation format on decision strategy use

In the first experiment, the aforementioned presentation formats *matrix* and *map* are contrasted. In line with previous findings (Ahlgrimm, Glöckner, & Bröder, 2010,

mode of presenting information, not only employed by proponents of the PCS model, but by many others researchers as well (e.g., Ben Zur & Bresnitz, 1981; Bröder & Schiffer, 2006a; Hass & Pachur, 2011, March; Newell & Lee, 2010; Newell & Shanks, 2003; Payne, Bettman, & Johnson, 1988; 1993; Rieskamp & Hoffrage, 1999).

Figure 1: Presentation formats *Matrix* (left), *Map* (center), and *Complex Map* (right) in Experiment 1.



May; Glöckner & Betsch, 2008b; Glöckner & Bröder, 2011; Horstmann et al., 2009), we assume that behavior consistent with PCS's predictions should be highly prevalent in the matrix presentation format.

In contrast, we hypothesize that PCS-consistent behavior will be less frequently observed in the map format. Because the pieces of information are not conveniently presented in the well-organized matrix format, the decision maker needs to restructure the given information before it can be integrated. This additional task may impair the decision maker's ability to integrate the available pieces of information in a perception-like process as proposed by PCS and thus may lead to more frequent decision strategy use.

In a third condition, further irrelevant distractor features were included in the map presentation format, presumably leading to even more need for information search and restructuring. Previous research has shown that the need to (extensively) search for information influences the way people process information (for an overview see Gigerenzer, Dieckmann & Gaissmaier, 2012). Analogous to Glöckner and Betsch's (2008b) reasoning concerning the closed information board, we assume that the need to intensively search for information further impedes the use of PCS and fosters the employment of decision strategies in this map with high information costs.

2.1 Method

2.1.1 Presentation formats

This experiment used three different presentation formats as experimental conditions. Each presentation format displayed the formally identical information and employed the same decision trials.

The *Matrix* presentation format entailed an open information board (Payne et al., 1988; 1993; Figure 1, left part). The city names[3] headed the columns of the matrix and were randomly assigned to the different options. The four relevant cues were depicted on the left side of the computer screen. The letters A to D were employed as abstract cue labels in order to prevent participants from using any background knowledge. From top to bottom they were displayed in decreasing order of validity, with cue A on the top to cue D on the bottom. The presence of a cue for an option was indicated by a plus sign in the respective cell of the matrix, whereas a minus sign showed its absence.

The *Map* presentation format is shown in the middle part of Figure 1. A grey rectangle symbolized the area of each city and the presence of a cue was indicated by a letter that identified the respective cue, shown in a small white square. Thus, just as in the *Matrix* format, the cues in this presentation format were kept in an abstract form with the letter A indicating the most valid cue and the letter D specifying the least valid one. Following the example of a city map, the absence of a cue in a city was indicated by not-displaying it on the city area. The squares symbolizing the present cues were distributed randomly across the grey area.

For the *Complex Map* format, distractor cues were added to the map in order to increase information costs for the participants (Figure 1, right part). Ten to 14 of the letters I to Z were presented in random distribution across the city area. Participants were explicitly told that all these additional letters (except the letters A to D that symbolize the four relevant cues) indicated cues with the chance validity of .50 and thus yield no relevant information for their decision.

2.1.2 Design and procedure

In each decision trial of the experiment, participants were presented with two fictitious cities described by four binary cues and asked to choose the option that probably

[3]To ensure that participants could not employ any background knowledge, the names of Burkina Faso's departments were employed as city names.

has more inhabitants. After indicating the decision, participants provided a corresponding confidence judgment. In each trial, choice, decision time, and confidence judgment were recorded.

Each experimental condition comprised 70 decision trials presented in random order. In order to enable an optimal decision strategy classification with the MM-ML method, the six diagnostic pairs (cue value patterns) proposed by Glöckner (2009) were employed (Appendix C). Each pair was presented ten times—each option displayed five times on the left side and five times on the right side of the computer screen. In addition to these 60 decision trials relevant for the strategy classification, ten filler trials[4] were included in each experimental condition.

As this experiment incorporated a pure within-subjects design, each participant completed all experimental conditions. The set-up of each experimental condition was held constant: After the initial instructions the participant worked on five practice trials which could be repeated optionally. Another short instruction followed before the 70 decision trials were presented. Between the three experimental conditions (presentation format blocks), breaks (at least 2.5 minutes) were included. The order of the three presentation format blocks was counter-balanced across the participants.

2.1.3 Hypotheses

As the open information board displays all applicable pieces of information conveniently to the decision maker, information should be easy to access and information integration compatible with PCS's predictions should be highly prevalent in the *Matrix* presentation format. This would be in line with previous studies (Ahlgrimm et al., 2010, May; Glöckner & Betsch, 2008b; Glöckner & Bröder, 2011; Horstmann et al., 2009). Since the *Map* presentation format requires restructuring the available information in order to make a decision, we assume that PCS-consistent behavior will be impaired and thus less prevalent in this alternative presentation format. Here, sequential decision strategies should be employed more frequently than in the *Matrix* presentation format. Further, we assume that this effect should also be true—and possibly more pronounced—for the comparison between *Complex Map* and *Matrix* —even if it cannot be found for the simple *Map*.

[4]The filler trials were meant to detract people from the fact that the same six diagnostic pairs were repeatedly tested. Furthermore, they should prevent people from employing a simplifying "take-the-option-favored-by-cue A" strategy that seemed sensible in face of the exclusivity of the cues inherent in the six diagnostic pairs of Experiment 1.

2.1.4 Participants

Eighty-three students of the University of Mannheim participated in the experiment (70 female, mean age 21.5). They received course credit for their participation.

2.1.5 Model predictions and classification

For a model classification with the MM-ML method, predictions for the models under consideration and each of the six diagnostic pairs (cue value patterns: Appendix C) were derived for three dependent measures: Choices, decision times, and confidence judgments. The exact steps for deriving the model predictions are described by Glöckner (2010). Appendix D displays the predictions for all models, diagnostic pairs and dependent measures for Experiment 1 as they can also be found in Glöckner (2009).

In line with Bröder's (2000) recommendation, we tested a corrected version of WADD that assumes that participants correct their decision weights for the fact that cues with a validity of .50 predict the decision criterion only with chance probability (w = v–.50, see Glöckner & Betsch, 2008b; Glöckner, 2009). Following Glöckner's (2009; 2010) procedure, we also included a simple guessing strategy *Random*.

We conducted the model classification with the MM-ML method using the free software R and the code provided by Jekel et al. (2010). In order to control for occasional inattentiveness of participants, we replaced decision time outliers (more than 3 SD above the participant's mean decision time) with the median decision time of the participant for the respective diagnostic pair. As suggested by Jekel et al. (2010), decision times were log-transformed. In order to control for learning effects, decision time residuals were used after partialing out the trial number. If the estimated choice error rate ε_k for the best-fitting model was $\geq .40$ the respective participant was not classified and excluded from further analyses (Bröder & Schiffer, 2003b).[5]

2.2 Results and discussion

Table 1 (upper part) shows the results of the MM-ML model classification for each presentation format. In line with our hypothesis, PCS-consistent behavior was frequently found in the *Matrix* (47 participants), but only rarely in the *Map* (18 participants) and in the *Complex*

[5]Furthermore, we assessed the absolute model fit for choices as suggested by Moshagen and Hilbig (2011). As the general patterns remained stable for all three experiments, we do not report the detailed results of these analyses.

Map (17 participants). For the decision strategies (EQW, TTB, and WADD) the opposite pattern was observed: frequent use in the *Map* (65 participants) and the *Complex Map* (64 participants) presentation format, but low prevalence in the *Matrix* (36 participants).

To test our format hypothesis, the presentation formats *Matrix* and *Map* were compared first. The McNemar test (McNemar, 1947) for dependent samples showed a significant effect in the predicted direction: $\chi^2(1, N = 83) = 19.56$, $p < .001$. The conditional Odds ratio (*OR*) was 5.14 in the sample. When the presentation formats *Matrix* and *Complex Map* were compared, a significant effect in the predicted direction was observed: $\chi^2(1, N = 81) = 20.51$, $p < .001$, $OR = 5.83$. No differences could be found between the presentation formats *Map* and *Complex Map*: $\chi^2(1, N = 81) = 0.05$, $p = .82$. Thus, PCS-compatible behavior was much more prevalent in the *Matrix* presentation format than in the *Map* and the *Complex Map*, whereas the latter two presentation formats (*Map* and *Complex Map*) did not differ from each other.

However, we found differences between the simple *Map* and the *Complex Map* concerning the sequential strategies: Taking into account only participants who were classified as being either TTB- or WADD-users in both newly established presentation formats, the McNemar test showed a significant effect: $\chi^2(1, N = 53) = 7.14$, $p = .01$, $OR = 6.00$. Thus, a strategy shift between these two decision strategies was found: When information costs are increased (*Complex Map*), the fast and frugal heuristic TTB is more prevalent whereas the more complex WADD strategy decreases in prevalence. This result confirms earlier findings on the influence of information costs (Bröder, 2000; Lee & Cummins, 2004) and indicates that information costs can effectively be manipulated via distracters that make information search time-consuming. High information search demands lead to a more frequent use of heuristics like TTB (Gigerenzer et al., 2012).

Our hypothesis is supported by these results: The PCS model could describe the behavior of the majority of participants in the *Matrix* (i.e., open information board) best. By contrast, behavior in the alternative *Map* and *Complex Map* presentation formats was typically best accounted for by decision strategies' prediction of sequential information processing. Thus, the format in which the formally identical information is presented to participants profoundly influences how the information is processed and integrated. This effect is not limited to alternative formats that impose considerably high information costs (*Complex Map*).

3 Experiment 2: Examining two presentation format features: Information search and negative cue value presentation

Experiment 1 found a substantial difference in information processing between two different presentation format conditions. In the classic matrix-like presentation format of the open information board, behavior consistent with PCS's predictions was much more prevalent than in an alternative presentation format that resembles a city map. As this constitutes a novel finding in regard to PCS, the first goal of Experiment 2 is to replicate this basic result.

However, even if the difference in information processing found in Experiment 1 can be replicated, the question remains, what feature of the presentation format facilitates (or hinders) PCS-consistent computation. The two presentation formats employed in Experiment 1 differ from each other in several aspects. Two important differences are (1) whether negative cue values are explicitly displayed or need to be inferred and (2) whether information search is necessary or reduced to a minimum. In the *Matrix* presentation format, positive and negative cue values are displayed and information search demands are low, whereas in the *Map* negative cue values have to be inferred and the information about the presence of the cues is randomly distributed (spatially), which increases information search effort.

Theoretically, both presentation format features could influence the ease with which a PCS network as postulated by Glöckner and Betsch (2008a) can be generated. According to our working hypothesis, the need to search and recode information due to reduced information accessibility may impair the spontaneous generation of the proposed PCS network. Therefore, the preferred "automatic" decision making might not be applicable here, and decision makers are left to employ one of the remaining decision strategies for information integration.

First, if negative cue values are not displayed, information is incomplete at the first glance and has to be recoded before it can be processed further. The decision maker has to infer from the absence of positive cue values that the cue value for the respective cue must be negative. We hypothesize that this additional step of recoding might hinder the spontaneous generation of the proposed PCS network and thus foster step-wise information integration as postulated by multiple strategy approach instead. Hence, behavior consistent with one of the decision strategies TTB, EQW, and WADD is more frequently observed when negative cue values are not dis-

Table 1: Model classification for Experiments 1 to 3.

		Model classification						
Exp.	Presentation format	EQW	TTB	WADD	PCS	Random	Unclassified*	Total
1	Matrix	2 (2%)	12 (14%)	22 (27%)	47 (57%)	0 (0%)	0 (0%)	83
	Map	1 (1%)	22 (27%)	42 (51%)	18 (22%)	0 (0%)	0 (0%)	83
	Complex Map	0 (0%)	31 (37%)	33 (40%)	17 (20%)	2 (2%)	0 (0%)	83
2	Matrix	20 (19%)	12 (11%)	19 (18%)	57 (53%)	0 (0%)	0 (0%)	108
	Map	16 (15%)	20 (19%)	43 (40%)	29 (27%)	0 (0%)	0 (0%)	108
	Fixed Map	5 (14%)	8 (22%)	10 (28%)	13 (36%)	0 (0%)	0 (0%)	36
	Negative Map	12 (34%)	3 (9%)	9 (26%)	9 (26%)	0 (0%)	2 (6%)	35
	Negative Fixed Map	7 (19%)	4 (11%)	12 (32%)	13 (35%)	0 (0%)	1 (3%)	37
3	adjusted Matrix	0 (0%)	3 (8%)	7 (18%)	30 (75%)	0 (0%)	0 (0%)	40
	Map	0 (0%)	10 (25%)	16 (40%)	14 (35%)	0 (0%)	0 (0%)	40
	Random Row Matrix	1 (3%)	4 (10%)	20 (50%)	15 (38%)	0 (0%)	0 (0%)	40
	Random Display Matrix	0 (0%)	4 (10%)	19 (48%)	14 (35%)	0 (0%)	3 (8%)**	40

Note. EQW: "Equal Weight Rule", TTB: "Take-The-Best"-heuristic, WADD: corrected "Weighted Additive Rule", PCS: "Parallel Constraint Satisfaction".

* Choice error rate $\varepsilon_k \geq .40$.

** One of these three unclassified participants was excluded, because this person indicated that he or she did not comprehend the confidence judgment instruction properly.

played to the decision maker and have to be inferred.

Second, the increase in information search (that was induced in the *Map* format) might have hindered PCS-consistent behavior. Gigerenzer et al. (2012) highlighted the important role of information search as a vital determinant for decision making processes. Although Gigerenzer et al. (2012) focus on the shift from compensatory decision strategies to heuristics like TTB due to high information search demands, the basic principle can be adapted for our research focus: The way people process and integrate information depends on the extent of information search imposed by the environment. Building on Glöckner and Betsch's (2008b) observation that forced sequential information search in the closed information board reduces PCS-consistent behavior, we suggest that not only this particular mode of information search induction, but increased information search costs *per se* might hinder the generation of the postulated PCS network. If therefore "automatic" decision making is not applicable anymore, decision strategies have to be employed more frequently.

Thus, in Experiment 2, both presentation format features are manipulated within the original *Map* presentation format of Experiment 1. We assume that displaying negative cue values and minimizing information search requirements facilitate the spontaneous generation of the mental network proposed by the PCS model. If "automatic" decision making is applicable, it will be observed frequently.

A side issue that will also be addressed in Experiment 2 concerns one finding of Experiment 1 that was not discussed so far. Especially in the *Map* presentation format, but also in the *Matrix* the lack of participants using EQW was surprising. Simply counting the number of squares (*Map*, Figure 1, middle part) or pluses (*Matrix*, Figure 1, left part) seems an obvious and easy-to-apply strategy that should be chosen by at least some participants. However, only 1.2% of the strategy classifications of Experiment 1 favored EQW as the most probable decision strategy. Experiment 2 will test the idea that EQW was employed so rarely in Experiment 1 because this strategy predicts guessing for four of the six diagnostic pairs. Thus, participants who strive to use efficient strategies might have abstained from using this strategy, simply because it rarely favored one option over the other in this specific environment.

3.1 Method

3.1.1 Presentation formats

In this experiment, the two presentation formats *Matrix* and *Map* from Experiment 1 (Figure 1, left and center) were presented to all participants. Additionally, we introduced three presentation formats as variations of the original *Map* presentation format. In these new conditions, two presentation format features were systematically manipulated: (1) whether negative cue values are displayed or not and (2) the extent of information search induced by the spatial distribution of cue values.

In the first new map[6] (*Negative Map*, Figure 2, left part) negative cue values are displayed as white letters in black squares and positive cue values as black letters in white squares. The cue values are randomly distributed across the grey rectangles that symbolize the city area. Thus, this presentation format differs from the *Map* and resembles the *Matrix* insofar as it eliminates the need to actively infer negative values. Importantly, it still requires search of the cues.

The second new map (*Negative Fixed Map*, Figure 2, middle part) has negative and positive cue values displayed and in addition, information search is reduced, because each cue appears only in its own quarter of the rectangle symbolizing the city area: The most valid cue A in the upper left, cue B in the upper right, cue C in the lower left, and the least valid cue D in the lower right quarter. Correspondingly, the *Negative Fixed Map* differs from the *Map* and resembles the *Matrix* on both considered presentation format features: Negative cue values are displayed, and information search is reduced.

In the third new map (*Fixed Map*, Figure 2, right part) only positive cue values are displayed, whereas negative cue values have to be inferred from the absence of the respective cue on the city area. Information search is reduced, because each cue only appears in its respective quarter. Thus, the presentation format *Fixed Map* differs from the *Map* and resembles the *Matrix* in respect to the reduced information search.

3.1.2 Design and procedure

The design of Experiment 2 closely resembled the one of Experiment 1. Each participant worked on three different presentation formats, interspersed with breaks of at least 2.5 minutes length. Two important changes were made in comparison to Experiment 1—one concerned the formats used (see above) and the other related to the diagnostic pairs. For each presentation format, seven diagnostic pairs were tested ten times—each one five times with one option on the left side of the screen and five times with this option on the right side. The diagnostic pairs were chosen in respect to two goals: The diagnostic pairs should be able to differentiate between the considered models, and EQW should predict guessing in only few cases. Therefore, four new diagnostic pairs plus the diagnostic pairs 1, 3, and 6 from Experiment 1 were selected (Appendix E). For these seven diagnostic pairs EQW predicts guessing only in one case (see Appendix F for the complete model predictions).

In terms of experimental design, we manipulated the presentation format within and between participants: Each participant completed the original presentation formats *Matrix* and *Map* from Experiment 1 (Figure 1, left and center). The third presentation format for the participants was one of the three new maps (*Fixed Map*, *Negative Map*, and *Fixed Negative Map*)—each one completed by about one third of the total sample.

3.1.3 Hypotheses

Hypothesis 1: Replicating the findings of Experiment 1, we predict that PCS-consistent behavior is more often found in the *Matrix* presentation format than in the (original) *Map*. Correspondingly, behavior best described by one of the decision strategies TTB, EQW, and WADD should be more prevalent in the *Map* presentation format than in the *Matrix*.

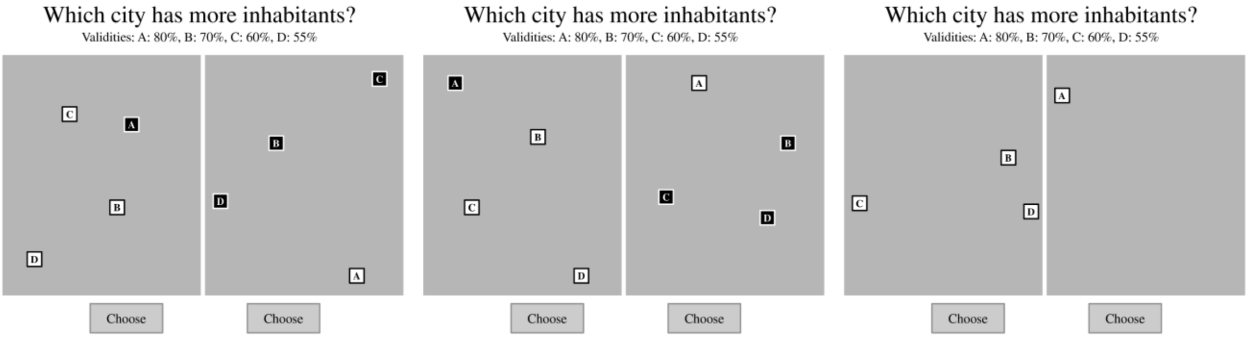
Hypothesis 2: Building on the presentation format effect found in Experiment 1, we assume that displaying negative cue values facilitates behavior compatible with PCS, whereas the need to infer negative cue values fosters the use of decision strategies instead.

Hypothesis 3: In Experiment 1, PCS was more prevalent in the *Matrix* presentation format (minimal information search) than in the Map (increased information search). We hypothesize that minimal information search facilitates PCS-consistent behavior, whereas the need to search for information leads to more frequent use of decision strategies.

Hypothesis 4: In Experiment 2, diagnostic pairs are employed for which EQW predicts guessing only in 14.29% of all cases, whereas for the diagnostic pairs used in Experiment 1 this strategy predicted guessing in two thirds of all cases. We assume that participants employ the principally useful EQW more often in this environment, now that it predicts guessing only rarely.

[6]Note that the characterization as a "map" is only used for reasons of convenience here. Of course, the resemblance to common maps decreases with the current manipulations, as common maps only contain positive information—though this could, in theory, include information that is negatively related to the criterion. In any case, the main aim of this manipulation was not to approximate a realistic map-reading scenario, but to scrutinize potential reasons for the differences between the matrix and the original map representation.

Figure 2: Presentation formats *Negative Map* (left), *Negative Fixed Map* (center), and *Fixed Map* (right) in Experiment 2.



3.1.4 Participants

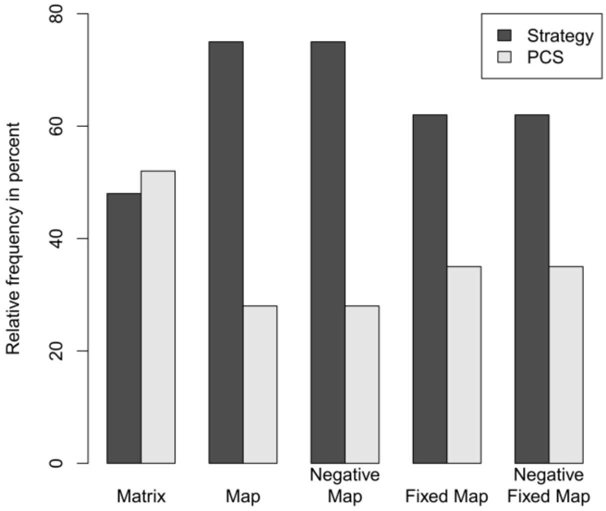
In this experiment, 108 participants took part (73 female, mean age 21.42). Most of them (107) were students from the University of Mannheim. For their participation, 93 participants received course credit, 15 participants received monetary compensation.

In order to replicate the basic presentation format effect of Experiment 1, all participants completed both the *Matrix* and the *Map* presentation format. 35 of them were also tested in the *Negative Map* condition, 36 completed the *Fixed Map* presentation format, and 37 were confronted with the *Negative Fixed Map* condition. The presentation order of the three presentation format blocks (*Matrix*, *Map*, plus one the aforementioned additional maps) was counter-balanced across all participants.

3.1.5 Model predictions and classification

As in Experiment 1, model classification was carried out with the MM-ML method. Thus, choices, decision times, and confidence judgments were again recorded for each trial. Data were transformed and exclusion criteria set exactly as in Experiment 1.

Figure 3: Relative frequencies of decision strategy (TTB, EQW, or WADD) or PCS-consistent behavior in Experiment 2. The N for each of the presentation formats Matrix and Map is 108, whereas the total N of the remaining three presentation formats sums up to 108 as well (between-subjects manipulation).



3.2 Results and discussion

Table 1 (middle part) shows the result of the model classification with the MM-ML method. In line with Hypothesis 1, PCS was more often classified in the *Matrix* (57 participants) than in the *Map* (29 participants), whereas decision strategy use (EQW, TTB, or WADD) was more frequent in the *Map* (79 participants) than in the *Matrix* (51 participants) presentation format. Figure 3 shows the relative frequencies for all presentation formats of Experiment 2.

Employing the McNemar test for dependent samples, the comparison of the presentation formats *Map* and *Matrix* showed a significant effect in the direction assumed under Hypothesis 1: $\chi^2(1, N = 108) = 20.63$, $p < .001$, *OR* = 6.60. Thus, the result of Experiment 1 was replicated in this experiment: PCS-consistent behavior was more prevalent in the *Matrix* presentation format, whereas behavior compatible with one of the decision strategies was found more often in the *Map*.

In order to test the importance of the presentation format effect of whether or not negative cue values are displayed (Hypothesis 2), one can (a) compare the maps with fixed cue orders with each other or (b) contrast the maps with random cue distribution with each other. The first comparison (a) showed no difference between the *Fixed Map* and the *Negative Fixed Map*: $\chi^2(1, N = 72) = 0.00$, $p = 1.00$. For the within-subjects comparison between the *Negative Map* and the (original) *Map* (b), the McNemar test was not significant ($\chi^2(1, N = 33) = 0.20$,

p = .66). According to these results, the presence/absence of negative cue values did not influence the information integration process.

The relevance of the extent of information search induced by the presentation format (Hypothesis 3) can be investigated with two comparisons: Comparing the maps with each other (c) where negative and positive cue values are displayed or (d) where only the positive cue values are displayed in both maps. Though for the first comparison (c) between the *Negative Map* and the *Negative Fixed Map* the assumed shift could be observed descriptively, it was not significant ($\chi^2(1, N = 69) = 0.62$, p = .43). The second within-subjects comparison (d) between the *Fixed Map* and the (original) *Map* confirmed this finding: $\chi^2(1, N = 36) = 0.50$, p = .48. Thus, reduced information search did not significantly facilitate PCS-consistent behavior. We did not find support for Hypothesis 3: The extent of information search—as manipulated in Experiment 2—does not seem to influence whether "automatic" decision making is frequently observed or not.

Hypothesis 4 deals with the side issue whether the frequency of EQW use depends on the nature of the diagnostic pairs presented to the participants. We predicted that EQW use should be more prevalent when this strategy predicts guessing only in few cases, as was the case in the current environment. In line with this assumption, we found that 18.52% of all data sets collected in Experiment 2 were classified as being best described by EQW. This result is supported by two cross-experimental comparisons between the identical conditions (presentation formats) of Experiments 1 and 2: When EQW is contrasted with all other strategies pooled into one category, the difference in EQW use between Experiments 1 and 2 is significant for the presentation format *Matrix* ($\chi^2(1, N = 191) = 11.95$, p = .001, w = 0.25) and for the *Map* presentation format ($\chi^2(1, N = 191) = 10.72$, p = .001, w = 0.24). Thus, the choice of the diagnostic pairs employed in an experiment seems to influence the prevalence of EQW use.

To sum up the findings of Experiment 2, we can first conclude that the presentation format effect found in Experiment 1 appears to be robust. PCS-consistent behavior is more prevalent in the *Matrix* than in the *Map* presentation format, whereas behavior best accounted for by the multiple strategy approach (EQW, TTB, and WADD) is more frequently found in the *Map* presentation format than in the *Matrix*. However, the results do not support a distinct influence of any of the two presentation format features (extent of information search and negative cue value presentation) investigated herein. Possibly, the manipulation of the information search costs was not strong enough between the search-intensive random order maps (*Map* and *Negative Map*) and the fixed order maps (*Fixed Map* and *Negative Fixed Map*) that did not completely eliminate information search, but required an intermediate level of search. Hence, the crucial difference between the *Map* and the *Matrix* might be whether search is necessary at all, whereas the amount of costs associated with it has no further impact, at least within the variations realized in this experiment.

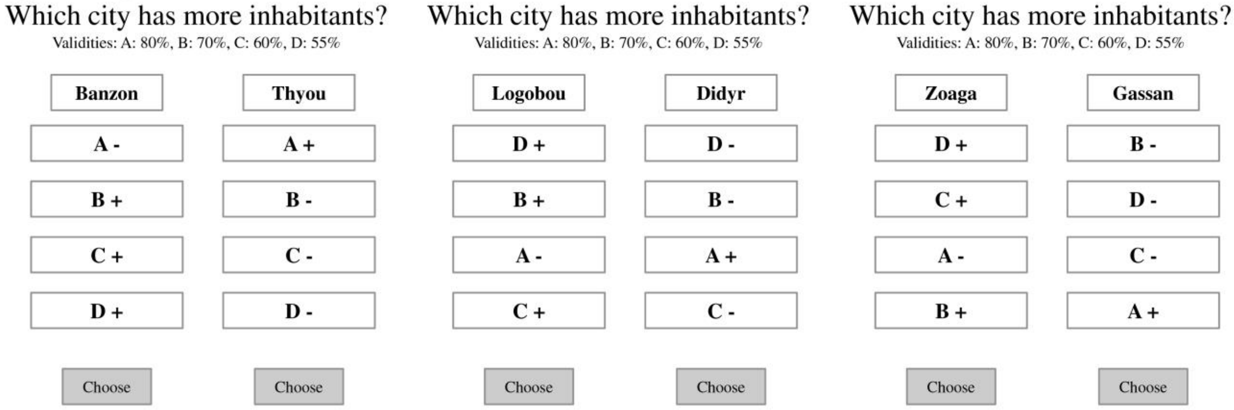
Apart from these presentation format considerations, Experiment 2 showed that participants seem to choose their decision strategies adaptively contingent on the task environment, that is, the cue patterns presented to them. If a principally useful strategy (in the current case EQW) does not allow for making a distinct choice often enough (but rather implies guessing on many trials), individuals adapt their decision behavior and employ an alternative strategy that will discriminate between choice options more frequently. This finding is well in line with approaches to strategy selection that stress the role of learning processes (e.g., Bröder & Schiffer, 2006a; Rieskamp & Otto, 2006). Thus, experimenters need to be careful when constructing experimental environments and drawing conclusions that aim to generalize to other environments—not only in terms of, for example, discrimination rate, validity and redundancy of cues (see, for example, Bröder & Newell, 2008, or Gigerenzer et al., 2012, for an overview), but also in regard to the diagnostics pairs themselves that are presented to the participants.

4 Experiment 3: Examining the influence of information search in the matrix format

In Experiment 2, the presentation format effect of Experiment 1 was replicated. PCS-consistent information integration was more prevalent in the matrix-like presentation format (open information board) than in the presentation format that resembles a map. None of the newly established maps caused a clearly detectable increase in PCS-consistent behavior. As the manipulation of the presentation format feature information search might have been too weak in Experiment 2, Experiment 3 aims for a stronger manipulation of this feature within the original *Matrix* presentation format.

Gigerenzer et al. (2012) stressed the importance of information search processes to processes of information integration within the multiple strategy approach. As Glöckner and Betsch (2008b; 2012) pointed out, the relevance of information search processes for the PCS network model as well, we deemed this presentation format feature worth a closer look despite the non-significant result of Experiment 2. We suspect that the information

Figure 4: Presentation formats *adjusted Matrix* (left), *Random Row Matrix* (center), and *Random Display Matrix* (right) in Experiment 3.



search manipulation in Experiment 2 might have been too weak, because even in the maps with reduced information search (*Fixed Map* and *Negative Fixed Map*) a certain extent of search was unavoidable: Cue values were displayed in the quarter assigned to the respective cue, but within this quarter the exact spot of appearance for cue values was random. In contrast to this reduced information search, in the *Matrix* each spot of appearance for the cue values was completely predefined. Thus, information search is reduced to a minimum in the *Matrix*.

As a further reduction of information search in our view would eliminate the basic idea of a *map* presentation format, we decided to manipulate the considered presentation format feature within the matrix. As such, Experiment 3 tests two alternative matrix presentation formats that pose higher information search demands on the participants. This was done in order to be able to attribute the effects found in Experiments 1 and 2 to the theoretically interesting variable *search* rather than to potential other accidental differences between the formats.[7]

Apart from the information search manipulation, Experiment 3 aims to replicate the search cost effect established in the within-subjects designs of Experiments 1 and 2 in a between-subjects design.

[7]Interestingly, Glöckner and Betsch (2008b) concentrated their skeptical note on the compatibility of information search and "automatic" decision making consistent with their PCS network model on the closed information board that necessarily induces sequential information search. However, they did not ask whether a random cue order within the matrix format (as in their Experiment 3) might also hamper PCS-consistent behavior, and they did not compare the results of this variation of the original matrix format with the typical matrix comprising a fixed order. Our Experiment 3 will provide this comparison and test whether such a mild form of increased information search might already substantially hamper PCS.

4.1 Method

4.1.1 Presentation formats

In Experiment 3, four different presentation formats were included. Apart from the *Map* presentation format that has been tested in both Experiments 1 and 2, three matrices with different degrees of induced information search were employed.

The first matrix presentation format of Experiment 3 (*adjusted Matrix*, Figure 4, left) closely resembles the *Matrix* employed in Experiments 1 and 2 (Figure 1, left). The only slight adjustment relates to the cue labels. In contrast to Experiments 1 and 2 where the cue labels are displayed on the left side of the screen and function as row headings, in the *adjusted Matrix* the cue labels directly accompany the cue values. The cue order is constant across all trials with the most valid cue in the first row and the others following in descending order of validity. As this order is constant across all trials, information search is reduced to a minimum.

The second matrix presentation format (*Random Row Matrix*, Figure 4, center) demands more information search than the *adjusted Matrix* described previously (Figure 4, left). This manipulation is achieved by randomizing the cue rows of the matrix for each trial anew. Consequently, each cue might appear in any of the four rows on a given trial. Apart from this row-wise randomization the *Random Row Matrix* presentation format equals the *adjusted Matrix*.

In the third matrix presentation format (*Random Display Matrix*, Figure 4, right) information search is further increased as the cue order is not only randomized row-wise, but additionally within each column (i.e., option) for each trial anew. Thus, participants have to extensively search for the desired cue value information.

4.1.2 Design and procedure

The design and procedure of Experiment 3 closely resembled Experiment 1 (including the diagnostic pairs and filler trials). However, in contrast to Experiment 1, each participant was randomly assigned to and worked on only one presentation format and thus completed the experiment after practice trials plus 70 decision trials.

4.1.3 Hypotheses

Hypothesis 1: In Experiments 1 and 2, a within-subjects presentation format effect was found: PCS-consistent behavior was more frequently found in the *Matrix* presentation format and decision strategies (WADD, EQW, or TTB) were more prevalent in the *Map*. We hypothesize that this effect should also hold in a between-subjects design when a (slightly) *adjusted Matrix* is compared to the original *Map*.

Hypothesis 2: We hypothesize that the presentation format feature extent of information search predominantly drives the presentation format effect assumed under Hypothesis 1. Specifically, increased information search should lead to more frequent use of decision strategies, whereas PCS-compatible behavior is facilitated by particularly low information search costs.

4.1.4 Participants

In this experiment, 160 individuals participated (108 female, mean age 22.07), most of them (151) students of the University of Mannheim. They received course credit for their participation. In each presentation format condition, 40 participants were tested.

4.1.5 Model predictions and classification

In Experiment 3 the same diagnostic pairs as in Experiment 1 were used. Model predictions and classification with the MM-ML method for Experiment 3 equal those of Experiment 1.

4.2 Results and discussion

In Table 1 (lower part) the results of the model classification with the MM-ML method are displayed. The influence of increased information search can easily be seen here: Descriptively, the distribution in the matrices with increased information search (*Random Row Matrix* and *Random Display Matrix*) resembles the distribution observed for the *Map* presentation format, whereas the *adjusted Matrix* shows the opposite pattern.

In line with Hypothesis 1, use of decision strategies (EQW, TTB, or WADD) was more frequent in the *Map* (26 participants) than in the *adjusted Matrix* (10 participants), whereas PCS-consistent behavior was more often found in the *adjusted Matrix* (30 participants) than in the *Map* (14 participants) presentation format. Thus, the presentation format effect shown in Experiments 1 and 2 was replicated: $\chi^2(1, N = 80) = 12.93$, $p < .001$, $w = 0.40$.

The influence of information search extent (Hypothesis 2) can be tested in two different ways: (1) Comparing the *adjusted Matrix* with minimal information search to the matrix with medium information search (*Random Row Matrix*), a distinct difference in the assumed direction was observed. A chi-square test corroborated the effect ($\chi^2(1, N = 80) = 11.43$, $p = .001$, $w = 0.38$) which was medium to large in size (Cohen, 1988). To test (2) whether a further increase in information search would intensify the change in information processing, the *Random Row Matrix* was compared with the *Random Display Matrix*. There was no difference between these two presentation formats ($\chi^2(1, N = 77) = 0.01$, $p = .98$). As such, further increasing the extent of information search did not cause any additional shifts from PCS to decision strategy consistent behavior (or vice versa). Thus, a moderate necessity for information search sufficed to induce more frequent use of sequential decision strategies (EQW, TTB, and WADD), whereas an additional increase did not change information processing.

In order to test whether the presentation format effect observed under Hypothesis 1 can be eliminated by equalizing information search demands, the information search-intensive *Map* presentation format is compared to the matrix with maximal information search (*Random Display Matrix* with completely random cue value order). The chi-square test shows that, when information search is comparable, no presentation format effect can be found anymore ($\chi^2(1, N = 77) = 0.07$, $p = .80$).

To sum up the results of Experiment 3, the presentation format effect observed in the within-subjects designs of Experiments 1 and 2 is also clearly visible in the between-subjects design of Experiment 3. Automatic, parallel information integration as proposed by the PCS model was more prevalent in the *adjusted Matrix* and sequential computation in the *Map* presentation format. We found this effect in three different samples and in within- as well as between-subjects designs. Thus, the effect of the presentation format on information processing seems to be robust.

Additionally, the importance of the presentation format feature *information search* could be established. A moderate increase in the extent of information search appeared to hinder PCS-consistent information integration considerably. However, a further increase in the extent of information search did not affect information processing beyond that. Interestingly, the presentation format effect disappeared when the extent of information search was most comparable across the two presentation formats. Thus, the presentation format feature information search seems to predominantly drive the aforementioned presentation format effect.

5 General discussion

Previous research on the format of information presentation (Bergert & Nosofsky, 2007; Bröder & Newell, 2008; Newell et al., 2007; Newell & Lee, 2010; Platzer & Bröder, 2012) suggests that the accessibility of information might influence the process of decision making. Whereas proponents of the PCS network model have shown that PCS-consistent behavior is highly prevalent when information is presented in the standardized *matrix* format (e.g., Glöckner & Betsch, 2008b; Horstmann et al., 2009), the role of the presentation format itself—and, more importantly, the accessibility of information—in fostering reliance on PCS-like processes has not yet been tested systematically. Employing the City-Size task for probabilistic inferences, we developed an alternative presentation format (based on the idea of a *map*) to test the assumption that decision makers' ability to rely on PCS-like processes is bounded by information accessibility and thus hampered once the "wrong" presentation format is used.

Across all three experiments, a robust presentation format effect between the *matrix* with high accessibility of information and the *map* with reduced information accessibility could be found: PCS-compatible behavior was much more prevalent in the former than in the latter, whereas participants used one of the sequential decision strategies (WADD, TTB, or EQW) more frequently in the *map* than in the *matrix*. Whereas Experiment 1 established this basic effect, Experiments 2 and 3 aimed to clarify which specific feature of presentation formats might have driven the observed effect. However, in Experiment 2 there was neither an effect of (1) whether negative cue values are displayed (or have to be inferred by the participant) nor of (2) the extent of information search induced by the presentation format. Hence, search per se rather than its amount seemed to hamper PCS use. Varying the search demands within the matrix format, Experiment 3 revealed that already a moderate increase in the extent of information search reduces PCS-consistent behavior considerably. In turn, once the extent of information search was held constant across presentation formats, the presentation format effect was no longer observable.

Thus, although a presentation format effect was reliably found in all three experiments, it was not the presentation format *per se* that caused this shift in information integration processes, but the *accessibility* of information induced by the format. Only when all pieces of information are instantly and simultaneously available, PCS-consistent behavior is predominantly observed. In turn, even moderate information search demands reducing the accessibility of information, suffice to hamper PCS-compatible processes. Consequently, decision makers are more likely to engage in sequential information processing as assumed by the multiple strategy approach.

One may argue that the information accessibility effect reported here may alternatively be attributed to spurious WADD-classifications of actual PCS-users in the presentation formats with decreased information accessibility (especially the "maps"). Both models make the same predictions for choice outcomes and confidence judgments, but WADD is the null-model in terms of decision times (assuming no decision time differences between different item types). Thus, adding noise to the decision times—as is the case with decreased information accessibility—might blur the actual time differences between item types, resulting in an advantage of the null-model WADD over the alternative model PCS. Although it is possible that noise in the decision times might have contributed to the pattern observed in our data, it cannot account for the reported "strategy shifts" comprehensively, mainly for two reasons: First, in the presentation formats with decreased information accessibility, although we do observe more WADD-classifications as opposed to PCS (which is what the noise interpretation predicts), we also find a considerable increase in TTB-classifications and TTB is not a null-model in terms of decision times. Thus, this "strategy shift" cannot be accounted for by the noise interpretation. Second, analyzing the absolute decision time differences between item types that should provoke particularly different decision times according to the PCS model (but not according to all other models), we mostly find results that are incompatible with a mere noise-based interpretation, but instead corroborate the interpretation of our results as being produced by different underlying processes.[8]

[8]For each experiment, we contrasted the two item types with the most extreme decision time contrast weights for PCS (where all other models do not predict a decision time difference). According to our hypothesis and interpretation, the difference in decision times between these two item types should be greater in absolute terms in the original Matrix (PCS predicts a large difference) than in conditions with decreased information accessibility (all non-PCS models predict no difference). The noise interpretation, by contrast, would predict that this difference is equivalent in both conditions (as it presumes that PCS is the underlying mechanism throughout). For each participant, we computed the median log-transformed decision time per item type for the conditions Matrix and Map and subsequently determined the absolute difference between the two item types with the most extreme decision time contrast weights for PCS (see Appendices D and F). We then performed paired t-tests for Experiments 1 and 2 and an independent samples t-test for Experiment 3. In Experiment 2 (contrasting item types 1 and 2), we found no difference between the two conditions (t (107) = 0.050, p = .961). However, in Experiments 1 and 3, (contrasting item types 1 and 3) we found the expected difference between the Matrix

Our results are aligned with previous research on the (ir)relevance of information presentation format for decision strategy use. Reviewing their own empirical work, Bröder and Newell (2008) concluded that the format of the stimulus material seems to have little effect—as long as solving the decision problem does not burden working memory too much. Platzer and Bröder (2012) reported that the "format effect" reported by Bröder and Schiffer (2003b; 2006b) disappeared when controlling for salience. Testing a sequential evidence accumulation model (Lee & Cummins, 2004), Newell and Lee (2010) found little systematic effect of the stimulus format on choice behavior. These findings suggest that decision processes depend on the accessibility of information fostered or hampered by certain formats rather than on the format *per se*. The current findings extend this conclusion to a different class of processes as specified in a model assuming automatic, parallel information integration (PCS).

The important role of information accessibility to PCS-consistent behavior was only recently discussed for inferences from memory. Comparing their research results with the findings of Bröder and colleagues (Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b), Glöckner and Hodges (2011) conclude that the accessibility of information might constitute a relevant variable that influences the process of decision making. When all applicable pieces of information are quickly available without high memory costs, PCS-consistent behavior can be observed, whereas it is only rarely found when retrieval imposes high memory costs and information accessibility is therefore reduced. Our results show that this reasoning can be transferred to inferences from givens as well.

The work reported here refines Glöckner and Betsch's (2008b) note on one possible condition for selecting PCS-like processes in information integration: the influence of information search. Analogous to Lohse and Johnson (1996) who compared different process tracing methods (see also Norman & Schulte-Mecklenbeck, 2010), Glöckner and Betsch (2008b) reported a shift in the information integration process contingent on the method employed for information presentation (open versus closed information board): If all pieces of information were simultaneously displayed, PCS-consistent behavior was highly prevalent, whereas sequential information search lead to a marked decrease. The current results extend such conclusions in showing that—even in presentation formats that display all pieces of information simultaneously—a moderate reduction in information accessibility also reduces the prevalence of PCS-consistent behavior.

But why does the ability to integrate information in a PCS-consistent manner seem to crucially depend on a high accessibility of information? Glöckner and colleagues emphasized that the PCS model integrates automatic, perception-like processes (Glöckner & Betsch, 2012; Glöckner & Hodges, 2011). They explicitly draw a parallel between their PCS network model and Gestalt psychology's basic idea of automatic consistency maximization (Glöckner & Betsch, 2008a). From this we deem it plausible that automatic, parallel information integration as assumed by the PCS model heavily relies on the immediate accessibility of information. If all applicable pieces of information can—without recoding—be captured by a simple perception-like process, a mental representation ("Gestalt") of the choice situation can quickly be constituted in a holistic process (see Peterson & Rhodes, 2003, for an overview on holistic processing in perception). PCS-consistent information processing relies on this immediate constitution of a mental network and is thus hampered when information needs to be restructured and recoded before it can be integrated. If the quick, automatic default for decision making (PCS) cannot be applied, the decision maker has to resume to sequential decision making strategies instead.

This reasoning is well in line with Marewski and Schooler's (2011) cognitive niche framework: For different environments, different processes are applicable. From a cost-benefit-view, "automatic" decision making should prevail whenever it is applicable. If, however, the constitution of the proposed mental network is impaired, the default strategy is no longer applicable and people have to select a different decision strategy from the set of applicable options.

Our findings emphasize the importance of considering both information acquisition processes on the one hand and processes of information integration on the other hand (see also Glöckner & Betsch, 2008a; Glöckner & Hilbig, 2012, and for a similar finding in the domain of risky choices Hilbig & Glöckner, 2011) as two interdependent but nonetheless separate parts of the whole decision making process. Gigerenzer et al. (2012) recently highlighted the importance of information search processes for the processes of information integration, illustrating that within the multiple strategy approach shifts between fast and frugal heuristics and more complex decision strategies (e.g., WADD) have repeatedly been reported. Gigerenzer et al. (2012) demonstrate that these results can be attributed to differences in the extent of information search induced by the respective choice environment. Clearly, it is well in line with such arguments that automatic, parallel information integration as proposed by the PCS network model is also crucially influenced by information search demands.

and the Map (Experiment 1: t (82) = 2.463, p = .016; Experiment 3: t (78) = 2.025, p = .046). Hence, the noise interpretation cannot be ruled out conclusively for Experiment 2, but for Experiments 1 and 3 we find a decision time pattern that (1) is in line with a change in underlying mechanisms (i.e., a "strategy shift") and (2) cannot be accounted for by the noise interpretation alone.

Building on these results, it might be possible to create real-life choice situations in a way so as to facilitate PCS-consistent information processing. Here, the focus should be on the accessibility of information in general and the extent of information search in particular (Gigerenzer et al., 2012; Glöckner & Betsch, 2012), because these variables considerably influence the information integration process. Future research on the potentiality of automatic, parallel information integration as proposed by the PCS network model should aim to identify further variables (see, for example, Ahlgrimm et al., 2010, May; Horstmann et al., 2009; Hass & Pachur, 2011, March) that facilitate (or hamper) this quick way to normatively optimal decisions that does not necessitate much time and effort.

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Appendix A: Multiple Measure Maximum Likelihood ($L_{k(total)}$) of a model k.[9]

The MM-ML method (Glöckner 2009, 2010) allows for model classification on an individual level. Predictions for each of the dependent measures (choices, decision times, confidence judgments) and employed diagnostic pairs are derived for each model. Accordingly, up to seven free parameters are necessary to specify a model k. The MM-ML method estimates optimal values for each of the free parameters of model k and calculates the maximum conditional likelihood for the observed data pattern given the application of model k:

$$\begin{aligned} L_{k(total)} &= P(n_{jk}, \vec{x_T}, \vec{x_C} | k, \varepsilon_k, \mu_T, \sigma_T, R_T, \mu_C, \sigma_C, R_C) \\ &= \prod_{j=1}^{J} \binom{n_j}{n_{jk}} (1-\varepsilon_k)^{n_{jk}} \varepsilon_k^{(n_j - n_{jk})} \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma_T^2}} e^{-\frac{(x_{Ti} - (\mu_T + t_{Ti} R_T))^2}{2\sigma_T^2}} \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma_C^2}} e^{-\frac{(x_{Ci} - (\mu_C + t_{Ci} R_C))^2}{2\sigma_C^2}} \end{aligned}$$

Choices

n_j Number of presentations (tasks) for diagnostic pair *j*

n_{jk} Number of correct choice predictions by model k for the tasks of diagnostic pair j

ε_k Error rate for model k

Decision times

$\vec{x_T}$ Set of i independent observations (when $x_T \ldots$ log-transformed decision time)

μ_T Mean of the normal distribution for the log-transformed decision times

σ_T Standard deviation of the normal distribution for the log-transformed decision times

R_T Scaling parameter (for models that predict different decision times for the i independent observations)

t_{Ti} Model k's predictions for decision time contrasts ($\sum t_{Ti} = 0$)

Confidence judgments

$\vec{x_c}$ Set of i independent observations (when $x_c \ldots$ confidence judgment)

μ_c Mean of the normal distribution for the confidence judgments

σ_c Standard deviation of the normal distribution for the confidence judgments

R_c Scaling parameter (for models that predict different confidence judgments for the i independent observations)

t_{Ci} Model k's predictions for confidence judgment contrasts ($\sum t_{Ci} = 0$)

Appendix B: Bayesian Information Criterion (BIC_k) of a model k[10]

$$BIC_k = -2\, ln(L_{k(total)}) + ln(N_{obs})N_p$$

$L_{k(total)}$ Multiple Measure Maximum Likelihood (see Appendix A)

N_{obs} Number of modeled observations; here: number of independent categories: N_{obs} = Number of different diagnostic pairs · 3 (number of independent variables: Choice, Decision time, Confidence judgment)

N_p Number of parameters for model k

[9] Glöckner (2010, Appendix A).

[10] Glöckner (2010, Appendix A).

Appendix C: Diagnostic pairs of Experiments 1 and 3

Cue	Pair 1 Option		Pair 2 Option		Pair 3 Option		Pair 4 Option		Pair 5 Option		Pair 6 Option	
	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"
Cue A (v = .80)	+	–	+	–	+	–	+	–	+	–	–	–
Cue B (v = .70)	+	–	+	–	–	+	–	–	–	+	–	–
Cue C (v = .60)	+	–	–	+	–	+	–	–	+	–	+	–
Cue D (v = .55)	–	+	–	+	–	+	–	+	–	+	–	+

Appendix D: Model predictions for all considered strategies, diagnostic pairs and dependent measures for Experiments 1 and 3 (see Glöckner, 2009)

	Pair 1	Pair 2	Pair 3	Pair 4	Pair 5	Pair 6
Choice						
EQW	A	Guessing	B	Guessing	Guessing	Guessing
TTB	A	A	A	A	A	A
WADD	A	A	B	A	A	A
PCS	A	A	B	A	A	A
Decision time (contrasts)						
EQW	0	0	0	0	0	0
TTB	–0.167	–0.167	–0.167	–0.167	–0.167	0.833
WADD	0	0	0	0	0	0
PCS	–0.400	–0.310	0.600	–0.120	0.110	0.130
Confidence judgment (contrasts)						
EQW	0.667	–0.330	0.667	–0.330	–0.330	–0.330
TTB	0.167	0.167	0.167	0.167	0.167	–0.833
WADD	0.630	0.230	–0.370	0.030	–0.170	–0.370
PCS	0.620	0.280	–0.320	–0.010	–0.190	–0.380

Note. EQW: "Equal Weight Rule", TTB: "Take-The-Best"-heuristic, WADD: corrected "Weighted Additive Rule", PCS: "Parallel Constraint Satisfaction".

Appendix E: Diagnostic pairs of Experiment 2

Cue	Pair 1		Pair 2		Pair 3		Pair 4		Pair 5		Pair 6		Pair 7	
	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"
Cue A (v = .80)	+	–	+	–	–	–	–	–	+	+	+	–	+	–
Cue B (v = .70)	+	–	–	+	–	–	+	–	+	–	+	+	+	+
Cue C (v = .60)	+	–	–	+	+	–	+	–	–	+	–	+	+	–
Cue D (v = .55)	–	+	–	+	–	+	+	+	–	+	–	+	–	–

Appendix F: Model predictions for all considered models, diagnostic pairs and dependent measures for Experiment 2

	Pair 1	Pair 2	Pair 3	Pair 4	Pair 5	Pair 6	Pair 7
Choice							
EQW	A	B	Guessing	A	B	B	A
TTB	A	A	A	A	A	A	A
WADD	A	B	A	A	A	A	A
PCS	A	B	A	A	A	A	A
Decision time (contrasts)							
EQW	0	0	0	0	0	0	0
TTB	−0.286	−0.286	0.714	0.214	0.214	−0.286	−0.286
WADD	0	0	0	0	0	0	0
PCS	−0.422	0.578	0.351	−0.301	0.169	−0.074	−0.301
Confidence judgment (contrasts)							
EQW	0.286	0.286	−0.714	0.286	−0.214	−0.214	0.286
TTB	0.286	0.286	−0.714	−0.214	−0.214	0.286	0.286
WADD	0.657	−0.343	−0.343	0.157	−0.343	−0.143	0.357
PCS	0.650	−0.298	−0.350	0.149	−0.269	−0.140	0.257

Note. EQW: "Equal Weight Rule", TTB: "Take-The-Best"-heuristic, WADD: corrected "Weighted Additive Rule", PCS: "Parallel Constraint Satisfaction".

Appendix G: Posterior probability (p) of a model k given the data D[11]

$$p(k|D) = \frac{e^{-\frac{1}{2}BIC_k}}{\sum\limits_{l=0}^{m-1} e^{-\frac{1}{2}BIC_l}}$$

BIC Bayesian Information Criterion (cf. Appendix B)

m Number of tested models

l One of the *m* models

[11] Wagenmakers (2007, p. 797).

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Single-process versus multiple-strategy models of decision making: Evidence from an information intrusion paradigm☆

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ABSTRACT

When decision makers are confronted with different problems and situations, do they use a uniform mechanism as assumed by single-process models (SPMs) or do they choose adaptively from a set of available decision strategies as multiple-strategy models (MSMs) imply? Both frameworks of decision making have gathered a lot of support, but only rarely have they been contrasted with each other. Employing an *information intrusion* paradigm for multi-attribute decisions from givens, SPM and MSM predictions on information search, decision outcomes, attention, and confidence judgments were derived and tested against each other in two experiments. The results consistently support the SPM view: Participants seemingly using a "take-the-best" (TTB) strategy do not ignore TTB-irrelevant information as MSMs would predict, but adapt the amount of information searched, choose alternative choice options, and show varying confidence judgments contingent on the quality of the "irrelevant" information. The uniformity of these findings underlines the adequacy of the novel *information intrusion* paradigm and comprehensively promotes the notion of a uniform decision making mechanism as assumed by single-process models.

1. Introduction

Every day, humans are confronted with a multitude of choice problems and situations that differ, for example, in complexity, information accessibility, time constraints, and so on. Most researchers in the field of multi-attribute decision making agree that decision makers are able to adapt their behavior to these task features (Bröder & Schiffer, 2003a; Gigerenzer, Todd, & ABC Research Group, 1999; Payne & Bettman, 2001; Rieskamp & Hoffrage, 1999). There is, however, no consensus about how people adapt their behavior. Instead, two frameworks of multi-attribute decision making coexist that make fundamentally different assumptions about the process underlying this adaptivity.

Although several authors have advocated for the importance of distinguishing between these two frameworks (Glöckner & Betsch, 2011; Newell, 2005; Newell & Bröder, 2008) and a few attempts have been made to do so (Bergert & Nosofsky, 2007; Glöckner, Betsch, & Schindler, 2010; Hausmann & Läge, 2008; Lee & Cummins, 2004; Newell, Collins, & Lee, 2007), there is no conclusive evidence, yet, to decide which framework fares better. The reason for this shortfall is an "empirical challenge," as Newell (2005, p. 13) puts it. Both frameworks can often account for empirical findings equally well and are therefore virtually impossible to tease apart. As one potential solution to this problem, we introduce the *information intrusion* paradigm that builds on very basic assumptions of the two frameworks. Using this paradigm, we tested basic predictions of both approaches against each other.

In the remainder of the introduction, we describe the two frameworks of multi-attribute decision making in more detail and subsequently discuss some attempts that have been made to disentangle the two approaches. After introducing the theoretical foundations and the basic idea of the novel *information intrusion* paradigm, we present two empirical implementations of the paradigm. The first experiment contrasts the two frameworks of interest by means of information search, choice outcomes, and, additionally, memory performance, whereas the second study also considers confidence judgments.

1.1. Two frameworks of decision making

Multi-attribute decision making deals with preferential choice and probabilistic inferences. The difference between these two domains is

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that in the former decisions are made in relation to a subjective criterion (e.g., "Which dessert do you like better?"), whereas in the latter the decision criterion is an objective one (e.g., "Which dessert contains more calories?"). Formally, these domains are similar: The decision maker chooses between two or more options that are characterized by a categorical set of attributes (cues). The cue values display the, often binary (positive versus negative), evaluation of the options by the respective cue. The cues differ with regard to the strength of the correlation between their evaluation and the actual decision criterion (cue validity). As empirical similarities suggest similar cognitive processes in both domains (Bröder & Newell, 2008; Payne, Bettman, & Johnson, 1993; Todd, Gigerenzer, & ABC Research Group, 2012), we will consider models that were developed for preferential choice as well as models for probabilistic inferences in the subsequent discussion of frameworks for multi-attribute decision making.

1.1.1. Multiple-strategy models

One popular framework for multi-attribute decision making can be summarized by the notation of "multiple-strategy models" (MSMs, e.g., Beach & Mitchell, 1978; Gigerenzer et al., 1999; Payne et al., 1993; Scheibehenne, Rieskamp, & Wagenmakers, 2013). MSMs propose that decision makers have several distinct decision strategies or heuristics at their disposal (for example, the "adaptive toolbox," Gigerenzer & Todd, 1999) and choose adaptively between them. The selected decision strategy determines the sequence of information search (search rule), the amount of information searched (stopping rule), and how information is integrated (decision rule).

One prominent decision strategy for multi-attribute decision making has received great attention: the "take-the-best" heuristic (TTB, Gigerenzer, Hoffrage, & Kleinbölting, 1991). It assumes a cue-wise information search along a cue validity hierarchy—from the cue with the highest validity to the cue with the lowest validity (TTB's search rule). Information search terminates as soon as a cue discriminates between the considered options and favors only one of them (TTB's stopping rule). The decision maker chooses the option favored by the discriminating cue (TTB's decision rule). Thus, TTB offers a prominent example of a decision strategy that, if the stopping rule is satisfied before all cues have been investigated, uses only a subset of available and applicable information (so-called *frugality*, Gigerenzer & Goldstein, 1999).

The question, how the decision maker selects a decision strategy from the set of alternatives, has been posed by several researchers (e.g., Payne & Bettman, 2001; Payne et al., 1993). Whereas many authors seem to suggest a top–down mechanism (Beach & Mitchell, 1978; Marewski & Schooler, 2011; Payne et al., 1993), evidence accumulated that bottom–up learning also shapes strategy selection (Bröder, Glöckner, Betsch, Link, & Ettlin, 2013; Bröder & Schiffer, 2006; Rieskamp, 2006; Rieskamp & Otto, 2006). In addition to this strategy selection problem, the MSMs need to deal with the question, how many strategies actually comprise the set of possible alternatives (cf., Marewski & Schooler, 2011; Scheibehenne et al., 2013).

1.1.2. Single-process models

The "single-process models" (SPMs, e.g., Busemeyer & Johnson, 2004; Busemeyer & Townsend, 1993; Glöckner & Betsch, 2008a; Hausmann & Läge, 2008; Lee & Cummins, 2004) comprise the second, coexisting framework for multi-attribute decision making. Here, it is assumed that instead of selecting one decision strategy from a set of different alternatives, the decision maker employs one single decision making mechanism (for example, the "adjustable spanner (or wrench)," Newell, 2005) that might be adjusted to the particular task at hand. Two prominent classes of the SPMs are connectionist models (e.g., Glöckner & Betsch, 2008a; Simon & Holyoak, 2002; Thagard & Millgram, 1995) and evidence accumulation models (e.g., Busemeyer & Johnson, 2004; Busemeyer & Townsend, 1993; Hausmann & Läge, 2008; Lee & Cummins, 2004; Newell, 2005).

Connectionist models assume that decisions are formed by parallel consideration of all available decision-relevant information in a neural network representing the decision problem (e.g., Glöckner & Betsch, 2008a; Simon & Holyoak, 2002; Thagard & Millgram, 1995). Activation spreads in the network until a stable state is reached and consistency is maximized. The option with the highest positive activation is chosen. The connectionist models focus on the process of information integration, given a set of information.

Evidence accumulation models, to name another class of SPMs, assume a sequential sampling process that terminates as soon as one option surpasses a certain threshold of preference or confidence (e.g., Busemeyer & Townsend, 1993; Hausmann & Läge, 2008; Lee & Cummins, 2004; Newell, 2005). Whenever this happens, a choice is made in favor of this option. Evidence accumulation models do not focus exclusively on information integration, but often also model the process of information search—either in a probabilistic (e.g., Busemeyer & Townsend, 1993) or a deterministic (e.g., Lee & Cummins, 2004) way.

Although the SPMs avoid the aforementioned strategy selection problem by assuming only one single mechanism that is applied to all multi-attribute decisions, one might argue that they merely replace this issue with a different problem (e.g., Marewski, 2010; Newell & Lee, 2011): How do decision makers adjust the proposed uniform mechanism? Some attempts have been made to answer this question for the SPMs in particular (e.g., Glöckner & Betsch, 2008a; Hausmann & Läge, 2008; Jekel, 2012; Newell & Lee, 2009) and some work on the strategy selection problem of the MSMs (e.g., concerning the central role of *learning*, Rieskamp & Otto, 2006) can probably be transferred to this problem. The theoretical advantage of the SPMs over the MSMs, however, lies in the fact that the MSMs often do not confine the set of decision strategies in a principled fashion. Hence, new behavioral phenomena may be captured by extending the toolbox with more sophisticated strategies (e.g., Glöckner & Betsch, 2011; Newell & Lee, 2011; Newell, 2005, but see Marewski, 2010). The downside of SPMs is, however, that they currently do not provide strict predictions for search or the selection of decision boundaries.

1.2. How to distinguish between the two frameworks?

The coexistence of the two frameworks (SPMs and MSMs) is theoretically disappointing (Glöckner & Betsch, 2011), but consequential as both frameworks can often account for empirical data equally well. For example, a well-documented finding in multi-attribute decision problems refers to the influence of information costs on decision behavior: Increasing information costs leads to a more frequent use of fast and frugal heuristics like TTB instead of compensatory[1] strategies (MSM interpretation, Bröder, 2000, 2003; Newell & Shanks, 2003). This empirical finding can, however, also be interpreted from a SPM view—for example, as a lowering of the evidence threshold in an evidence accumulation model. Hence, both frameworks invoke different metaphors that explain and capture contingent decision behavior.

The crux is that the SPMs aim at unifying the different decision strategies incorporated in the MSMs (Glöckner & Betsch, 2008a; Hausmann & Läge, 2008; Lee & Cummins, 2004; Newell, 2005). Thus, it comes as no surprise that these SPMs can equally well account for decision behavior that can be described by the decision strategies. The quest to empirically distinguish between the two frameworks poses a challenging research task that some authors have doubted is solvable at all (Newell, 2005; Newell & Bröder, 2008). Nevertheless, in the next section some recent attempts to separate the two frameworks will be discussed.

[1] The term *compensatory* (or *noncompensatory* respectively) can describe a decision strategy as well as an environment. It refers to the degree of tradeoffs among cues. Noncompensatory decision strategies (like TTB) do not allow for a good value on one cue to make up for a bad value on a different one, whereas compensatory decision strategies allow for these tradeoffs (e.g., Payne et al., 1993). If the term is used for environments, it refers to the environment's payoff structure—favoring either noncompensatory or compensatory cue integration (e.g., Bröder, 2003).

1.2.1. Recent attempts to disentangle the two frameworks

Lee and colleagues (Lee & Cummins, 2004; Newell & Lee, 2011; Newell et al., 2007) contrasted the evidence accumulation model proposed by Lee and Cummins (2004) with *pure* decision strategy models that assume that only one strategy (e.g., TTB) is employed by all participants in a particular multi-attribute decision problem. Across all cited studies, Lee and Cummins' (2004) model that unifies TTB and a compensatory, "rational" strategy yielded a better model fit for the observed choice outcomes than the *pure* decision strategy models. Although the SPM was penalized for its complexity in the model comparison (model fit criterion was the Minimum Description Length (MDL), e.g., Grünwald, 2000), this test does not invalidate the MSM view, because the assumption that all participants employ the same decision strategy is not an essential part of this framework (Rieskamp, 2006; Rieskamp & Otto, 2006) and has been shown to be empirically invalid (e.g., Bröder, 2000). Therefore, Newell and Lee (2011) included in their model fit analysis a naïve strategy selection model that assumes that each participant has an individual probability of selecting a particular decision strategy in each decision trial. Again, Lee and Cummins' SPM faired the best—achieving a better model fit (MDL) than the pure decision strategy models as well as the naïve strategy selection model.

Employing a Bayesian approach, Scheibehenne et al. (2013) showed that a model that assumes a toolbox containing a noncompensatory as well as a compensatory decision strategy can be superior to models that contain only one decision strategy. Although Scheibehenne et al. profess that their approach also in principle enables a comparison between SPMs and MSMs, such a model comparison is not reported in the publication. Nevertheless, Scheibehenne et al.'s explicit model specification of the adaptive toolbox approach (Gigerenzer & Todd, 1999) as well as their promising application of Bayesian inference techniques for the comparison of this approach to other models are valuable contributions to the quest of disentangling SPMs and MSMs.

Hausmann and Läge (2008) proposed an evidence accumulation model that unifies one-reason decision making (i.e., TTB) and more-reason (compensatory) decision making. In their study, Hausmann and Läge (2008, Experiment 1) estimated an evidence threshold for each participant based on the 51 trials of the first experimental phase. Based on this threshold (*Desired Level of Confidence*, Hausmann & Läge, 2008), twenty additional, individually tailored decision trials were created that allowed for specific information search predictions to contrast a one-reason decision strategy, a more-reason decision strategy, and the proposed SPM. The information search behavior on the individual level was better explained by Hausmann and Läge's model, using the estimated individual evidence thresholds, than by either a one-reason or a more-reason decision strategy. Hence, participants did not choose a strategy which they retained throughout the experiment, but they adjusted their behavior on a trial-by-trial basis, depending on the validity of the information encountered first.

Glöckner and colleagues investigated the connectionist Parallel Constraint Satisfaction (PCS) model proposed by Glöckner and Betsch (2008a). Some studies (e.g., Glöckner & Betsch, 2008b; Glöckner & Hodges, 2011; Horstmann, Ahlgrimm, & Glöckner, 2009) contrasted the SPM with different decision strategies, thus, treating the SPM as if it was one of several decision strategies in a MSM (cf. Söllner, Bröder, & Hilbig, 2013 for a more detailed discussion). From our point of view, this approach demonstrates that individual decision behavior can successfully be modeled by PCS, but offers no clear distinction between SPMs and MSMs. Glöckner et al. (2010) investigated a specific prediction made by connectionist models, but not by MSMs: In the course of consistency maximization in the proposed network, (subjective) cue validities are modified due to the assumed bidirectional connections between options and cues (*coherence shifts*, Glöckner et al., 2010). Across three experiments, Glöckner et al. (2010) found the predicted coherence shifts in subjective cue validities, highlighting an empirical result that cannot easily be accounted for by MSMs (but see Marewski, 2010, for a different view). Glöckner and Hilbig (2013) scrutinized whether the repeatedly demonstrated finding (e.g., Bröder, 2003; Newell & Shanks, 2003) that high cue dispersion leads to more frequent use of the non-compensatory decision strategy TTB (MSM interpretation) can better be accounted for by an SPM like Glöckner and Betsch's PCS model. Including choices, decision times and confidence judgments in their analyses, Glöckner and Hilbig concluded that the expected "strategy shift" observable in choice outcomes, is better explained by assuming adjusted weights in the proposed network structures. Confidence judgments and decision times in the condition with high cue dispersion were better accounted for by PCS than by TTB. Finally, Glöckner and Betsch (2012) contrasted response time predictions derived from MSMs against PCS' predictions. In line with PCS, response time patterns were better explained by the coherence of the information set than by the number of computational steps as assumed by MSMs.

Summing up these recent attempts to separate the two frameworks, we first conclude that SPMs can often account very well for empirical data. These studies, however, also illustrate that the task to separate SPMs and MSMs is indeed challenging. When model fit is assessed the challenge lies in fully (and satisfactorily) specifying the competing models. Also, the general question arises, what models should enter the competition—single decision strategies, specific SPMs and MSMs (and how many of them), or even whole frameworks? And, to mention yet another caveat: What dependent variables should be considered? We believe that, although the described studies each contributed to our understanding of especially the SPMs, the question of which framework captures decision making in multi-attribute tasks best has not yet been answered satisfactorily.

1.2.2. The information intrusion paradigm

In the present article, we present a new attempt to empirically distinguish between the two frameworks to multi-attribute decision making. As such, we do not concentrate on specific models, but rather on the superordinate frameworks themselves. One approach for contrasting MSMs and SPMs is to flesh out their formal properties precisely and to compare them in terms of model fits for diagnostic data (e.g., Newell & Lee, 2011; Scheibehenne et al., 2013). Although this approach has many merits (e.g. the need for an explicit model specification), a potential drawback is that conclusions may be restricted to very specific instantiations of the model classes. Therefore, we do not engage in model fitting, but in testing basic assumptions shared by all models within one framework. Finally, we do not concentrate on either information search or choice outcomes alone, but consider both (and more) dependent variables for a broader empirical basis.

1.2.2.1. The theoretical foundation. Our approach rests on basic assumptions of the two frameworks. MSMs comprise decision strategies of different degrees of complexity (Beach & Mitchell, 1978; Gigerenzer et al., 1999; Payne et al., 1993). A key feature of the less complex strategies is that they concentrate on a specific part of the available information only, ignoring the remaining strategy-irrelevant part. One example for such a strategy is the aforementioned TTB heuristic. The cue-wise search follows a cue validity hierarchy and stops as soon as a cue discriminates between the considered options and favors only one of them (stopping rule). The favored option is chosen based on this one reason only—the less valid, so far not considered cues are ignored altogether and, therefore, do not influence the decision maker's behavior (e.g., Gigerenzer & Goldstein, 1999). Accordingly, Gigerenzer and Goldstein (1996, p. 653) described the TTB algorithm as "take the best, ignore the rest."

SPMs, in contrast, do not share this notion of valid, but potentially irrelevant information. Instead, they would predict that any applicable piece of information readily available to the decision maker is fed into the single decision making mechanism (Busemeyer & Townsend, 1993; Glöckner & Betsch, 2008a; Lee & Cummins, 2004; Newell, 2005) and therefore influences the decision maker's behavior. Importantly, SPMs can, of course, ignore information by giving a weight of zero to it. This should be the case for invalid cue information that is unrelated to the decision criterion.

Hence, if people have learned or decided to employ a specific strategy as assumed in the MSM framework, their behavior should *ceteris paribus* not be influenced by information that is irrelevant to execute this strategy. If, however, valid information is automatically evaluated as is assumed in evidence accumulation or connectionist models, the decision maker's behavior should be influenced by this information.

1.2.2.2. The task. For the information intrusion paradigm we use a well-established task as starting point: forced choices in a closed information board (Payne, 1976; Payne et al., 1993). Here, decision makers uncover initially hidden cue value information by opening the respective cells in an option–cue-matrix (cf. Fig. 1). The decision maker searches for as many cue values as he or she wishes, terminates the information search at some point, and chooses one of the offered options. In the next trial, new options are offered and cue values have to be accessed. Information costs (Bröder, 2000, 2003; Newell & Shanks, 2003) are imposed in a way that has previously been shown to substantially increase the frequency of behavior in line with TTB's predictions (Bröder, 2003).

The novel contribution of the information intrusion paradigm is that not only the intentionally accessed cue values are uncovered, but additionally cue value information intrudes—particular cells in the matrix open without being clicked on. The participants are told that these cells open randomly, but in fact, they are chosen systematically. Our hypotheses refer to the influence of intruding information on decision makers' behavior.

The content of the intruding information can be described as follows: Taking the view of a genuine TTB-user (MSM), cue value information can either be *relevant* (i.e., it comes prior to the information search termination point defined by TTB's stopping rule) or *irrelevant* (i.e., it comes after that point) for a specific decision problem. For example, when the most valid cue discriminates between options and favors one of them, only cue value information for this one cue is relevant to employ the strategy. After this cue has been uncovered, information search is terminated and the choice is made. Importantly, cue value information on all less valid cues is irrelevant to the TTB-user and will therefore be ignored if someone uses a TTB strategy. A vital feature of this strategy-irrelevant information is that it is *not* irrelevant for the decision problem per se (as it is valid and applicable to the problem), but for the execution of the TTB algorithm it is not necessary. Thus, we refer to it as "irrelevant", meaning that it is valid and applicable information that should therefore not receive a weight of zero within a SPM, but that is irrelevant from the perspective of a genuine TTB-user.

In our experiments reported below, we made sure that participants learned to use TTB as the optimal strategy in the task at hand. One can further classify the strategy-irrelevant information into two subgroups: Cue value information can either support the option favored by TTB (*compatible* information) or weaken it (*incompatible* information). Fig. 1 shows an example for compatible (Fig. 1, left part) and incompatible (Fig. 1, right part) TTB-irrelevant information. As the most valid cue ("Broker 1") discriminates and favors "Stock B," only cue value information on this cue is TTB-relevant, whereas cue value information on the less valid cues ("Broker 2," "Broker 3," and "Broker 4") is irrelevant to a TTB-user. Compatible TTB-irrelevant information supports the option favored by TTB and incompatible information weakens it. In the example depicted in Fig. 1, a positive evaluation of "Stock B" (i.e., the option favored by TTB) from "Broker 2" means compatible information, whereas a positive evaluation of an alternative option represents incompatible information.

2. Overview of the experiments

Both experiments reported here employed an identical task structure: Participants were repeatedly asked to choose one of three options that were described by four attributes (cues). The cue information was initially hidden, but participants could buy information (cue values) by clicking on it with the computer mouse. Once purchased, each piece of information remained visible on the screen until the participant finally chose one of the three options.

Participants were told that in each trial they were to invest 1000 *Penunzen* (a fictitious currency) in their favorite option, e.g., a drilling site in the oil drilling task of Experiment 1. The gain or loss made with this investment would be added to an account visible throughout the whole experiment. To ensure high motivation for optimal responding, four participants with the highest end balance would win a voucher worth 25 Euros. In order to aid their decision, the participants could buy information from four different sources (cues), e.g., test institutes in Experiment 1. For each purchase of cue value information participants had to pay 4% of their potential gain.

In each trial one or two pieces of this information showed up for free—they were not actively purchased by the participant and no information costs were attached to them. These information intrusions happened as soon as the first cue value information was intentionally acquired by the participant and remained visible until the participant made a choice for one of the three available options. If the participant happened to intentionally uncover the predefined cell for an information intrusion, no information costs were imposed for the acquisition. Note that amount and timing of the intrusions ensured that the need to search for information was not circumvented in our experiments. In fact, only in the rare event of two pieces of information intruding on the most valid cue *and* the participant clicking on the third cue value for this cue *and* this cue discriminating between the options, a TTB-user would not have to search for more information according to TTB's stopping rule. Therefore, in the vast majority of trials participants needed to employ some sort of search and stopping rule (e.g., the ones of the induced TTB heuristic) in order to make a (non-random) decision.

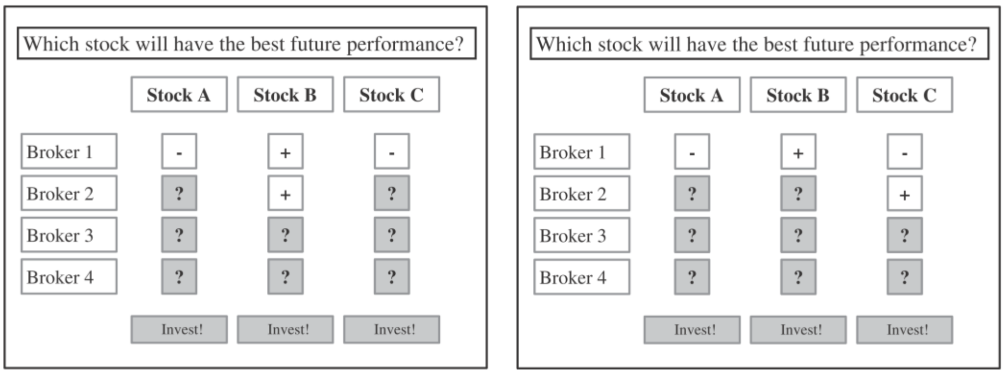

Fig. 1. Examples for compatible (left part) and incompatible (right part) TTB-irrelevant information.

Unbeknownst to the participants, the experiments consisted of two different phases: a learning phase and a test phase. In the initial learning phase participants should learn that TTB is the adaptive decision strategy for the environmental payoff structure. Previous research has demonstrated that by manipulating information costs, the use of the fast and frugal TTB heuristic can reliably be induced (Bröder, 2000, 2003; Bröder & Schiffer, 2006; Newell & Shanks, 2003).[2] The environmental structure of the experiments reported herein was taken from Bröder (2003, Experiment 2). In this experiment, the author classified a majority of 80% of his participants as TTB-users. As we aimed for a reliable TTB induction in our learning phase, we decided to employ the same weighing function for the cues: Payoff $= 47 \times c1 + 25 \times c2 + 17 \times c3 + 10 \times c4 +$ random. The payoff is measured as the percentage increase (or decrease) of the invested 1000 Penunzen. Cues (c1, c2, c3, c4) are coded "+1" for a positive cue value and "−1" for a negative cue value. The random component was drawn from a uniform distribution with a mean of zero and a range from −5 to 5. We also adopted the information cost manipulation, yielding a relative cost for each piece of information of 4% of the profit. The cue weights in this equation are not strictly noncompensatory, but they show a high dispersion, and although there are some trials in which TTB's payoff is slightly lower than that of a compensatory strategy, the saved information acquisition costs clearly favor TTB in the long run as well as in the vast majority of trials. Participants' decision strategies were classified according to the maximum likelihood outcome-based classification method by Bröder and Schiffer (2003b) on the basis of the 60 learning phase trials. In order to aid a successful strategy induction, 90% of the information intrusions were TTB-relevant and only 10% TTB-irrelevant in the learning phase. The within-subject manipulations relevant to our hypotheses were administered in the subsequent test phase. Thus, our analyses (apart from the aforementioned strategy classification) exclusively refer to the test phase. Importantly, in both phases the mean payoff for TTB was considerably better than for WADD (weighted-additive integration of all available information), the "equal weight rule" (EQW, Dawes, 1979, unweighted-additive integration of all available information), and random guessing—the competing decision strategies for the strategy classification method (Bröder, 2010; Bröder & Schiffer, 2003b). Importantly, the payoff function did not change from learning to test phase and TTB was the optimal decision strategy in both phases. Choice deviations from TTB due to "irrelevant" information as predicted by SPMs therefore could not be explained by adapting to a new environment. Rather, they would never be reinforced in this paradigm and can thus be considered maladaptive.

3. Experiment 1: Examining the influence of strategy-irrelevant information on information search, choice outcomes, and attention

In the first experiment, basic assumptions of SPMs and MSMs are contrasted. The logic of SPMs implies that if an accessible piece of information is applicable for a decision problem, it cannot be ignored but will be fed into the uniform mechanism proposed by the respective model. According to MSMs, in contrast, some pieces of information will be irrelevant for certain decision strategies and, therefore, they will be ignored by the decision maker who selected this strategy based on learning or explicit cost–benefit tradeoffs.

Following this reasoning, assumptions for two measures of decision behavior can be derived. First, with respect to search behavior TTB use implies search in order of validities terminating when a differentiating cue is found. Information search should not be affected by applicable information that lies behind the point defined by the stopping rule. As SPMs do not ignore applicable information, TTB-irrelevant information is not irrelevant here and search behavior may be affected by the content of this information. In particular, evidence accumulation models predict information search contingent on the magnitude of accumulated evidence (that is influenced by the content of intruding information) in relation to the proposed evidence threshold (that is rather stable and established in the learning phase). As soon as the threshold is passed, information search terminates. Connectionist models such as PCS (Glöckner & Betsch, 2008b) capture the process of information integration, but do (so far) not specifically model the process of information search (but see Betsch & Glöckner, 2010 and Glöckner & Herbold, 2011, for general predictions of PCS concerning information search). Thus, they do not make predictions concerning the effect of additionally revealed information on information search.

Second, we can derive contrasting assumptions for the choice outcomes. TTB's decision rule states that after information search is terminated the particular option will be chosen that is favored by the most valid discriminating cue. Again, this choice outcome is predefined by TTB's decision rule and will not be affected by TTB-irrelevant information. According to SPMs, TTB-irrelevant information can affect choice outcomes, because it will not be ignored. In particular, such information incompatible with TTB's predicted choice outcome might cause decision makers to choose an alternative option. For example, evidence accumulation models would predict that the incompatible information reduces the evidence accumulated in favor of the TTB-option. If it falls below the evidence threshold, information search proceeds and the choice outcome might deviate from the option predicted by TTB. Connectionist models, to give another example, would predict that the additional information becomes part of the neural network and thus influences the activation of the choice options. The TTB-option is only chosen when its activation (after the network has maximized its consistency) is higher than the activation of the alternative options.

In addition to information search and choice outcomes, we examined a third variable in Experiment 1: attention to cue information. Building on MSMs' basic assumption that only strategy-relevant information is considered, whereas strategy-irrelevant information is ignored, we included a potential measure for attention to cue value information in Experiment 1: memory performance for the respective cue value. If participants attend to cue values, their memory for this information should be superior to memory for information that was largely ignored.

3.1. Method

3.1.1. Design and procedure

We manipulated two factors within-subject: intrusion content (compatible TTB-irrelevant vs. incompatible TTB-irrelevant) and number of intrusions (1 vs. 2 fields of the information board). TTB-use was induced bottom–up by the information cost manipulation and additionally top–down as the instruction encouraged participants to employ the TTB heuristic which would be the best strategy for the task at hand. Participants' memory performance was tested in about 25% of the trials. For the 60 trials of the learning phase 90% of the intrusions were TTB-relevant (meaning that a TTB-user would have accessed this information anyway), whereas only 10% were TTB-irrelevant. The test phase consisted of 46 trials. In 40 trials the information intrusions were TTB-irrelevant. Half of them were compatible with the option favored by TTB and half of them were incompatible with it (cf. Fig. 1)—each with 50% one-field intrusions and 50% two-field intrusions. As attention to irrelevant as well as relevant information was of interest, additionally six trials with intruding relevant information were included in the test phase.

Participants were told to imagine being head of an oil drilling company (Rieskamp, 2006; Rieskamp & Otto, 2006). The company always looks for potential drilling sites and whenever three sites are available, the most promising one (containing most oil) has to be chosen. For each oil drilling, 1000 *Penunzen* of drilling costs are invested. As a decision aid, four different test institutes with varying levels of validity, which each perform a particular analysis (e.g., "seismic analysis"), can be commissioned to evaluate the available options (positive or negative

[2] Note that this labeling stems from the MSM view. This calibration phase can, however, of course also be described from the SPM view, e.g. in evidence accumulation models as learning to lower the evidence threshold.

Table 1
Overview of hypotheses for Experiment 1.

Dependent variable	Hypothesis	Independent variable	MSM prediction	SPM prediction
Information search	1.a	Content of TTB-irrelevant intrusion	Purchased pieces of information: (incompatible) = (compatible)	Purchased pieces of information: (incompatible) > (compatible)
	1.b	Interaction: Number of intrusions ∗ content	No interaction	Effect for Hypothesis 1.a: (2 fields) > (1 field)
Choice outcomes	2.a	Content of TTB-irrelevant intrusion	Proportion of choices in line with TTB: (incompatible) = (compatible)	Proportion of choices in line with TTB: (incompatible) < (compatible)
	2.b	Interaction: Number of intrusions ∗ content	No interaction	Effect for Hypothesis 2.a: (2 fields) > (1 field)
Attention	3	TTB-relevance of intrusion	Memory performance: (relevant) ≫ (irrelevant)	Memory performance: (relevant) = (irrelevant)

Note: MSM = multiple-strategy model; SPM = single-process model; TTB = "take-the-best" heuristic.

evaluation of the drilling site). The concept of validity was explained and cue validities for the four test institutes were stated: 97%, 75%, 67%, and 60% respectively. Further, participants were told that each purchased piece of information would cost them 4% of their potential investment profit (percentage payoff as determined by the payoff function ∗ 1000 Penunzen), whereas no costs would occur for a loss. The gain (profit minus information costs) or loss would be added to a virtual account and the four best managers would earn a voucher worth 25 Euros. Participants learned that they would get one or two randomly chosen pieces of information for free in each trial. After each decision, feedback (graphical and percentage payoff) would be given on how well each of the three drilling sites would have turned out, and for the chosen drilling site monetary feedback (in Penunzen) on profit, costs, and gain (or loss) was displayed. Participants were additionally encouraged to use the TTB strategy. The instruction veridically said that this strategy would be the best for the task at hand. It introduced the strategy and explained to the participants that the low costs for this strategy would compensate for the fact that sometimes the optimal option would not be chosen.

Participants were also informed that in about 25% of the trials their memory performance would be assessed. In these trials, immediately after the performance feedback, participants were shown an empty information board with three[3] cells of the information board highlighted. For each of the highlighted pieces of information, participants were asked to indicate, whether it was a positive evaluation (+), a negative evaluation (−), or an unknown piece of information (?) in the previous choice problem. After the instructions participants could familiarize themselves with the task in a practice trial and subsequently start working on the experimental trials.

All our hypotheses build on the following basic assumptions of the competing frameworks: From the MSM perspective, applicable information can be regarded as either relevant or irrelevant for the chosen strategy (i.e., TTB). Irrelevant information will be ignored by the TTB-user. SPMs, on the other hand, maintain that no applicable information is irrelevant to a decision problem. Therefore, TTB-relevant and -irrelevant information will be fed into the uniform decision making mechanism. From these assumptions we can derive specific predictions concerning search behavior (Hypotheses 1.a and 1.b), choice outcomes (Hypotheses 2.a and 2.b), and attention (Hypothesis 3) as they are depicted in Table 1.

3.1.2. Participants

Forty-eight participants (39 female, mean age 21.6) took part in the experiment, all but one being students from the University of Mannheim. They received course credit for their participation. The best four participants additionally received a voucher worth 25 Euros (approx. USD 35).

3.2. Results and discussion

3.2.1. Strategy classification

The decision strategy classification was based on the choice outcomes of the 60 trials of the learning phase that comprised three different item types: 18 trials of item type 1 (TTB predicts choosing one option, WADD and EQW predict choosing an alternative option), 20 trials of item type 2 (TTB and WADD predict choosing the same option, EQW predicts guessing between two options), and 22 trials of item type 3 (TTB, WADD, and EQW predict choosing the same option).[4] The upper part of Table 2 shows the result of the outcome-based strategy classification (Bröder, 2010; Bröder & Schiffer, 2003b). Strategy learning was successful as 47 participants were classified as TTB-users. Only one participant had to be excluded due to an estimated choice error rate for the best fitting strategy that exceeded .40 (Bröder & Schiffer, 2003b). Accordingly, 47 TTB-users were included in the analyses reported below.

3.2.2. Information search

The information search behavior can be characterized by the number of purchased pieces of information. As a dependent variable, we calculated the difference between the number of actual information purchases and the number predicted by TTB. Hence, this relative number of purchases is 0 if the stopping rule conforms to TTB and larger than 0 if the purchases exceed TTB's prediction. Fig. 2 shows the mean relative number of purchased pieces of information separated by the within-subject factors.

For Hypothesis 1.a we find a significant effect of the factor content of information ($F(1, 46) = 47.17$, $p < .001$, partial $\eta^2 = .51$) in line with the SPM prediction: When incompatible information intrudes, participants engage in a more extensive information search than when the content of the intrusion is compatible with the option preferred by TTB. As the interaction term suggests, this effect is more pronounced when two pieces of information intrude than when only one field gives the compatible or incompatible information ($F(1, 46) = 24.79$, $p < .001$, partial $\eta^2 = .35$), which is in line with the SPM prediction for Hypothesis 1.b. Additionally, we find a main effect of the factor number of intrusions ($F(1, 46) = 17.70$, $p < .001$, partial $\eta^2 = .28$): Participants engage in a more extensive information search when two

[3] We decided to assess memory performance for three pieces of information instead of one for several reasons: (1) Participants should not become aware of the fact that we were mainly interested in their memory for intruding information. Asking for non-intrusions therefore seemed advisable. (2) As there were only three answering options available (+,−,?), all three should be included in the correct response pattern. That would not have been the case if we asked for intruding pieces of information only. (3) The number of trials with subsequent memory performance assessment should not exceed 25% of the total number of trials as participants should concentrate on their choice task. We worried that more frequent memory performance assessments might lead to the unsatisfactory result that participants try to memorize each cue information in order to be successful in the upcoming memory test.

[4] Due to a data collection error five trials (0.083% of all trials) could not be analyzed and were therefore excluded from the analyses.

Table 2
Strategy classification for Experiments 1 and 2.

Experiment, condition	TTB			WADD			EQW		Unclassified	
	Number	Percent	Mean ε[a]	Number	Percent	Mean ε[a]	Number	Percent	Number	Percent
1, top–down	47	98%	.07	0	0%	–	0	0%	1	2%
2, top–down	28	93%	.08	2	7%	.23	0	0%	0	0%
2, bottom–up	26	87%	.12	4	13%	.22	0	0%	0	0%

Note: TTB = "take-the-best" heuristic; WADD = "weighted-additive rule"; EQW = "equal weight rule".
[a] ε is the error probability for choosing the nonpredicted option (see Bröder, 2010).

pieces of information intrude than when only one piece of information shows up for free.

3.2.3. Choice outcomes

As TTB only predicts a different choice outcome than WADD and EQW for one item type, choice outcomes were only analyzed for the 16 trials of this diagnostic item type in the test phase. Fig. 3 shows the mean proportion of choices in line with TTB separated by the within-subject factors.

Again, the result for Hypothesis 2.a is more in line with the SPM than the MSM view. The factor content of information significantly influences participants' choices ($F(1, 46) = 68.19$, $p < .001$, partial $\eta^2 = .60$): Participants refrain from choosing the option preferred by TTB more frequently when incompatible information is given than when compatible information intrudes. Testing Hypothesis 2.b, we find further support for the SPM view: As the interaction term suggests, the aforementioned effect is more pronounced when two pieces of information intrude than when an intrusion consists of only one piece of information ($F(1, 46) = 46.71$, $p < .001$, partial $\eta^2 = .50$). In addition to the predicted effects, we again find a main effect of the factor number of intrusions ($F(1, 46) = 21.56$, $p < .001$, partial $\eta^2 = .32$): Participants decide against the option favored by TTB more frequently when two pieces of information intrude than when only one field opens for free.

3.2.4. Attention

In order to assess attention to cue information, we tested participants' memory for eight irrelevant (four incompatible and four compatible with TTB's choice outcome prediction) intrusions in the test phase. Additionally, in each of the six trials with relevant information intrusions, we assessed memory performance for intruding information. Although in some of the trials the intruding information consisted of two pieces of information rather than only one (within-subject manipulation "number of intrusions"), memory performance was always assessed for one piece of information only.

Memory performance for irrelevant information intrusions ($M = .58$, $SD = .23$) significantly exceeds the chance level[5] of .50 ($t(46) = 2.24$, $p = .03$). Testing the directional MSM prediction for Hypothesis 3 that memory performance is better for relevant intrusions than for irrelevant ones with a paired *t*-test, we find a small, but significant effect in the assumed direction. The mean number of correct responses is higher for relevant ($M = .66$, $SD = .27$) than for irrelevant pieces of information: $t(46) = 1.83$, one-tailed $p = .04$, $d_z = 0.27$.

3.2.5. Discussion

The reported analyses largely support SPMs' basic assumption that applicable information is not ignored when making multi-attribute decisions. Specifically, participants successfully trained to employ the TTB heuristic do not adhere to TTB's stopping rule when incompatible irrelevant information intrudes. Furthermore, these "TTB-users" refrain from choosing the option favored by TTB more frequently when incompatible information is given than when compatible information intrudes. Both effects are more pronounced when two pieces of information convey the incompatible irrelevant information. Note that deviations from TTB are maladaptive since TTB was the decision strategy with the highest payoff—both in the learning phase as well as in the test phase. Hence, the effects can *not* be explained by a re-learning of contingencies in the test phase since deviations from TTB were not reinforced.

These so far unanimous findings in line with SPMs' predictions are challenged by the observation in line with MSMs' prediction that strategy-relevant information receives more attention than strategy-irrelevant one. However, it is possible that this difference merely mirrors the assumption largely shared by SPMs and MSMs that more valid information receives more attention. Due to TTB's search rule that entails information search in descending order of cue validity, it comes as a confound in our paradigm that relevant information is associated with cues of higher validity than irrelevant information. When only the ten trials (four irrelevant and all six relevant information intrusions trials) are included that test intruding information of the same validity (i.e., for the second most valid cue), the difference in the mean number of correct responses between relevant ($M = .66$, $SD = .27$) and irrelevant ($M = .61$, $SD = .25$) pieces of information is not observed: $t(46) = 1.01$, one-tailed $p = .16$. Thus, when controlling for cue validity, relevant information does not receive more attention than irrelevant information—a finding that does not support the MSM view, but is in line with SPMs' prediction. However, strong conclusions from the memory measure are not warranted because of the inevitable confound with validity that we did not think of before the experiment. We also cannot rule out the possibility that the memory assessment might have caused participants to pay more attention to the information intrusions than they would have done without this instruction. Thus, one could argue that the memory assessment might have biased the participants against the ignorance of information as predicted by TTB. Therefore, in Experiment 2 we did not assess memory performance, but asked for confidence judgments for which competing hypotheses can be derived from MSMs and SPMs.

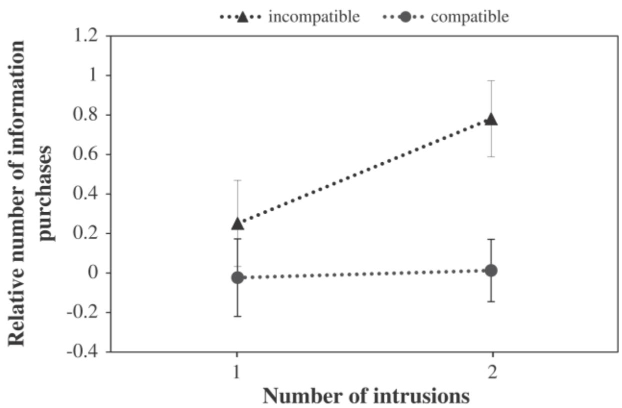

Fig. 2. Mean relative number of purchased pieces of information in Experiment 1 (error bars represent standard errors).

[5] Note that we administered a conservative test here by, instead of adopting the obvious chance level of .33 given the three answering options, choosing a chance level of .50 that assumes that decision makers are aware that the tested cell had been uncovered.

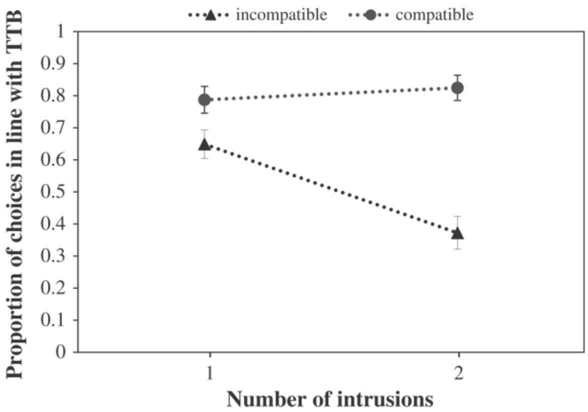

Fig. 3. Mean proportion of choices in line with TTB for the diagnostic item type in Experiment 1 (error bars represent standard errors). *Note*: TTB = "take-the-best" heuristic.

4. Experiment 2: Examining the influence of strategy-irrelevant information on information search, choice outcomes, and confidence judgments

The results of Experiment 1 are compatible with a uniform decision making mechanism as assumed by single-process models (SPMs). Participants classified as users of the TTB strategy did not ignore TTB-irrelevant information intrusions, but adapted their information search as well as their choice behavior to the content and the amount of the "irrelevant" information. Importantly, there was no recognizable change from the learning to the test phase—the task was identical.

As the results of the previous experiment constitute a novel finding, Experiment 2 aims to replicate the results within another task domain. Therefore, in Experiment 2 participants were repeatedly asked to choose among three stocks the one that will probably have the best future performance (Bröder, 2000, 2003; Newell & Shanks, 2003).

To further broaden the empirical basis for contrasting the two frameworks of decision making in Experiment 2, we asked the participants for confidence ratings on their choices. If decision makers choose the option predicted by TTB, SPMs would assume that confidence judgments should be lower when (TTB-irrelevant) incompatible information is presented than when compatible information intrudes. On the other hand, a decision maker employing the TTB heuristic will base a confidence judgment exclusively on TTB-relevant information. The confidence judgment should mirror the validity of the best discriminating cue (Gigerenzer et al., 1991) and not depend on the content of TTB-irrelevant information.

Finally, in Experiment 2 two different strategy induction procedures are employed in an explorative manner. Use of the TTB heuristic is either induced bottom–up only or in combination with a top–down instruction as in Experiment 1. This manipulation was introduced to test (1) whether the bottom–up induction alone would suffice to reliably induce TTB-use and (2) whether the induction method influences, how persistently TTB-users stick to their decision strategy, in particular to TTB's stopping and decision rule.

4.1. Method

4.1.1. Design and procedure

The design of Experiment 2 closely resembled the one of Experiment 1. Instead of testing the memory performance, participants were asked to judge their confidence. The additional factor strategy induction (bottom–up vs. bottom–up plus top–down) was manipulated between participants, whereas the factors intrusion content (compatible TTB-irrelevant vs. incompatible TTB-irrelevant) and number of intrusions (1 vs. 2 fields of the information board) were within-subject manipulations as in Experiment 1. Participants were randomly assigned to the two strategy induction conditions (with forced equal size of 30 participants per condition). In the bottom–up condition TTB use was induced by the reinforcement structure of the environment only, whereas in the second condition participants were additionally asked to employ the TTB heuristic (cf. Experiment 1). As we did not assess memory performance, we excluded the six test trials with relevant information intrusions of Experiment 1. Thus, Experiment 2 comprised 100 experimental trials—Experiment 1's 60 learning phase trials plus Experiment 1's 40 test trials with irrelevant information intrusions.

The procedure of Experiment 2 also closely resembled the one of Experiment 1. Participants were told that they would play a stock market game. In each trial they were to invest 1000 *Penunzen* into one of the three available stocks. For each of the stocks they could buy information (positive or negative evaluation of the respective stock) from four different brokers whose judgments had varying levels of validity. The remaining procedure was equivalent to Experiment 1's procedure, except that (1) participants in the bottom–up condition were not instructed to use the TTB heuristic and (2) memory performance was not assessed. Instead, in 25% of the trials the participants were asked for a confidence judgment for the just chosen option prior to the feedback. Confidence judgments were assessed on a scale ranging from "very unconfident" (0) to "very confident" (100).

Again, our hypotheses are derived from the basic assumptions of SPMs and MSMs concerning the ignorance of strategy-irrelevant information (cf. Experiment 1). For Experiment 2, we test the hypotheses for information search (Hypotheses 1.a and 1.b) and choice outcomes (Hypotheses 2.a and 2.b) displayed in Table 1. For the third dependent variable (i.e., confidence judgments) we are also interested in the main effect of the content of TTB-irrelevant intrusions (Hypothesis 3.a) and the interaction between content and number of intrusions (Hypothesis 3.b). MSMs predict that the content of the irrelevant information will not influence participants' confidence judgments. SPMs, on the other hand, predict that when encountering incompatible information participants should be less confident in choosing the outcome favored by TTB than when compatible information is given. This effect should be more pronounced when two pieces of incompatible or compatible information intrude than when only one field gives the information. Additionally, we explore whether the strategy induction method influences participants' search and choice behavior.

4.1.2. Participants

Sixty participants (50 students of the University of Mannheim plus 10 advanced level high school graduates, 33 female, mean age 21.0) took part in Experiment 2. They received course credit or monetary compensation (5 Euros) for their participation. The best four participants (with the highest end account balance in *Penunzen*) received a voucher worth 25 Euros.

4.2. Results and discussion

4.2.1. Strategy classification

Strategies were again classified with the outcome-based classification method (Bröder, 2010; Bröder & Schiffer, 2003b) on the basis of the 60 learning phase trials. As can be seen in the lower part of Table 2, the strategy induction procedure was successful: 90% of all participants were classified as users of the intended TTB strategy and therefore included in the subsequent analyses. There was no significant difference between conditions ($\chi^2(1, N = 60) = 0.74, p = .39$). Thus, the success of the bottom–up strategy induction was not worse than when strategy-use was induced bottom–up and top–down.

4.2.2. Information search

As for Experiment 1, we first analyzed the relative number of information purchases (absolute number minus the number predicted by TTB's stopping rule). Fig. 4 shows the mean relative number of

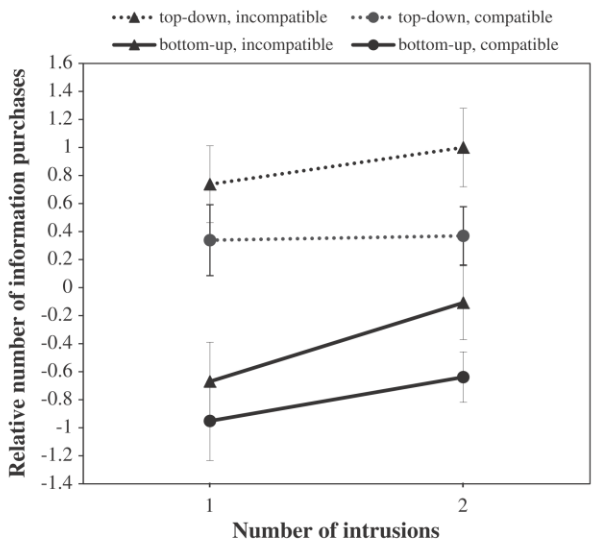

Fig. 4. Mean relative number of purchased pieces of information in Experiment 2 (error bars represent standard errors).

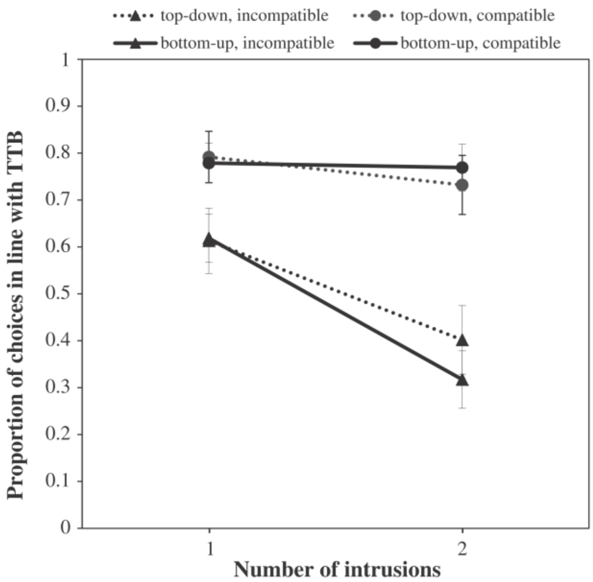

Fig. 5. Mean proportion of choices in line with TTB for the diagnostic item type in Experiment 2 (error bars represent standard errors). *Note*: TTB = "take-the-best" heuristic.

purchased pieces of information separated by conditions and by the within-subject factors content of information and number of intrusions.

Testing Hypothesis 1.a, we find support for the SPM prediction that the factor content of information systematically influences information search behavior: Participants classified as TTB-users purchase more pieces of information when the content of TTB-irrelevant intrusions was incompatible rather than compatible ($F(1, 53) = 54.60$, $p < .001$, partial $\eta^2 = .51$). The results for Hypothesis 1.b are also more in line with the SPM prediction as we find a significant interaction of the within-subject factors ($F(1, 53) = 4.25$, $p = .04$, partial $\eta^2 = .07$): The aforementioned effect is stronger when two pieces of information intrude than when only one field gives the information. In addition to these predicted effects, we find a significant main effect of the factor number of intrusions ($F(1, 53) = 20.05$, $p < .001$, partial $\eta^2 = .27$): When two pieces of information intrude participants purchase more information than when only one field gives the compatible or incompatible TTB-irrelevant information.

Employing a *t*-test for independent samples, we find that the method of strategy-induction also significantly influences information search behavior: When TTB-use had been induced bottom–up TTB-users purchase less pieces of information than when TTB-use had additionally been suggested in the instructions ($t(52) = 3.48$, $p = .001$, $d = 0.95$).

4.2.3. Choice outcomes

Choice outcomes were considered for the 16 test trials of the diagnostic item type, because only for this item type the choice outcome predictions of TTB and the other decision strategies (i.e., WADD and EQW) differ from each other. The mean proportion of choices in line with TTB separated by the conditions and the within-subject factors is displayed in Fig. 5.

For Hypothesis 2.a the factor content of information shows a significant main effect in the direction predicted by the SPM view ($F(1, 53) = 97.79$, $p < .001$, partial $\eta^2 = .65$): When the "irrelevant" information is incompatible to the TTB-option participants choose this option less often than when the intruding information is compatible with it. In line with the SPM prediction for Hypothesis 2.b, this effect is more pronounced when two pieces of information intrude than when only one field opens ($F(1, 53) = 27.16$, $p < .001$, partial $\eta^2 = .34$). Thus, for choice outcomes, the results are again more in line with the SPM than the MSM view. Again, we find a significant main effect of the factor number of intrusions ($F(1, 53) = 30.23$, $p < .001$, partial $\eta^2 = .36$): When two pieces of information intrude participants choose the option favored by TTB less frequently than when only one field gives the intruding information.

The method of strategy-induction shows no significant effect on choice outcomes ($t(49.39) = 0.17$, $p = .86$). Thus, the choice behavior of participants who were additionally encouraged to employ the TTB heuristic did not differ from the behavior of participants who learned the decision strategy bottom–up only.

4.2.4. Confidence judgments

The analyses for this variable were conducted on the basis of the same test trials that have been analyzed for choice outcomes. Only for these test items TTB predicted a different choice outcome than the compensatory decision strategies WADD and EQW.

Hypotheses 3.a and 3.b refer to confidence judgments for choices in line with TTB. Thus, in order to test these hypotheses we analyzed choices of the TTB-option for the diagnostic item type. As there were only 22 TTB-users (13 in the top–down and nine in the bottom–up condition) whose choices were in line with TTB at least once for all combinations of the two within-subjects factors, our analyses for confidence judgments rely on a reduced sample size.

Testing Hypothesis 3.a we find a significant main effect of the factor content of information as predicted by the SPM view: When information intrudes that is incompatible with the option favored by TTB, participants are less confident when choosing this option than when the "irrelevant" information is compatible with the option ($F(1, 21) = 14.04$, $p = .001$, partial $\eta^2 = .40$). Eight participants classified as TTB-users (four in the top–down and four in the bottom–up condition) chose the option favored by WADD and EQW at least once for all combinations of the two within-subject factors. Therefore, we were able to additionally analyze the confidence judgments for choices in line with these compensatory decision strategies for the diagnostic item type. Again, the factor content of information has a significant main effect ($F(1, 7) = 7.49$, $p = .03$, partial $\eta^2 = .52$), but in the opposite direction than for choices in line with TTB: If participants classified as TTB-users choose the compensatory option *not* favored by TTB, they are more confident when the intruding information was incompatible with the TTB-option than when the intruding information was compatible with the TTB-option. Fig. 6 shows the mean confidence judgments for choices in line with TTB (left part) and choices in line with WADD and EQW (right part) for the diagnostic

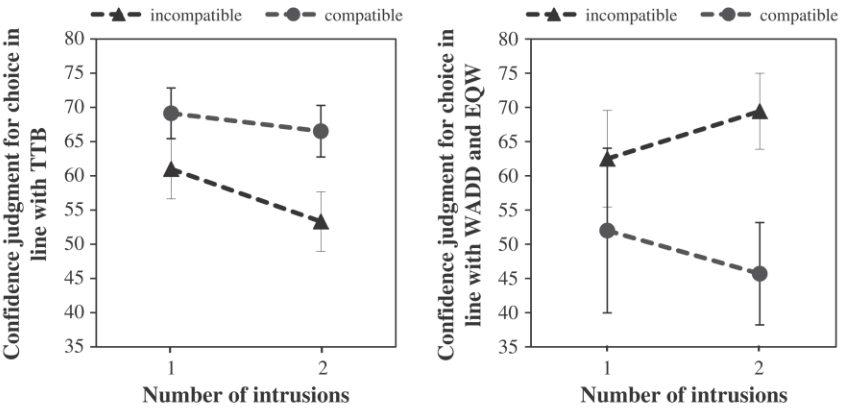

Fig. 6. Mean confidence judgments for choices in line with TTB (left part) and choices in line with WADD and EQW (right part) for the diagnostic item type in Experiment 2 (error bars represent standard errors). *Note*: TTB = "take-the-best" heuristic; WADD = "weighted-additive rule"; EQW = "equal weight rule".

item type, separated by the within-subject factors and pooled across conditions.

Though a trend is observable in Fig. 6, the interaction predicted by the SPMs for Hypothesis 3.b is neither significant for choices in line with TTB ($F(1, 21) = 2.10$, $p = .16$) nor for choices in line with compensatory decision strategies ($F(1, 7) = 4.07$, $p = .08$). The small N for these analyses ($N = 22$ for choices of the TTB-option and $N = 8$ for choices of the option favored by WADD and EQW) reduced the power of the tests considerably and gives a plausible explanation for the insignificance.

Nevertheless, in addition to the predicted effects we find a significant main effect for the TTB-option choices of the factor number of intrusions ($F(1, 21) = 9.79$, $p = .01$, partial $\eta^2 = .32$): When two pieces of information intrude participants are less confident in their choice in line with TTB than when only one piece of information intrudes. For the choices in line with the compensatory decision strategies there is no significant effect of the factor number of intrusions ($F(1, 7) = 0.01$, $p = .95$).

4.2.5. Discussion

Experiment 2 replicated Experiment 1's unanimous results concerning information search and choice outcomes: "TTB-users" did not generally adhere to TTB's stopping rule, but adapted their information search to the content of the intruding "irrelevant" information. Also, they refrained from choosing the TTB-option when the "irrelevant" information was incompatible with this option more frequently than when it was compatible. Both effects were more pronounced when two fields conveyed the intruding information. Taken together, these findings exactly replicate Experiment 1's results and thus concordantly support SPMs' predictions rather than the MSM view. Importantly, as we did not assess memory performance in Experiment 2, it can be ruled out that the observed violation of TTB's ignorance prediction is due to participants' desire to do well in the memory test.

As a complement to these variables, we investigated confidence judgments in Experiment 2. Again, the results were more in line with the predictions of SPMs than MSMs: "TTB-users" choosing the TTB-option were less confident with their choice when incompatible information intruded than when the "irrelevant" information was compatible with their choice. Interestingly, we observed the opposite pattern for "TTB-users" choosing an alternative option (favored by the compensatory decision strategies) over the one favored by TTB: When the "irrelevant" information was incompatible with the TTB-option they were more confident with their deviance than when the information was compatible with the TTB-option. Thus, the findings for the third dependent variable – confidence judgments – comprehensively corroborate the aforementioned results.

To account for the confidence results, one might argue that choices and confidence judgments are generated separately and based on different strategies and pieces of information. Although choices might be generated using a TTB strategy, the process of generating confidence judgments could include further available information and might be conducted only after the decision has been made (e.g., Pleskac & Busemeyer, 2010). We cannot rule out that the latter process might be influenced by information intrusions independent of the choice strategy, which could account for the confidence results as well. Thus, although the confidence judgment results are well in line with our predictions derived from SPMs and corroborate our findings for information search and choice outcomes, they can only be considered as weaker empirical arguments since their interpretation depends on the previously made assumption (e.g., Gigerenzer et al., 1991; Glöckner, 2009; Jekel, Nicklisch, & Glöckner, 2010) that people base choices and confidence judgments on the same strategies and pieces of information.

All results of Experiment 2 are in line with SPMs' basic assumption that applicable information cannot be ignored, but will be integrated in the decision making mechanism. Although the TTB heuristic outperforms (in terms of monetary payoff) other decision strategies in our environment, decision makers do not generally adhere to its stopping and decision rule, but adapt information search, choices, and confidence judgments to the content of TTB-irrelevant information. Importantly, this adaption cannot be attributed to learning processes in the test phase since deviations from TTB choices were not reinforced.

In Experiment 2, we also explored the role of how strategy-use is induced. Specifically, we compared one condition with top–down as well as bottom–up TTB-induction (as in Experiment 1) with one condition that relied on a bottom–up induction of the respective strategy only. Although both induction methods worked equally well concerning the outcome-based strategy classification (Bröder, 2010; Bröder & Schiffer, 2003b) of the learning phase, in the test phase we observed a discrepancy in information search behavior: Participants, classified as TTB-users, that acquired a decision strategy without top–down instruction purchased less pieces of information than those who were advised to employ the TTB heuristic. In fact, these participants regularly acquired less information than predicted by TTB. There was, however, no difference in choice outcomes between the two conditions. Thus, the bottom–up "TTB-users" evidently employed "heuristics" that are even more frugal than TTB, but lead to a high percentage of choices in line with TTB. Possibly, the instruction to purchase single cue values (Newell & Shanks, 2003; instead of cues as a whole, cf. Newell, Weston, & Shanks, 2003) leads participants to apply especially frugal "heuristics". This tendency is annihilated when a top–down instruction is added. However, it might be the case that this frugality effect was caused (or enhanced) by the task domain of Experiment 2: The stock market task might have worked as a prime for self-sufficiency (Vohs, Mead, & Goode, 2006, 2008), which could lead to the employment of heuristics that require especially few information from advisors. Importantly, our conclusions concerning the distinction between SPMs and MSMs are not invalidated by the observation that (some) participants employed an even more frugal decision strategy than the TTB heuristic. As long as this alternative decision strategy entails precise search, stopping, and decision rules and ignores strategy-irrelevant information, it can serve as an adequate substitute for the TTB heuristic for the purpose of our investigation.

5. General discussion

In multi-attribute decision making two frameworks coexist that make profoundly different assumptions about how people adapt to different environments. Empirical findings can often be explained very well by both frameworks. Previous attempts to distinguish between the two approaches have not yet satisfactorily shown which one of the frameworks is superior to the other.

We approached this question by introducing the novel information intrusion paradigm that builds on basic assumptions of the competing frameworks: Whereas MSMs propose that applicable information will be ignored when irrelevant for the chosen decision strategy, SPMs hold that any applicable information is relevant and will therefore influence a decision maker's behavior. In two experiments, information search and choice behavior followed SPMs' predictions—the strategy-irrelevant information intrusions were not ignored as their content influenced the decision makers' behavior in the direction predicted by the SPMs. In line with the SPM perspective, both effects were more pronounced when more information intruded. Experiment 1 additionally assessed memory performance, whereas Experiment 2 investigated confidence judgments instead. The findings for the latter are in line with SPMs' predictions as the content of the strategy-irrelevant information intrusions also influences confidence judgments in the predicted direction.

The uniformity of these findings speaks for the adequacy of the novel information intrusion paradigm to distinguish between the two frameworks of decision making. We believe that by concentrating on the basic assumptions of the two frameworks and thus contrasting the frameworks themselves rather than specific models that represent them, the current work appreciably contributes to the quest to distinguish between the two coexisting frameworks. Furthermore, the paradigm allows the assessment of a broad empirical basis that comprises search and choice behavior as well as confidence judgments. Thus, our conclusions rest on a considerable amount of diverse, but concordant findings.

A potential criticism from a MSM view could be that there was an environmental change from learning to test phase since, on average, the nature of the intruding information changed. This change might have led participants to question the initially learned decision strategy TTB and therefore caused the observed shift in the participants' behavior in the test phase. We believe this objection to be implausible for two reasons: (1) The payoff function did not change throughout the experiment, the performance feedback was identical, TTB was the strategy with the highest payoff in both learning and test phase (this is also true when compatible and incompatible test trials are considered separately) and the additional tasks (memory assessment in Experiment 1 and confidence judgment in Experiment 2) were also administered in both phases. Thus, we took all measures to design learning and test phase as similar to each other as possible. (2) During the learning phase TTB-irrelevant information intruded in 10% of all trials. Therefore, participants employing the TTB heuristic should have realized already in the learning phase that the intruding information can be either helpful or useless. Since there was no recognizable change in the task structure and appearance, no change in payoffs, and a consequent further reinforcement of using TTB, a strategy selection approach would certainly have to pull up ad hoc assumptions to explain the consistent behavioral effects observed here.

A related criticism of our conclusion might argue that we circumvented strategy selection in the first place by focusing on TTB. However, the MSM view assumes that a strategy is selected contingent on task and environmental demands, and our predictions concern processing after people have allegedly selected the TTB strategy. In fact, not all participants were classified as using TTB, so they apparently selected other strategies. However, the "top–down" conditions may still be criticized to cause a rather unnatural selection situation by providing an instruction how to use TTB. This criticism does not touch the "bottom–up" condition, however, in which only the environmental payoff led most people to select TTB in an adaptive manner (Bröder, 2003; Rieskamp & Otto, 2006). The pattern of results is identical if only this condition is analyzed (see Appendix). Hence, the conclusions also hold for a situation typically characterized by MSMs to involve strategy selection.

To summarize, our results are in line with the SPMs' assumption that any applicable information will be fed into an assumed single decision making mechanism. From the view of evidence accumulation models (e.g., Lee & Cummins, 2004), our results can be interpreted as follows: In the learning phase the evidence threshold is lowered until any discriminating cue reliably causes the overstepping of the threshold. Thus, information search and choice behavior are in line with TTB's predictions (e.g., Hausmann & Läge, 2008). In the test phase, TTB-incompatible information intrusions automatically will be fed into the mechanism and can therefore cause an undershooting of the threshold. As information search is only terminated when the threshold is reached, in these cases decision makers need to search for additional information before making a decision. Furthermore, in these cases they will not blindly follow TTB's decision rule, but integrate the searched (and intruded) information in their decision. Confidence judgments mirror the stopping point of the evidence accumulation in relation to the threshold: With additional compatible information, the decision maker is very confident with choosing the option favored by TTB, because the threshold is considerably overstepped. Incompatible information reduces evidence for and thus confidence in a choice in line with TTB's prediction.

Also another prominent class of SPMs, the connectionist models (e.g. PCS, Glöckner & Betsch, 2008a), can account for our findings although it has to be augmented with auxiliary assumptions to account for search behavior. For example, the PCS model (as well as other connectionist models, cf., Simon & Holyoak, 2002; Thagard & Millgram, 1995) precisely describes the process of information integration, but gives only a general idea of how the process of deliberate information search might interact with it. However, in line with Betsch (2005, p. 51), one can assume that "suboptimal outcomes of prior decisions" lead to a deliberate mode of decision making that entails a thorough consideration of what information is searched for and fed into the neural network. Thus, in the learning phase, decision makers can learn to calibrate their information search to the environment. Glöckner and Betsch (2008a, p. 222) further propose that "deliberate constructions" help to form and adjust the network. As this process is not fully specified, we can only assume that incompatible information intrusions might lead to such a low level of consistency (achieved after the automatic maximization process) that deliberate information search is initiated (Betsch & Glöckner, 2010; Glöckner & Betsch, 2008a). With regard to choice outcomes and confidence judgments, the predictions of the PCS model are precise and in line with our findings: When feeding incompatible information into the network, the activation of the TTB-option decreases and the alternatives' activation increases. Thus, the difference in activation is reduced, leading to lower confidence judgments when choosing the TTB-option (e.g., Glöckner, 2009; Jekel et al., 2010). If the activation of an alternative option exceeds the activation of the TTB-option, this alternative will be chosen and confidence judgments will mirror the absolute difference in activation between the TTB-option and the chosen alternative.

One might argue that our findings are also in line with MSMs. Of course, one can make the assumption that whenever information is for free and applicable, it is not ignored. Instead, whenever this "irrelevant" information is incompatible with the option favored by the (bottom–up learned and sometimes additionally top–down induced) TTB heuristic, this successful decision strategy is abandoned in favor of a compensatory one. This interpretation would speak against findings that show routine effects in decision strategy use (c.f., Bröder & Schiffer, 2006; Rieskamp, 2006) and violate the standard assumption underlying most strategy classification methods (e.g., Bröder & Schiffer, 2003b; Glöckner, 2009; Payne et al., 1993) that the same strategy is employed throughout one experiment when the environment remains stable. Moreover, if one assumed a screening mechanism that checks for every trial whether an application of a strategy is worthwhile, and the application of this decision rule is changed contingent on this screening, the term "strategy" as an ordered set of processes to solve a task would hardly retain its meaning. Nevertheless, we cannot rule out this post hoc MSM interpretation on the basis of our results. But we can reflect on the parsimony of this interpretation.

A possible limitation of the approach used here is the focus on serial heuristics in the toolbox that are rather nested within an SPM view. For example, we have not considered similarity-based mechanisms as proposed, for instance, in exemplar models of decision making (e.g. Juslin, Olsson, & Olsson, 2003).[6] These models, however, currently do not specify search mechanisms, but they rely on similarity matches between whole cue patterns. Hence, the search data presented here are *prima facie* not compatible with assuming a similarity-based mechanism. In addition, empirical evidence seems to suggest that exemplar-based mechanisms in judgment are only used in restricted sets of situations (see Karlsson, Juslin, & Olsson, 2008, for an overview). It is an open question for future research whether the similarity mechanisms demonstrated in these situations can also be subsumed under an evidence accumulation perspective, for example by assuming that the internal decision criterion is switched to similarity when objective information is hard to encode (Platzer & Bröder, 2013). Furthermore, it might be possible to capture similarity mechanisms also in parallel constraint satisfaction approaches, which have been successfully applied as models for similarity based analogical reasoning (Holyoak & Thagard, 1989).

Both frameworks to multi-attribute decision making are metaphors that try to describe human behavior, and as Ebbinghaus (1885) elegantly put it, the only thing we know for sure about our metaphors is that they are ultimately wrong. Sometimes, competing metaphors are so flexible that they are able to account for any empirical finding (see the discussion on mental rotation, Shepard & Metzler, 1971; Pylyshyn, 1979, on persuasion, Kruglanski & Thompson, 1999; Manstead & van der Pligt, 1999, or, in decision making research, on the indistinguishability of exemplar memory and rule abstraction, Barsalou, 1990) and it becomes therefore impossible to empirically distinguish between them. Here, one should ask for the more elegant metaphor that can account for the variety of empirical findings with only a minimum of amendments. Thus, the parsimony of a metaphor must be taken into account. Even our highly consistent empirical findings, that are completely in line with the predictions a priori derived from SPMs' basic assumptions, can be explained by the MSM interpretation that participants adapt their decision strategy from each trial to the next. The more elegant explanation for the results presented here is given, however, by assuming a single uniform mechanism for decision making. Given, that contingent decision making can be "explained" equally well by assuming either a shift in decision strategies or an adjustment of decision thresholds (or a connectionist network), the parsimony consideration rather favors the SPM view.

To end with an amicable notion for researchers preferring the MSM metaphor and methodology, however, it must be acknowledged that their findings and interpretations are by no means invalidated by this conclusion. In fact, most of our own work would be questioned if we took such an extreme position! Rather, we suggest to scrutinize strategy shift interpretations of former work for the possibility to reinterpret them as, for example, threshold shifts. We expect this to be possible in most instances.

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[6] We thank an anonymous reviewer for pointing this out.

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Toolbox or Adjustable Spanner?

A Critical Comparison of two Metaphors for Adaptive Decision Making

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Abstract

For multi-attribute decision tasks different metaphors exist that describe the process of decision making and its adaptation to diverse problems and situations. Multiple-strategy-models (MSMs) assume that decision makers choose adaptively from a set of different strategies (toolbox metaphor), whereas evidence accumulation models (EAMs) hold that a uniform mechanism is employed, but adapted to the environmental change (adjustable spanner metaphor). Despite recent claims that the frameworks are hard to disentangle empirically, both metaphors make distinct predictions concerning the information acquisition behavior – namely, that search is terminated according to the selected strategy (MSMs) or that information is acquired until an evidence threshold is passed (EAMs). In three experiments, we contrasted these predictions by providing participants with different degrees of evidence in a half-open-half-closed information board. For the majority of participants we find that their stopping behavior is well captured by the notion of an evidence threshold that is either undercut or passed by the given evidence.

1 Introduction

When choosing between multiple options, decision makers sometimes rely on one good reason only and sometimes they search for a lot of arguments before making their decision. Observing these adaptations, one can conclude that humans employ different decision strategies in different situations (*toolbox metaphor*, e.g., Gigerenzer, Todd, & ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993). But the behavioral changes can also be explained by assuming that a uniform mechanism is used – with its input adapted to the situation at hands *(adjustable spanner metaphor*, e.g., Lee & Cummins, 2004; Newell, 2005). These two metaphors or frameworks of decision making coexist – primarily, because they are both able to account for the vast majority of empirical findings, but also because they are hard to disentangle empirically (Jekel, 2012; Newell, 2005; Newell & Bröder, 2008). In the current paper, we concentrate on predictions from the two frameworks concerning the termination of information acquisition and contrast them in a novel paradigm that systematically varies the level of given evidence.

The remainder of this introduction is organized as follows: First, we introduce the aforementioned two frameworks of decision making in more detail. We then address the question *why* disentangling these coexisting approaches poses an "empirical challenge" (Newell, 2005, p. 13) and give a brief overview of recent attempts to tackle this challenging task. Finally, we introduce a novel paradigm that enables us to contrast the two frameworks by concentrating on their predictions concerning the termination of information acquisition under varying levels of given evidence. This paradigm constitutes the basis for the three experiments reported and discussed in the remainder of this article.

1.1 Two frameworks of decision making

The two frameworks we will describe in turn address multi-attribute decision tasks. Here, decision makers have to choose among two or more options (e.g., potential oil drilling sites) the one that scores highest on a certain criterion (e.g., quantity of contained oil). As decision aids, attributes (or cues) that evaluate the options can be consulted (e.g., a chemical analysis yielding a positive or negative evaluation), and each cue has some validity in reference to the decision criterion (e.g., a validity of .80 means that in eight out of ten cases where the chemical analysis discriminates, it favors the site that actually contains the most oil). If the criterion is an objective one (e.g., the quantity of oil), the task is referred to as *probabilistic inference*, whereas a subjective criterion (e.g., preference for a day trip) characterizes a *preferential choice* task. As empirical similarities suggest similar cognitive processes in both domains (Bröder & Newell, 2008; Payne et al., 1993; Todd, Gigerenzer, & ABC Research Group, 2012) we do not address them separately, but subsume both under the more general term *multi-attribute decision* tasks.

In the laboratory, multi-attribute decision tasks are regularly presented in a matrix-like presentation format, called *information board* (Payne, 1976; Payne et al., 1993). To trace the process of information acquisition, closed information boards initially hide the cue values and participants have to intentionally acquire the information of interest before making a decision.

1.1.1 Multiple-strategy models

One well-established framework for multi-attribute decision making is the *toolbox metaphor*. Despite differences in other assumptions, the various multiple-strategy models (MSMs, e.g., Beach & Mitchell, 1978; Gigerenzer et al., 1999; Payne et al., 1993; Scheibehenne, Rieskamp, & Wagenmakers, 2013) in unison assume that decision makers are equipped with a set of distinct decision strategies – much like the numerous special tools contained in a toolbox (e.g., the "adaptive toolbox", Gigerenzer & Todd, 1999). Decision makers adaptively select the most appropriate one contingent on the current situation (e.g., Marewski & Schooler, 2011; Rieskamp & Otto, 2006).

Decision strategies can be described by three rules: a search rule, a stopping rule, and a decision rule (Gigerenzer et al., 1999). For example, the prominent "take-the-best" heuristic (TTB, Gigerenzer, Hoffrage, & Kleinbölting, 1991) holds that a decision maker searches information along the cue validity hierarchy starting with the most valid cue (TTB's search rule). The decision maker stops information acquisition as soon as a cue discriminates between the options (TTB's stopping rule) and chooses the option supported by the respective cue (TTB's decision rule). As TTB often uses only a subset of the available and applicable information (so-called *frugality*, Gigerenzer & Goldstein, 1999) and bases the decision on one valid cue alone (noncompensatory decision making) it is typically contrasted with compensatory decision strategies that use all available information and involve tradeoffs between cues (e.g., Bergert & Nosofsky, 2007; Bröder, 2000, 2003; Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b, 2006a, 2006b; Dieckmann, Dippold, & Dietrich, 2009; Gigerenzer & Goldstein, 1999; Lee & Cummins, 2004; Newell & Lee, 2009, 2011; Rieskamp, 2006; Rieskamp & Otto, 2006; Scheibehenne et al., 2013). This competing class of compensatory decision strategies includes strategies that weigh the cues according to their validities (e.g., the weighted additive rule, WADD, Payne et al., 1993, or Franklin's rule, Gigerenzer & Goldstein, 1999), but also strategies that give unit weights to the cues (e.g., the equal weight rule, EQW, Dawes, 1979; Payne et al., 1993, or Dawes's rule, Gigerenzer & Goldstein, 1999). Although the aforementioned decision strategies gained by far the most attention, the number of proposed strategies exceeds this selection considerably (e.g., Payne et al., 1993; Rieskamp & Hoffrage, 1999; Svenson, 1979). The bottom line of the toolbox metaphor is that each decision strategy or heuristic can be characterized as a set of production rules that govern search, stopping, and choice.

1.1.2 Single-process models

The "single-process models" (SPMs, e.g., Busemeyer & Johnson, 2004; Busemeyer & Townsend, 1993; Hausmann & Läge, 2008; Lee & Cummins, 2004) constitute a framework that is summarized by Newell's (2005, p. 13) "*adjustable spanner*" *metaphor*: SPMs assume that instead of selecting one from several distinct decision strategies, decision makers employ the same uniform decision making mechanism in every situation. They adapt this universal tool to the current situation – much like widening and narrowing the jaws of an adjustable spanner (Newell & Lee, 2009).

Within the framework of SPMs, several classes of models exist. Connectionist models, for example, assume that the decision problem is represented in a neural network that captures all decision-relevant information. Activation spreads in parallel through the network until a stable state of maximized consistency is reached and the option with the highest positive activation is chosen (parallel constraint satisfaction networks, e.g., Glöckner & Betsch, 2008; Simon & Holyoak, 2002; Thagard & Millgram, 1995). As connectionist models currently focus on the process of information *integration*, but do (so far) not specifically model the process of information *acquisition* (but see Betsch & Glöckner, 2010; Glöckner & Herbold, 2011, for general predictions of PCS concerning information search), we do not further address this model class in the current paper.

Another prominent class of SPMs that models the process of information search is called *evidence accumulation models* (EAMs, e.g., Busemeyer & Townsend, 1993; Hausmann & Läge, 2008; Lee & Cummins, 2004; Newell, 2005). EAMs assume a sequential sampling process that terminates as soon as the accumulated evidence passes an evidence threshold.[1] Although models from this class have successfully been applied to simple choice tasks (see, e.g., Krajbich, Lu, Camerer, & Rangel, 2012; Ratcliff & McKoon, 2008) and their application to multi-attribute decision tasks seems straightforward (Newell & Lee, 2011), only few models aim to capture the sequential information search usually investigated for multi-attribute decision tasks (but see, e.g., Diederich, 1997). The obvious reason for this shortcoming is that a multi-attribute decision task with hidden cue information (e.g., using a closed information board) constitutes a sequence of simple choice tasks (see, e.g., Busemeyer & Rapoport, 1988) – that is whether or not to uncover further cue information. In order to describe such a multi-attribute decision task by a single evidence accumulation model, we deem it helpful to adapt the step-size of the model from, for example, attention shifts (e.g., Busemeyer & Townsend, 1993) to the acquisition of a whole cue. Lee and Cummins (2004) developed such a model that assumes cue-wise information search along the cue validity hierarchy and termination of the sequential sampling process when either (1) the combined log-odds values of the so far sampled cues pass the threshold or (2) all cues have been sampled. Hausmann and Läge (2008) presented a model that predicts the termination of the sequential search process if the validity of the first discriminating cue corresponds to or lies above the individual confidence threshold. Their model remains unspecified in terms of information integration. Both models motivated empirical tests and some of this work will be addressed in the next section.

1.2 How to distinguish between the two frameworks?

The coexistence of the different frameworks (SPMs assuming a flexible, uniform mechanism and MSMs proposing a toolbox containing several qualitatively different

[1] Two subclasses of these sequential sampling models exist: (1) Diffusion models or random walk models (e.g., Busemeyer & Townsend, 1993; Diederich & Busemeyer, 2003; Ratcliff, 1978; Ratcliff & Smith, 2004) assume a single accumulator where positive evidence for one option simultaneously means negative evidence for the alternative option. (2) Accumulator models or counter models (e.g., Ratcliff & Smith, 2004; Usher & McClelland, 2001; Vickers, 1970) assume single accumulators or diffusion processes for each option. To discuss these subclasses in more detail is beyond the scope of this paper (but see Ratcliff & Smith, 2004, for an overview). However, we took care that our paradigm in principle applies to both subclasses by providing only negative evaluations as non-discriminating evidence in the test phase of our experiments. This should not affect diffusion models and accumulator models differentially as no evidence in favor of either option is conveyed.

mechanisms) has been deemed unsatisfactory (Glöckner & Betsch, 2011). However, it is consequential as it has been argued that the frameworks are hard to disentangle empirically due to their ability to mimic each other (Newell, 2005; Newell & Bröder, 2008). For example, behavior in line with TTB (MSM view) can be reinterpreted as evidence accumulation with a low evidence accumulation threshold (EAM view) and vice versa. In both interpretations, the decision maker stops information search as soon as the first discriminating cue is found and chooses the option favored by this cue. The use of compensatory decision strategies (MSM view) corresponds to evidence accumulation with a high evidence accumulation threshold (EAM view). Here, information search only stops when many or all available pieces of information have been inspected and the option is chosen that received more positive evidence.

1.2.1 Recent attempts to disentangle the two frameworks

In recent years, there have been some attempts to disentangle the two frameworks (see Söllner, Bröder, Glöckner, & Betsch, 2014, for a short overview). As the current paper focuses on information acquisition and, in particular, the termination of it, we concentrate our following critical overview on studies that addressed this dependent variable.

Hausmann and Läge (2008) contrasted their evidence accumulation model with the MSM prediction that decision makers either stick with one-reason decision making (as predicted by TTB) or more-reason decision making (as predicted by compensatory strategies). In two experiments they showed that their participants' stopping behavior was well captured by assuming an individual confidence threshold, but was only rarely in line with the MSM prediction. In particular, Hausmann and Läge's participants terminated information search when the validity of the first discriminating cue overshot the estimated individual confidence threshold and went on to search for information when its validity undershot this "desired level of confidence" (Hausmann & Läge, 2008). Manipulating the relative information cost per cue within subject, Hausmann-Thürig (2004) further showed that participants adapted their individual confidence threshold (according to Hausmann & Läge's model): Low relative information costs led to higher thresholds than high relative information costs.

In our view, this line of research concentrating on Hausmann and Läge's (2008) evidence accumulation model provided interesting and valuable support for the notion of evidence-based stopping behavior. Especially their consideration of individual (as opposed to aggregated) data constitutes an eligible analysis (e.g., Cohen, Sanborn, & Shiffrin, 2008; Gigerenzer & Gaissmaier, 2011; Pachur, Bröder, & Marewski, 2008). However, we argue that the concentration on solely the first discriminating cue (Hausmann & Läge, 2008; Hausmann-Thürig, 2004; Jekel, 2012), missed out a vital component of EAMs: the *accumulation* of several pieces of evidence (see also Jekel, 2012, for a similar argument).

The evidence accumulation model put forward by Lee and Cummins (2004) assumes that the log-odds values of the sampled cues are summed up sequentially, yielding evidence in favor of either one of two obtainable options. Newell and Lee (2009, 2011) investigated the stopping behavior as predicted by this model. Newell and Lee (2009) monitored the stopping behavior in dependence on environmental changes (i.e., whether a compensatory strategy had higher predictive performance than TTB or not). They found that participants adapted the number of cues acquired to these changes – on an individual level as well as in the aggregate. Newell and Lee reflected that the inconsistency of this finding with previous work based on choice outcome analyses showing inertia effects (Rieskamp, 2006) and strategy routines (Bröder & Schiffer, 2006a) suggests that analyzing the "the amount of evidence accumulated […] increases the likelihood of observing adaptation" (2009, p. 477). Thus, Newell and Lee (2011) did not only consider choice outcomes in a model fit comparison (see, e.g., Söllner et al., 2014, for a short summary), but extended their investigations (in Experiment 2) to participants' stopping behavior. Building on Lee and Cummins' (2004) model, they computed the mean level of evidence at which participants consistently choosing the TTB option and participants consistently choosing the alternative (compensatory) option terminate information search. They found that this threshold proxy significantly differed between these extreme groups – a finding that is well in line with the aforementioned mimicking relationship between the two frameworks (MSMs and EAMs). This approach to assessing the height of the assumed evidence accumulation threshold constituted a valuable further step towards disentangling MSMs and EAMs.

However, we believe that Newell and Lee's (2011) approach – although yielding essential findings – entails some weaknesses. Firstly, their results need to be interpreted carefully as the experiment entailed a cue validity learning phase that could result in an incorrect subjective cue validity hierarchy (cf. Bergert & Nosofsky, 2007; Newell & Lee, 2011). Therefore, the subjective cue weights could substantially differ from the objective cue validities, constituting the basis for the threshold assessment. Moreover, the threshold assessment was based on aggregated data, rather than estimating an individual evidence threshold for each participant. In our view, this should be the next step towards disentangling MSMs and EAMs.

Both research lines presented so far (concentrating on either Hausmann and Läge's model or Lee and Cummins' model) compared specific models of evidence accumulation to specific decision strategy models, instead of aiming at the more general frameworks. Therefore, the conclusions drawn were in principle only valid for the specific models considered and not easily generalizable to model classes and frameworks. In a recent paper (Söllner et al., 2014), we tried to overcome this drawback by concentrating on basic predictions derived from MSMs and SPMs (covering EAMs and connectionist models). The basic idea was to test, whether participants apparently using a frugal decision strategy do actually confirm to this decision strategy's production rules or, alternatively, behave more in line with SPMs' predictions. For this aim, we induced TTB-consistent behavior (e.g. via extensive training in a task with strictly noncompensatory payoff) and investigated, whether participants who had successfully undergone this induction procedure ignored freely available TTB-irrelevant information as predicted by TTB's famous algorithm "take the best, ignore the rest" (Gigerenzer & Goldstein, 1996, p. 653). In two experiments, we found that participants did *not* ignore this freely available extra information, but adapted their behavior to its compatibility with the TTB-relevant information. In regard to information search we observed that participants searched for more information when the extra information was incompatible (weakening the TTB-option favored by the most valid discriminating cue) than when it supported the TTB-option (compatible information). This finding was predicted by EAMs, but not easily accounted for by MSMs. Thus, we concluded that SPMs offer a better account for the observed behavioral data than MSMs can.

However, we believe that two disadvantages of this former approach need to be tackled in order to substantiate this conclusion: (1) The information intrusion paradigm (Söllner et al., 2014) entailed that in a closed information board certain pieces of information were opened for free without being intentionally uncovered by the decision maker. Critiques might argue that demand effects caused the decision makers to attend to this intruding information. (2) The paradigm necessitated apparent TTB usage as precondition for all analyses. Therefore a strategy induction procedure aiming at TTB was inescapable and analyses were limited to participants whose choice behavior was well-captured by TTB. Hence, the conclusion may only generalize to frugal decision strategies that ignore some information, whereas an EAM approach also claims validity for mimicking compensatory strategies.

To sum up, previous work on EAMs for multi-attribute decision tasks suggests that these models constitute a promising alternative to the MSMs predominantly investigated in decision making research. However, we argue that the aforementioned studies do not provide conclusive evidence for the superiority of the adjustable spanner metaphor as several aforementioned shortcomings need to be tackled. In the next section we introduce our latest attempt to do so.

1.2.2 A new paradigm: Varying the levels of given evidence

The basic idea for this paradigm is to confront participants with different levels of given evidence to contrast MSMs' and EAMs' predictions concerning the termination of information acquisition. Whereas EAMs predict stopping behavior in accordance to the proposed evidence threshold, MSMs predict stopping behavior in line with decision strategies' stopping rules. Thus, according to MSMs stopping behavior should comply with a few distinct stopping behavior patterns that characterize the different stopping rules. In line with all of the aforementioned studies (Hausmann & Läge, 2008; Hausmann-Thürig, 2004; Jekel, 2012; Lee & Cummins, 2004; Newell & Lee, 2009, 2011) as well as many studies within the MSM framework (e.g., Bergert & Nosofsky, 2007; Bröder, 2000, 2003; Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b, 2006a, 2006b; Dieckmann et al., 2009; Gigerenzer & Goldstein, 1999; Rieskamp, 2006; Rieskamp & Otto, 2006; Scheibehenne et al., 2013) we concentrate our considerations concerning the MSM framework on TTB and compensatory strategies. As MSMs, however, do incorporate considerably more decision strategies (e.g., the "Take Two" heuristic, Dieckmann & Rieskamp, 2007), we will address the generalizability of our conclusions to further decision strategies and stopping rules in the discussion of Experiment 1 and, additionally, in the general discussion.

To give an example for such a distinct stopping behavior pattern of the MSM framework, TTB's stopping rule entails the termination of information search as soon as the most valid discriminating cue is found. Compensatory decision strategies hold that information search only stops when no further information is available. We consider these two stopping rules as the quintessential ones for the MSM framework.

EAMs, in contrast, predict a more variable stopping behavior, contingent on the given evidence. For example, they allow for the termination of information search as soon as the most valid discriminating cue is found (adhering to TTB's stopping rule) when the cue validity of this cue is considerably high, whereas the same participant might continue information search (violating TTB's stopping rule) when its validity is rather low (cf. Hausmann & Läge, 2008).

From the EAM view, stopping behavior strictly in line with TTB's stopping rule corresponds to a very low evidence threshold that is overshot by any given evidence. The other extreme of possible stopping behaviors is marked by exhaustive sampling of all available information as predicted by compensatory strategies (MSM view) or a very high evidence threshold that is not overshot by any given evidence (EAM perspective). By presenting participants with different levels of given evidence, we aim to investigate the range between the aforementioned extreme points and see whether systematic stopping behavior can be observed that confirms to the assumption of variable evidence thresholds.

We implement this idea via half-open-half-closed information boards. The open part conveys different levels of given evidence and the closed part allows for further information acquisition. For each trial, we register whether a participant immediately stops information search or purchases more information alternatively. As TTB's and the compensatory decision strategies' stopping rules mark the MSM framework's predictions for our investigation, the different levels of given evidence are constructed to each satisfy TTB's stopping rule and miss the compensatory decision strategies' stopping rule.

Whereas the MSM framework therefore does not predict behavioral changes, the levels are designed in a way that EAMs do predict a distinct adaptation of the stopping behavior. For this aim, the given evidence in favor of one option increases from the lowest level 1 to the highest level 8. Table 1 shows the manipulation-relevant information openly displayed for each of the levels of given evidence. Here, cues are ordered from highest to lowest validity, and for simplicity, the displayed evidence in Table 1 always favors the left option. For example, the lowest level of given evidence, level 1, is characterized by non-discrimination of the two most valid cues (Cue1 and Cue 2) and positive evidence in favor of the left option given by the third most valid cue (Cue 3). According to TTB's stopping rule, a decision maker should immediately terminate information search as the most valid discriminating cue is already openly displayed. Compensatory decision strategies predict that information search continues as three more cues are hidden. Importantly, the same MSM predictions are valid for all levels of given evidence. The difference between the levels, however, lies in the given evidence. For example, in comparison to level 1, the second lowest level (level 2) gives more evidence, as it is the second most valid cue that discriminates between the options. The same logic applies to the remaining levels of given evidence.

Table 1: Cue value manipulation for the levels of given evidence.

	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1	- -	- -	+ -	+ -	+ -	+ -	+ -	+ -
Cue 2	- -	+ -						+ -
Cue 3	+ -						+ -	
Cue 4						+ -		
Cue 5					+ -			
Cue 6				+ -				

Note: “-” = initially displayed negative cue value; “+” = initially displayed positive cue value. Please note that this table shows only the manipulation-relevant cue values openly displayed. In sum, three cue values (manipulation-relevant plus further cue values) are openly displayed in each trial.

In our experiments, participants are confronted with the different levels of given evidence (within subject manipulation) and have to choose the superior option in each trial. To solve this task, they can purchase further information or rely on the information already available to them. In the instructions as well as during each trial (cf. Figure 1), we inform participants about the cue validity hierarchy to make sure that the assumed ordering of the levels of given evidence is valid for each participant’s subject cue ordering. Across all trials, we keep the number of openly displayed pieces of information constant – mainly for two reasons: (1) For each trial the same information costs shall incur and (2) MSM’s stopping rules relying on a fixed number of cues shall predict the same behavior for each level. Figure 1 shows exemplary trials for the lowest and the highest level of given information as employed in our experiments.

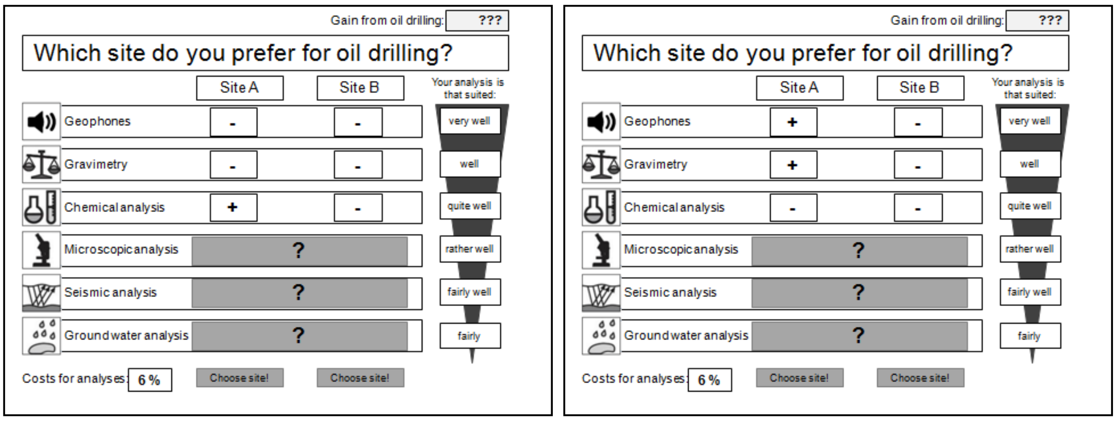

Figure 1: Test trials from level 1 (least given evidence, left part) and level 8 (most given evidence, right part). *Note* that on both levels, three cues are revealed, but the given evidence in favor of option A is much weaker in the left panel than in the right panel.

Employing this paradigm, we are able to contrast the two frameworks of decision making: MSMs predict for all eight levels of given evidence that TTB users should immediately decide without further information search, whereas users of compensatory decision strategies should continue information search. Thus, neither the stopping behavior of a TTB user nor that of a compensatory strategy user should depend on the level of given evidence.[2] According to EAMs, however, participants' stopping behavior does not necessarily follow these extreme predictions, but the stopping point could be located anywhere on a continuum in between. This stopping point is characterized by the postulated evidence accumulation threshold. If the given evidence undershoots the threshold, participants should continue information acquisition, but if it is passed, participants should immediately stop information search. Thus, EAMs predict (for intermediate evidence thresholds) that a characteristic stopping behavior can be observed – continued information acquisition for lower levels, but stopping behavior for higher levels of given information.

Based on these considerations we can derive three hypotheses concerning the stopping behavior – each focusing on a different level of aggregation – to contrast MSM and EAM predictions in our paradigm: Whereas MSMs predict a uniform stopping behavior across all levels, EAMs predicted a lower probability of immediate stopping

[2] As mentioned before, stopping rules relying on a fixed number of cues to be acquired (cf., e.g., Gigerenzer, Dieckmann, & Gaissmaier, 2012) do also predict independence between stopping behavior and the levels of given information in our paradigm, as the same number of cues is openly displayed across all levels (see also the general discussion).

for lower levels of given evidence and a higher probability for higher levels. This prediction should hold on the group level (Hypothesis 1.a), but also for participants apparently using TTB as well as for users of compensatory strategies (Hypothesis 1.b), and for the majority of participants on the individual level (Hypothesis 1.c). Table 2 (upper part) summarizes these three hypotheses that will be tested in all experiments reported herein.

In addition to these hypotheses concerning the immediate stopping behavior in our paradigm, we aim to complement our aforementioned previous work (Söllner et al., 2014) employing an information intrusion paradigm. Söllner and colleagues (2014) showed that decision makers seemingly using TTB do not ignore strategy-irrelevant information when it is given to them for free, without being intentionally acquired. However, critics might argue that these information intrusions caused demand effects, accounting for the consistent behavioral changes (e.g., concerning subsequent information search) in accordance with the content of these intrusions. Therefore, we investigate in the present work whether the content of intentionally purchased additional information will influence decision makers' subsequent search and stop behavior. The MSM framework, represented by TTB and compensatory strategies, does not predict stopping behavior contingent on the content of information purchased in addition to TTB-relevant information: TTB users should not purchase additional information, but if they do so (applying TTB's stopping rule with some random error), its content should not influence subsequent behavior. Compensatory strategies also predict stopping behavior independent of the content of the acquired information. However, if decision makers accumulate evidence as predicted by the EAMs, additional information that is in line (compatible) with the prior information, should more frequently lead to the termination of the search process, whereas incompatible information should lead to an extended information acquisition process. The rationale behind that EAM prediction is that a certain level of evidence plus further compatible evidence will more probably overshoot the fixed evidence threshold (and therefore terminate information search) than a certain level of evidence that is further reduced by incompatible evidence (cf. Söllner et al., 2014). We test this Hypothesis 2 (see Table 2, lower part) for all experiments reported herein.

Table 2: Overview of the hypotheses concerning stopping behavior in Experiments 1- 3.

Dependent variable (DV)	Independent variable (IV)	Hypo-thesis	Level of analysis	MSM prediction	EAM prediction
Immediate stopping of information search	Levels of given evidence	1.a	Group level: all participants	Probability of immediate stopping is equal across all levels	Probability of immediate stopping increases with increasing IV
		1.b	Subgroup level: TTB, COMP	Probability of immediate stopping is equally high (TTB) / low (COMP) across all levels	Probability of immediate stopping increases with increasing IV
		1.c	Individual level: each participant	Probability of immediate stopping is independent of IV	Probability of immediate stopping increases with increasing IV (threshold estimation is possible)
Extent of further information search	Compatibility with prior information	2	Group level: all participants	Number of purchased pieces of information: (compatible) = (incompatible)	Number of purchased pieces of information: (compatible) < (incompatible)

Note: MSM = multiple-strategy model; SPM = single-process model; EAM = evidence accumulation model; TTB = “take-the-best” heuristic; COMP = compensatory strategy.

Our novel paradigm combines several features, we believe to be advantageous as compared to former studies: (1) The paradigm includes the *accumulation* prediction of the evidence accumulation models. In contrast to Hausmann and Läge's (2008) paradigm that only compared single cue validities to thresholds, we also consider combinations of cues (levels 4 to 8 allow for the accumulation of the positive evidence given by the most valid cue and another less valid one, see Table 1) that form the basis of EAMs. (2) The paradigm is not restricted to the two extreme points of the stopping behavior continuum (i.e., TTB versus all cues), but concentrates on the range between them by systematically varying the levels of given evidence. From that feature the possibility arises to estimate an individual evidence threshold for each of the participants. Hence, we can test whether individual stopping behavior depends on the given information as predicted by EAMs, but not MSMs for our stimuli. (3) The paradigm aims at basic assumptions derived from the two frameworks of interest (MSMs and EAMs) instead of testing specific models like Decision Field Theory (Busemeyer & Townsend, 1993) or the diffusion decision model (Ratcliff & McKoon, 2008). Hence, conclusions generalize to whole model classes and do not depend on specific parameterizations (e.g., Newell & Lee, 2009; 2011; Scheibehenne et al., 2013). (4) In comparison to our previous work (Söllner et al., 2014), the levels of given evidence paradigm does not evoke demand effects due to intruding information and (5), most importantly, the predictions do not hinge on successfully inducing a specific decision strategy like TTB. Rather, participants can adapt their behavior in an individual fashion.

2 Overview of the experiments

All three experiments reported herein employed an identical task structure: Participants were repeatedly asked to choose among two alternatives the option that scores highest on a certain criterion. The criterion value for each option was obtained by the following equation: criterion value = 83 * c1 + 49 * c2 + 29 * c3 + 17 * c4 + 10 * c5 + 6 * c6.[3] For each correct choice (i.e., the option with the higher criterion value was chosen) participants received a constant reward, an incorrect choice did not affect their serial account. As decision aid, six cues were available that could take on either a positive cue value (depicted by a "+") or a negative cue value (depicted by a "-"). Participants were informed about the hierarchy of the cue validities – the cue presented on the top of the list being the most valid one and the one presented at the bottom being the least valid one (but still above chance level). In each trial, at least one cue had to be purchased before making a choice.

All experiments consisted of an initial calibration phase (60 trials), a test phase, a short break, a second calibration phase (30 trials), and a concluding test phase. This set-up was chosen for mainly two reasons: (1) Participants should first select their preferred decision strategy (or calibrate their evidence threshold respectively) bottom-up via feedback before being presented with the novel paradigm in the test phase. (2) As the considerably numerous test trials entailed no feedback, we decided to present the test phase in halves interspersed by a shorter calibration phase that should refresh the previous learning experience.

In the calibration phases participants were presented with closed information boards. Participants could uncover as many cues as they liked by clicking on them with the computer mouse. Each cue purchase implied a constant amount of information cost that would be subtracted from the potential reward for a correct choice. After each purchase, participants could stop information acquisition and make their choice by clicking on the respective button for each option. They got immediate feedback on

[3] C1 stands for the cue value of cue 1, i.e. the most valid cue, c2 for the cue value of cue 2, i.e. the second most valid cue, … A positive cue value ("+") for an option entered the equation as "1", whereas "-1" represented a negative cue value ("-") for an option.

whether they chose the correct option, which reward they therefore received, what information costs incurred and, finally, what amount would be added to the serial account. Accordingly, the openly displayed serial account was updated.

In the test phases, two changes occurred: (1) Participants received no feedback on their choices and although the serial account was updated in each trial, it was not openly displayed to the participants. (2) Participants were not presented with closed information boards, but with the aforementioned half-open-half-closed information boards of the levels of given evidence paradigm. In particular, three cues were openly displayed, whereas the remaining three cues could be purchased by the participants. Information costs, however, incurred for all visible cues – the three pre-opened ones and each additionally purchased one. Figure 1 shows two exemplary trials from the test phase of Experiment 3.[4]

3 Experiment 1: Establishing the levels of given evidence paradigm

In the first experiment, we aimed to establish our new approach to disentangle the two frameworks of multi-attribute decision making. We imposed an intermediate degree of information costs that yielded a comparable payoff for TTB and well-adapted compensatory decision strategies[5] (see Table 3, upper part). From the EAM view, this should lead to moderate evidence thresholds for the majority of participants. Note that

[4] Two further comments on the parallels between the three experiments seem warranted: (1) We employed the same diagnostic pairs in the calibration phases of the experiments. Thus, the basis for the strategy classification procedure is identical across all experiments. (2) We took care that the validity hierarchy displayed to the participants was veridical and in line with the discrimination rate hierarchy in both calibration phase and test phase. As several authors have pointed out the relevance of both variables to the search order in multi-attribute decision tasks with closed information boards (e.g., Hausmann-Thürig, 2004; Newell, Rakow, Weston, & Shanks, 2004; Rakow, Newell, Fayers, & Hersby, 2005; see also Gigerenzer, Dieckmann, & Gaissmaier, 2012, for further search rules) and both Lee and Cummins' (2004) as well as Hausmann and Läge's (2008) EAM consider both variables for their search predictions, we wanted validity and discrimination rate (and all reasonable combinations of them) to predict the same search order in our paradigm. Therefore, both validity and discrimination rate were highest for cue 1 (c1) and lowest for cue 6 ($c1 \geq c2 \geq c3 \geq c4 \geq c5 \geq c6$).

[5] We considered four different compensatory decision strategies (COMP1, COMP2, COMP3, and EQW) in the strategy classification. These decision strategies differed in their weight allocation to the different cues – from an almost non-compensatory strategy that allowed only four (or more) less valid cues to outweigh a more valid one (COMP1) to the so-called equal weight rule (EQW; Dawes, 1979; Payne, Bettman, & Johnson, 1993) that gave equal weights to all cues irrespective of the validity hierarchy.

we aimed at moderate evidence thresholds because extremely high and extremely low evidence thresholds are problematic for our approach – they cannot be captured by the eight levels of given evidence employed herein. Decision makers with such extreme thresholds (EAM view) are not diagnostic for our research question, as they will behave in line with MSMs' predictions. Therefore, we aimed to minimize extreme behavior that might be in line with the EAM prediction, but only for levels of given evidence outside our paradigm's observational window.

Table 3: Expected payoffs for decision strategies in Experiments 1 - 3.

Experiment, condition	decision strategies included in strategy classification					optimal COMP
	TTB	COMP1*	COMP2*	COMP3*	EQW*	
1, all	**28940**	25280	28320	28160	24240	29760
2, low relative cost	52590	49680	**53730**	51840	43875	54540
2, high relative cost	**33560**	29440	31840	30720	26000	32320
3, low relative cost	64984	64416	**69344**	68640	59136	71808
3, high relative cost	**54736**	38064	40976	40560	34944	42432

Note: TTB = "take-the-best" heuristic; COMP1 - COMP3 = compensatory decision strategies; EQW = equal weight rule; optimal COMP = compensatory strategy that predicts the correct choice in each trial. The decision strategy with the highest expected payoff is printed **bold**. Strategies marked with "*" are pooled for further analyses as compensatory strategies (COMP).

3.1 Method

3.1.1 Design and procedure

We manipulated within subject the levels of given information (8 levels) in the test phase. For each level of given evidence, we administered five different test trials in each of the two test phases. The three initially hidden cues were constant within each level and chosen in order to maximize the validity of the hidden information. Table 4 shows the initially openly displayed cue value constellation for each level of given evidence in the test phases of Experiment 1.

Table 4: Levels of given evidence (level 1: minimum evidence; level 8: maximum evidence) - manipulation in Experiment 1 with maximized validity of hidden information.

	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1	- -	- -	+ -	+ -	+ -	+ -	+ -	+ -
Cue 2	- -	+ -	? ?	? ?	? ?	? ?	? ?	+ -
Cue 3	+ -	? ?	? ?	? ?	? ?	? ?	+ -	? ?
Cue 4	? ?	? ?	? ?	? ?	? ?	+ -	? ?	? ?
Cue 5	? ?	? ?	- -	- -	+ -	? ?	? ?	? ?
Cue 6	? ?	- -	- -	+ -	- -	- -	- -	- -

Note: “-” = initially displayed negative cue value; “+” = initially displayed positive cue value; “?” = initially hidden cue value.

In addition to these manipulation-relevant test trials, eight distractor trials per test phase were presented that (1) were meant to distract participants from the fact that in the relevant test trials only one option obtained positive cue values whereas the other one had negative cue values openly displayed only and (2) helped to establish the same cue validity (and discrimination rate) hierarchy as in the calibration phase. In sum, we administered 90 calibration trials and 96 test phase trials.

For Experiment 1, we employed the following blind date task: Participants were told that they should imagine being new in town and in search for interesting people to meet. The dating portal that they chose to help them with this quest had an innovative approach to see whether people match with each other: Only shortly before the appointed dating time, the potential dating partner was presented with two restaurants located in the town, had to choose one of them and go there to wait for the (hopefully) upcoming date. The other person was presented with the same two restaurants and should ideally choose the same one as the potential dating partner. If so, the both of them had the chance to meet and spend an evening together, if not, they missed this opportunity. As our participants were new in town, they knew nothing about the two presented options, but they could ask advisors for help. The helpfulness (i.e., validity) of these advices (positive or negative evaluation of the respective restaurant) differed between advisors. The hierarchy of this helpfulness was depicted on the screen with the upmost advisor being the most helpful one and the lowermost being the least helpful, but better than chance. Each consultation with an advisor cost ten minutes time that were subtracted from the 220 minutes that could be spent with the date when the correct restaurant was chosen. Participants were repeatedly asked to solve this task for different restaurants (A and B) and the total dating time was recorded in a serial account. The goal for the participants was to maximize the total dating time as the four participants with the highest end balance would receive 25 Euros reward.

The procedure started with an initial practice trial. Then the first calibration phase was administered. Participants had to consult at least one advisor prior to making their choice. After each decision, participants got feedback on their choice – a binary verbal feedback ("YES!" or "NO!") whether the option with the higher criterion value had been chosen[6].

Having completed the first calibration phase, participants were told that they would go on with exactly the same task, apart from two changes: (1) No choice feedback was given anymore, but the hidden serial account was further updated. (2) Three advisors had been consulted already. Thus, a choice could instantly be made or further information could be collected.

After the first test phase, a short break was announced and participants left the room for approximately five minutes. When they came back, they were reminded of the instructions and subsequently worked through the second half of the experiment.

3.1.2 Participants

In this experiment, 63 participants (55 female, mean age 20.6) took part, all but one being students from the University of Mannheim. They received course credit for their participation. The best four participants (in terms of payoff achieved) additionally received 25 Euros (approx. USD 35).

3.2 Results and discussion

3.2.1 Strategy classification

The decision strategy classification was based on the choice outcomes of the 90 calibration trials administered in the two calibration phases. The outcome-based strategy

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[6] One half of the participants (31 of 63) additionally received continuous feedback after each choice. Here, a bar plot indicating the criterion value for both options was displayed. As this feedback manipulation did not affect participants' choice and search behavior, we pooled both feedback conditions for all reported analyses of Experiment 1. In Experiments 2 and 3, we gave binary verbal feedback only to all participants.

classification (Bröder, 2010; Bröder & Schiffer, 2003a) revealed that 24 participants were classified as most in line with TTB and 36 participants behaved most consistent with compensatory decision strategies. Three participants' choice outcomes were equally probable for TTB and one of the compensatory strategies (*unclear* strategy classification). No participant was excluded due to the estimated choice error rate (ε) as they all were below ε = .40 for the best fitting strategy (Bröder & Schiffer, 2003a).

3.2.2 Stop of information search

Hypotheses 1.a to 1.c related to the immediate stopping of information search in the test phase. MSMs predicted that the stopping behavior is independent of the levels of given evidence, whereas EAMs held that the probability of immediate stopping increases with increasing levels of given evidence. Figure 2 shows the observed mean percentage of immediate stopping for each level of given evidence in Experiment 1.

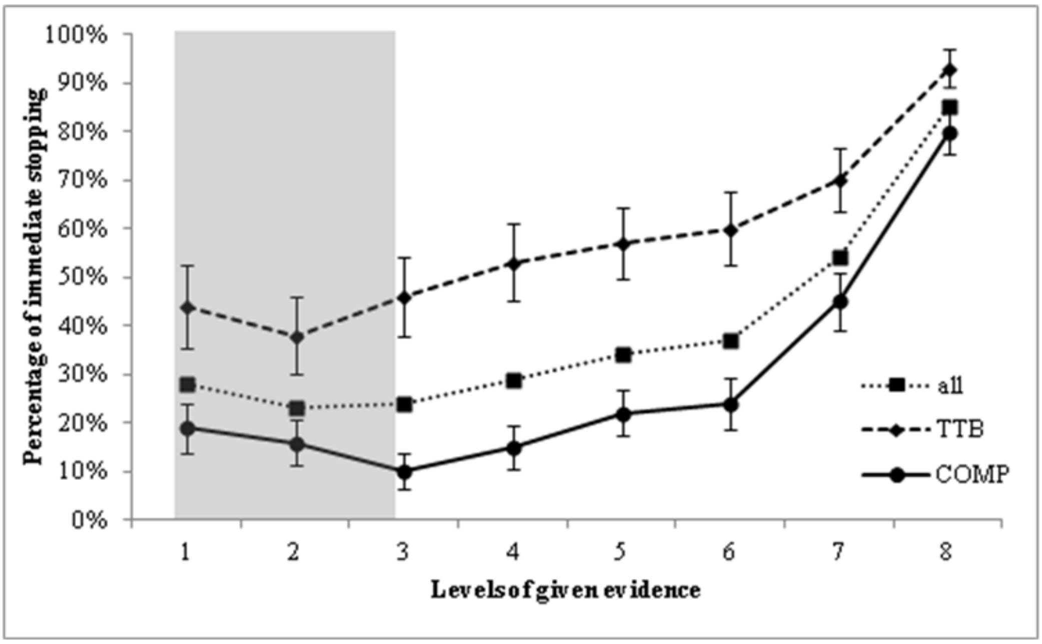

Figure 2: Percentage of immediate stopping of information search in Experiment 1 (error bars represent standard errors).

For Hypothesis 1.a on the group level of all participants, a repeated measures ANOVA revealed a significant effect (Greenhouse-Geisser-corrected $F(3.73, 231.18) = 70.69$, $p < .001$, $\eta^2 = .53$) of the levels of given information as predicted by the EAMs. We found a linear trend ($F(1, 62) = 134.95$, $p < .001$, $\eta^2 = .69$), indicating that with increasing levels of given information the percentage of immediate stopping also increased.

Analyzing the sub-groups of participants classified either as TTB or COMP participants (according to the calibration phase choices) for Hypothesis 1.b, we found a significant effect of the levels of given evidence on the stopping behavior for both of them (TTB: $F(3.38, 77.79) = 17.22$, $p < .001$; $\eta^2 = .43$; COMP: $F(3.58, 125.21) = 54.28$, $p < .001$; $\eta^2 = .61$) as predicted by the EAMs. For both sub-groups a linear trend was observed (TTB: $F(1, 23) = 36.74$, $p < .001$, $\eta^2 = .62$; COMP: $F(1, 35) = 88.43$, $p < .001$, $\eta^2 = .72$). As can be seen from Figure 2, the percentage of immediate stopping was higher for TTB participants than for COMP participants across all levels of given evidence (independent sample one-sided t-tests for each level: all p's $\leq .018$).

For Hypothesis 1.c we ran a binary logistic regression for each participant. Thus, an S-shaped psychometric function was fitted whose turning point indicated the proposed individual threshold. We used the Wald-test to determine whether the stopping behavior was independent of the levels of given evidence as predicted by MSMs. A positive effect of the levels of given evidence on the stopping behavior as predicted by the EAMs was indicated by a significant Wald-test for a positive regression weight. For five participants we observed behavior to such an extent in line with the EAM prediction that a regression weight estimation was not possible (due to (quasi-)complete separation, Albert & Anderson, 1984). Hence, these participants showed a deterministic threshold located between two adjacent levels of given information. For further 43 participants we found a positive regression weight with a significant Wald-test ($p < .05$). Taken together, these 76 % of our participants stopped information acquisition as predicted by the EAMs and significantly deviated from the MSM prediction. Fourteen participants' (22 %) stopping behavior did not significantly depend on the levels of given evidence. This behavior could either be interpreted as evidence accumulation with a very high or very low evidence threshold (EAM view) or, alternatively, as being in line with MSMs' prediction. For one participant we found a significant negative regression weight – a pattern that was neither predicted by EAMs nor MSMs. Thus, in regard to Hypothesis 1.c, the majority of participants behaved in line with the EAM prediction, whereas MSMs could only account for a minority of participants.

For the 76 % of participants whose behavior was well described by EAMs, we estimated the individual evidence thresholds, i.e. the (theoretical) level of given evidence where the turning point of the logistic function was located and the probability of immediate stopping equaled .50. Comparing participants whose behavior in the calibration phase was best described by TTB with COMP participants, we found a significantly lower mean evidence threshold for TTB (4.42) than for COMP users (6.53; one-sided $t(43) = 2.83$, $p = .004$). Figure 3 displays the estimated individual logistic functions.[7]

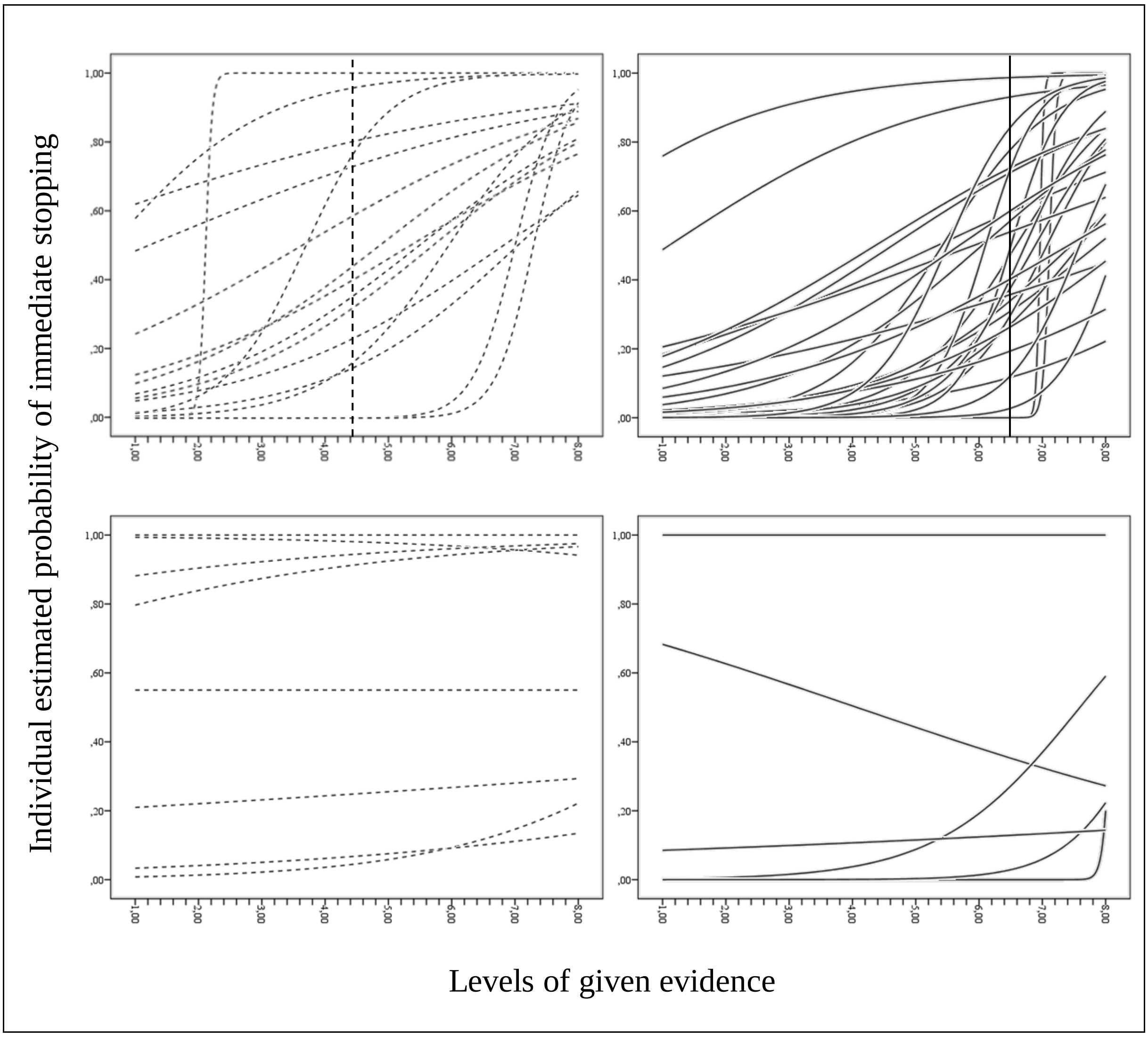

Figure 3: Individual estimated logistic functions for TTB (left part) and COMP (right part) participants in line with EAMs (upper part) or MSMs (lower part) in Experiment 1.[8]

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[7] For the participants with (quasi-)complete separation we estimated the evidence threshold by substituting one trial of the original data pattern to receive a less perfect (i.e., *not* quasi-completely separated) input for the binary logistic regression. From the then gained regression parameters the evidence threshold was estimated. The reported analyses concerning the mean evidence thresholds for TTB and COMP participants were not affected by this substitution; the results were similar when the participants were excluded from the analysis.

[8] The three participants with *unclear* strategy classification were excluded.

Note: For TTB and COMP participants compatible with EAMs (upper part) the mean estimated evidence threshold is displayed.

3.2.3 Further information search

In addition to the dichotomous variable whether participants immediately stop information search, we could investigate the subsequent search behavior when information acquisition was *not* immediately abandoned. From the MSM view, stopping behavior should not depend on the compatibility of the uncovered information with the initial evidence (at least, when considering only TTB and compensatory decision strategies, but see discussion). EAMs predicted a higher probability of continued information acquisition when incompatible information was found than when the uncovered information was in line (i.e., compatible) with the initial evidence.

To test Hypothesis 2, we contrasted two compatible trials and two incompatible trials per level of given evidence. A compatible (or incompatible) trial was defined as a trial where the most valid initially hidden cue plus at least one of the remaining cues supported (or weakened) the initially openly displayed evidence. As we did not include compatible trials in level 1 and 8, our analyses were limited to levels 2 to 7. Table 5 shows the mean number of additionally purchased cues across all participants. Note that the minimum value was 1 as only when at least one field was additionally purchased the trial could be analyzed; the maximum value was 3 as only three cues were initially hidden in each test phase trial. A repeated measures ANOVA revealed a significant effect of the compatibility of information as predicted by EAMs ($F(1, 55) = 326.77$, $p < .001$, $\eta^2 = .86$). Independent sample t-tests confirmed this finding for each level separately (all p's < .001).

Table 5: Mean number of additionally purchased cues in case of no immediate stopping in Experiment 1.

	Mean number of additionally purchased cues (N)						
	level 2	level 3	level 4	level 5	level 6	level 7	all
incompatible	2.40 (97)	2.34 (95)	2.41 (87)	2.46 (82)	2.35 (81)	2.25 (57)	2.38 (499)
compatible	1.15 (102)	1.12 (95)	1.07 (89)	1.10 (80)	1.05 (81)	1.02 (52)	1.09 (499)

3.2.4 Discussion

In this experiment, we set out to establish a novel paradigm manipulating levels of given information under optimal conditions, meaning an information cost manipulation that should induce moderate evidence accumulation thresholds (EAM view). The considerable number of both TTB and COMP classifications (MSM view) found constitutes a promising basis for that.

The analyses concerning the stopping behavior yielded results well in line with the EAM prediction: The probability of immediate stopping increased with increasing levels of given evidence on the group level, for the subgroups of apparent TTB and COMP users and on the individual level for the majority of our participants. Additionally, the compatibility analysis (cf. Söllner et al., 2014) for the continued information acquisition supported the EAM view.

The novel paradigm offered the possibility to estimate the postulated evidence accumulation threshold. The comparison of the estimated thresholds for apparent TTB and COMP users confirmed the adequacy of our approach: We observed a lower mean evidence accumulation threshold for participants classified as TTB-consistent – a finding that was predicted by the characteristic mimicking between EAM and MSM. Note that this relationship held despite relying on different data: The strategy classification was based on the calibration trials, the threshold estimate was derived from the test trials. Thus, we are confident that participants kept their initially selected strategy (or did not distinctly adjust their initial evidence threshold respectively) in the test phase.

An interesting finding that has not been addressed so far concerns the influence of the validity of the hidden cues on the stopping behavior. Although the linear trend in the stopping behavior (Hypothesis 1.a) was significant, descriptively we observed an unexpected drop in the percentage of immediate stopping for the three lowest levels of given evidence (see Figure 2, grey shaded area). We conjecture that this pattern is due to the different mean validity of hidden information employed in levels 1, 2, and 3 that worked against the EAM hypothesis viewing the level of given evidence as main predictor of stopping behavior: Level 1 offered the lowest validity of hidden information, meaning that participants could only purchase information of low value (validity and discrimination rate). For level 2, the average validity of hidden cues was higher – participants could purchase information of higher value – and for level 3, the validity was highest (and equal to the validity of hidden information employed for levels 4 and 5, see Table 4). Participants' stopping behavior was, as we have shown, strongly influenced by the levels of given evidence, but it also seems to depend on participants' consideration, how useful the cues are that can be purchased.

A potential criticism concerning the MSM prediction could relate to our concentration on TTB's stopping rule as only alternative to the exhaustive search predicted by compensatory strategies. Of course, other stopping rules have been discussed, for example stopping after two discriminating compatible cues ("Take Two" heuristic, Dieckmann & Rieskamp, 2007) or stopping after a certain number of cues (cf. Gigerenzer, Dieckmann, & Gaissmaier, 2012). As these stopping rules were far less frequently investigated in previous research than TTB's one-reason stopping rule, we concentrated on the latter one. However, our conclusions also hold when the aforementioned other stopping rules (within the MSM framework) are considered: If participants employed a stopping rule depending on the mere number of uncovered cues, we would again expect a uniform stopping behavior across all levels of given evidence as for all levels the same number of cues were openly displayed. If participants employed a two-reason stopping rule, an increase in the stopping probability between levels 3 (levels 1 to 3 displayed only one discriminating cue openly) and 4 (levels 4 to 8 displayed two compatible discriminating cues openly) would be expected. However, there should be no increase in the stopping behavior when analyzing levels 4 to 8 only (MSM prediction). The results of this additional analysis were again in line with the EAM prediction: The probability of immediate stopping increased with increasing levels of given evidence ($F(2.52, 156.48) = 88.09$, $p < .001$, $\eta^2 = .59$; linear trend: $F(1, 62) = 161.69$, $p < .001$, $\eta^2 = .72$). The same reasoning holds for the compatibility analysis: The compatibility effect predicted by EAMs was not limited to levels 2 and 3, but was observed for the remaining levels 4 - 7 as well. However, we will address this potential criticism of our approach again in the general discussion.

4 Experiment 2: Replication of Experiment 1 in a different task domain

Experiment 2 had three aims: First, we strove to replicate the finding of EAM-consistent behavior in another, more established task domain, namely the oil drilling task (Rieskamp, 2006; Rieskamp & Otto, 2006). Second, we investigated the impact of the validity of hidden cues by setting it to the lowest (instead of highest) possible level within each level of given information. If the conjecture posed in the discussion of

Experiment 1 is correct, this should eliminate the unexpected "drop" in stopping probabilities across levels 1 to 3 observed in Experiment 1. Third, to further explore the mimicking relationship between the multiple-strategy approach and the EAMs, we manipulated information costs between participants, impacting on the payoff structure of the environment. As this manipulation has been shown to affect strategy classifications (Bröder, 2000; 2003; Newell & Shanks, 2003; Rieskamp & Otto, 2006), we expected it to also affect the estimated thresholds in the EAM approach.

4.1 Method

4.1.1 Design and procedure

The design of Experiment 2 resembled the one of Experiment 1. We again manipulated the levels of given information within subject (8 levels) and additionally varied information costs between subjects (high versus low). We adopted the manipulation of Experiment 1 as *high cost* condition (relative costs per cue = 10 / 220 ≈ 4.5 %) and added a *low (relative) cost* condition (relative costs per cue = 10 / 330 ≈ 3.0 %). Whereas the *high cost* condition favored noncompensatory (TTB) strategy usage, the *low cost* condition slightly favored well-calibrated compensatory strategies over TTB in terms of payoff (see Table 3).

The same 90 calibration trials as in Experiment 1 were administered, but the test phase trials were adjusted for two reasons: (1) The compatibility of the hidden cue information was manipulated across all levels of given evidence, instead of only levels 2 to 7 as in Experiment 1. (2) Instead of maximizing the validity of hidden information for each level of given evidence (cf. Experiment 1), we minimized this factor to illustrate that the non-linear deviation observed for the lower levels of given evidence in Experiment 1 was caused by the discussed difference in the validity of hidden information for these levels. As can be seen in Table 6, the minimization of the validity of hidden information led to a constant mean validity of hidden information for levels 1 to 3, 7, and 8. Thus, the deviation on the lower levels should vanish in Experiment 2. In order to achieve a similar validity (and discrimination rate) hierarchy in the calibration and test phase, distractor trials were adjusted as well, leading to 56 trials (8 (levels) * 5 test trials + 16 distracters) for each of the two test phases.

Experiment 2's procedure also closely resembled the one of Experiment 1. Participants were told that they should imagine working for an oil drilling company. Their task was to repeatedly choose among two potential drilling sites the one that probably contains the most oil. As decision aid, a test institute could be commissioned to run analyses of varying helpfulness (validity). When choosing the correct site, the company paid a bonus of 220 (high relative cost condition) or 330 (low relative cost condition) Penunzen (a virtual currency). For each analysis, the test institute received 10 Penunzen from the bonus and no money when the incorrect option was chosen. A serial account kept track of the participant's earnings (not displayed in the test phases). The four participants with the highest end balance received a 25 Euro reward.

As for Experiment 1, in the calibration phase the information board was closed and (binary) feedback was given after each decision. In the test phase, participants were confronted with half-open-half-closed information boards and no feedback was given. Table 6 shows the test phase manipulation for Experiment 2.

Table 6: Levels of given evidence (level 1: minimum evidence; level 8: maximum evidence) - manipulation in Experiment 2 with minimized validity of hidden information.

	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1	- -	- -	+ -	+ -	+ -	+ -	+ -	+ -
Cue 2	- -	+ -	- -	- -	- -	- -	- -	+ -
Cue 3	+ -	- -	- -	? ?	? ?	? ?	+ -	- -
Cue 4	? ?	? ?	? ?	? ?	? ?	+ -	? ?	? ?
Cue 5	? ?	? ?	? ?	? ?	+ -	? ?	? ?	? ?
Cue 6	? ?	? ?	? ?	+ -	? ?	? ?	? ?	? ?

Note: "-" = initially displayed negative cue value; "+" = initially displayed positive cue value; "?" = initially hidden cue value.

4.1.2 Participants

Sixty-three participants (45 female, mean age 21.1) took part in this experiment, all but one being students from the University of Mannheim. They received either course credit or 5 Euros compensation for their participation. The best four participants (two per condition) additionally received 25 Euros. Thirty-two participants were tested in the *low information cost* condition, 31 participants completed the *high information cost* condition.

4.2 Hypotheses

For Experiment 2, we investigated the hypotheses depicted in Table 2. Additionally, we predicted that participants' choice behavior in the calibration phase should be more in line with TTB (and less in line with COMP) in the high information cost condition than in the low cost condition. This expected effect at the level of strategy classifications should translate to the mean estimated evidence accumulation thresholds as MSMs and EAMs mimic each other.

4.3 Results and discussion

4.3.1 Strategy classification

Decision strategies were classified with the outcome-based classification method (Bröder & Schiffer, 2003b; Bröder, 2010) on the basis of the 90 calibration trials. In the *low cost* condition, we classified 14 participants to be most consistent with TTB and 18 participants with COMP. In the *high cost* condition, we found TTB to be the best fitting strategy for six participants and COMP for 25 participants. Testing this difference, we found a significant effect of the information cost manipulation in the non-predicted direction (χ^2 (1, N = 63) = 4.33, p = .038): Participants in the high information cost condition showed somewhat less TTB-consistent behavior than participants in the low information cost condition. We will discuss this surprising finding below.

4.3.2 Stop of information search

Again, we analyzed for the test trials the dichotomous dependent variable whether information search was immediately abandoned when a certain level of evidence was presented. Figure 4 shows the mean percentage of immediate stopping across all participants and for the sub-groups of TTB and COMP participants separately.

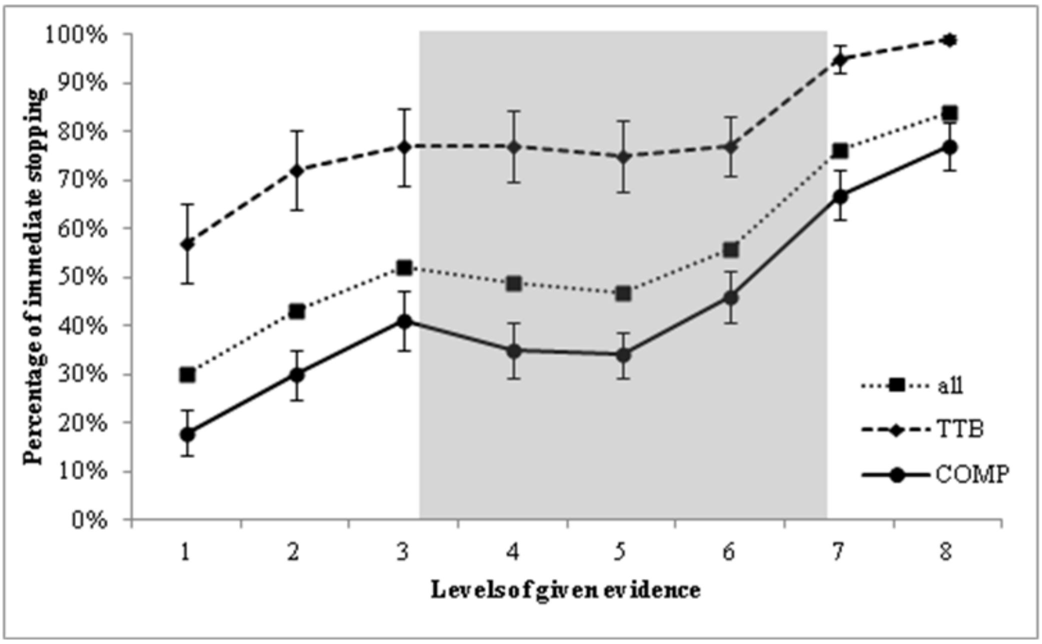

Figure 4: Percentage of immediate stopping of information search in Experiment 2 (error bars represent standard errors).

For Hypothesis 1.a on the group level of all participants, we found a significant effect ($F(4.13, 256.20) = 48.78$, $p < .001$, $\eta^2 = .44$) as predicted by the EAMs: With increasing levels of given evidence the percentage of immediate stopping increased (linear trend: $F(1, 62) = 118.06$, $p < .001$, $\eta^2 = .66$).

Hypothesis 1.b referred to two sub-groups (TTB and COMP participants) constituted on the basis of the calibration phase strategy classification. For both sub-groups we found support for the EAM prediction (TTB: $F(3.30, 62.66) = 10.33$, $p < .001$, $\eta^2 = .35$; COMP: $F(4.41, 185.09) = 40.10$, $p < .001$, $\eta^2 = .49$): Participants whose calibration phase behavior was best described by the decision strategy TTB as well as COMP participants showed more frequent stopping behavior with increasing levels of given evidence (linear contrast TTB: $F(1, 19) = 20.36$, $p < .001$, $\eta^2 = .52$; linear contrast COMP: $F(1, 42) = 108.71$, $p < .001$, $\eta^2 = .72$). Across all levels of given evidence the percentage of immediate stopping was higher for TTB participants than for COMP participants (independent sample one-sided t-tests: all p's $\leq .001$).

Hypothesis 1.c referred to the individual stopping behavior of the participants. Running binary logistic regressions for each of them, we found that one participant showed behavior almost perfectly in line with the EAM prediction (quasi-complete separation) and for 40 participants we found a significantly positive slope according to the Wald-test ($p < .05$). These 65 % of our participants showed stopping behavior in line with the EAM prediction, but deviated from MSM prediction. For the remaining 22 participants (35 %) we observed a slope that did not significantly differ from zero – an observation that is well predicted by MSMs, but does not necessarily contradict the EAM prediction (cf. Experiment 1).

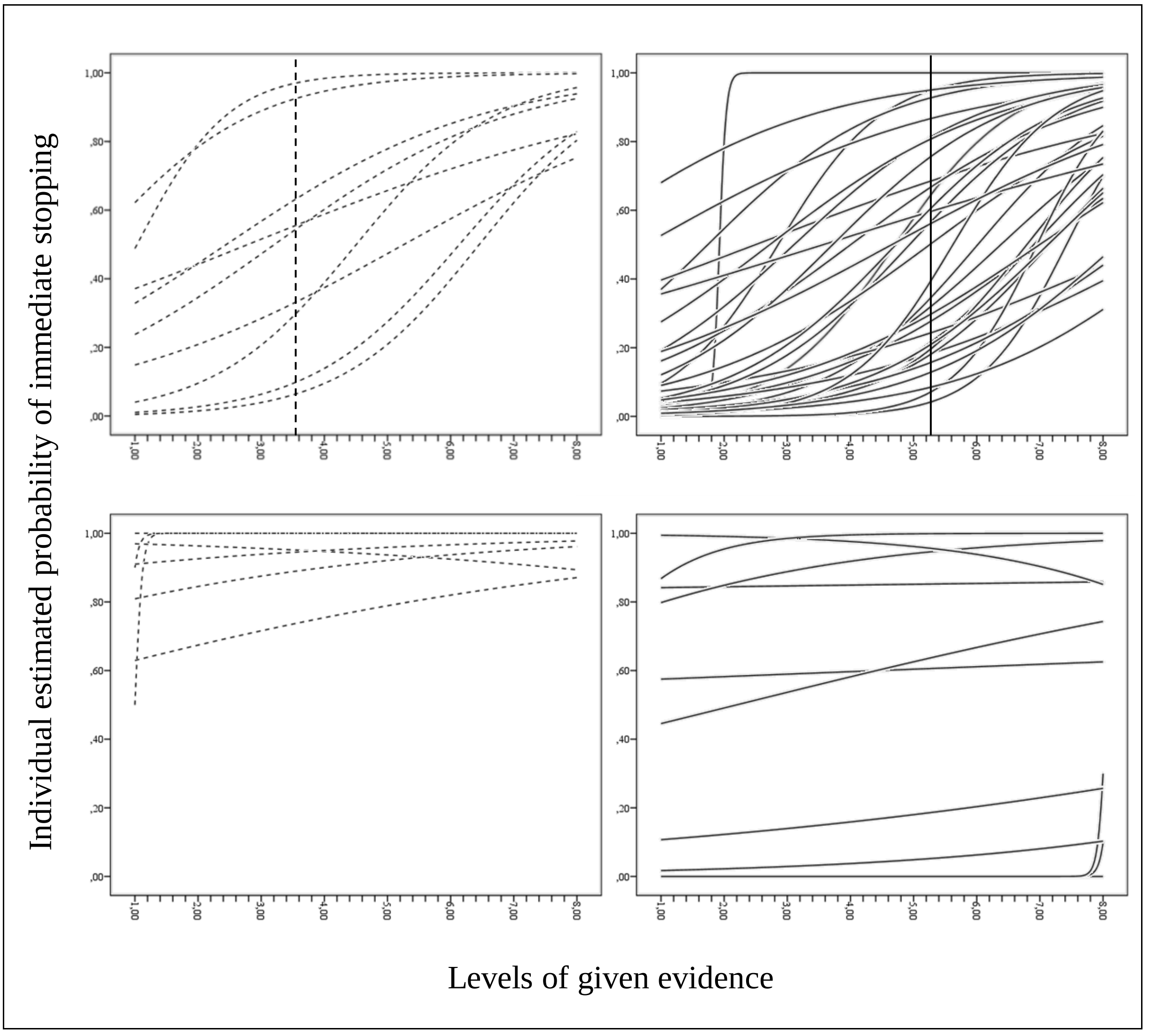

Figure 5: Individual estimated logistic functions for TTB (left part) and COMP (right part) participants in line with EAMs (upper part) or MSMs (lower part) in Experiment 2.

Note: For TTB and COMP participants compatible with EAMs (upper part) the mean estimated evidence threshold is displayed.

In Figure 5 the individual estimated logistic functions for all participants are displayed. Estimating the evidence threshold for those 65 % of our participants that showed a significantly positive slope[9], we found that participants classified as TTB users had a significantly lower evidence threshold (3.57) than COMP participants (5.27; one-sided $t(39) = 1.82$, $p = .039$). Hence, the expected mimicking relationship between MSM and EAM was observed.

4.3.3 Further information search

The information acquisition behavior could further be analyzed by concentrating on trials where at least one piece of information was additionally purchased by the participant. Here, we contrasted for each level of given evidence two trials with information compatible with the initially open information and two trials with incompatible information (see Experiment 1 for further details). Table 7 shows the mean number of additionally purchased pieces of information for the compatible and the incompatible trials.

Table 7: Mean number of additionally purchased cues in case of no immediate stopping in Experiment 2.

	Mean number of additionally purchased cues (N)								
	level 1	level 2	level 3	level 4	level 5	level 6	level 7	level 8	all
incompatible	2.47 (90)	2.47 (66)	2.36 (59)	2.38 (65)	2.20 (61)	1.88 (57)	2.39 (31)	2.00 (18)	2.30 (447)
compatible	1.11 (85)	1.10 (70)	1.12 (66)	1.09 (66)	1.05 (73)	1.06 (53)	1.03 (31)	1.00 (20)	1.08 (464)

Testing Hypothesis 2, we found a significant effect of the compatibility of the purchased information on the number of acquired pieces of information ($F(1, 52) = 198.70$, $p < .001$; $\eta^2 = .79$). This effect was observed for each level of given evidence (independent sample t-tests: all p's < .001).

4.3.4 Discussion

In Experiment 2, we succeeded in replicating Experiment 1's findings concerning participants' stopping behavior in an alternative task domain. These results unanimously support the EAM view (see discussion of Experiment 1). Consistent with our

[9] For the one participant with quasi-complete separation we estimated the evidence threshold by substituting one trial. With this less perfect data pattern a binary logistic regression was run and from the gained parameter the evidence threshold was estimated (cf. Experiment 1). The reported analyses concerning the mean evidence thresholds for TTB and COMP participants were not affected by this substitution; the conclusions were identical when the participant was excluded.

considerations, the previously observed drop in the percentage of immediate stopping for the lower levels of given evidence (cf. Experiment 1, Figure 2) vanished when the validity of hidden information for these levels was constant (see Figure 4). The grey shaded area in Figure 4 highlights an expected drop in the probability of immediate stopping that is consistent with Experiment 2's validity of hidden information manipulation (cf. Table 6): When participants could get more value (in terms of validity and discrimination rate) for the same information costs, they were more willing to purchase another cue. Hence, the individual stopping behavior did not only depend on the nature of the *given* information, but was also highly sensitive to the value (validity) of the information that could still be obtained.

Although the replication of Experiment 1 was our major aim, we additionally intended to investigate how a decision strategy shift caused by an information cost manipulation might translate to the evidence thresholds estimated within our novel paradigm. Unfortunately, our information cost manipulation failed to induce the expected decision strategy shift and further analyses of this factor were therefore obsolete. Although this significant result could, of course, be due to chance, we hypothesize that, possibly, the information cost manipulation was ineffective for mainly two reasons: (1) As we wanted to replicate Experiment 1's design and procedure as closely as possible, we did not convert the virtual currency into real money that is immediately given to the participants after the experiment (Newell, Weston, & Shanks, 2003), but gave a (delayed) reward to the best four participants only (Bröder, 2000, 2003). Possibly, this delayed, uncertain reward reduced participants' motivation to maximize their earnings (see Cardinal, 2006, for a review on delay discounting and uncertainty discounting). (2) The difference between the two conditions (3.0 % versus 4.5 %) was quite small and the manipulation itself therefore probably too weak. Although this information cost manipulation was included in Experiment 2 for demonstrational purposes only (namely that the estimated thresholds mirror the decision strategy use), we address this unsatisfactory result in Experiment 3.

5 Experiment 3: Examining the influence of a second factor (validity of hidden information) on the stopping behavior

In Experiment 2, we replicated the findings of Experiment 1, showing that the stopping behavior of our participants was well-captured by the EAM prediction, whereas MSMs could only account for the behavior of a minority of our participants. Both experiments supported the adequacy of our paradigm as the mean estimated evidence threshold for participants seemingly using TTB was significantly lower than for compensatory strategy users – a finding that is well in line with the aforementioned mimicking relationship of the two frameworks. Our attempt to further confirm the validity of our estimation procedure via shifting the decision strategy distribution (cf. Experiment 2) failed due to an unsuccessful information cost manipulation. Therefore, in Experiment 3 we employed a stronger manipulation to induce a shift as precondition for further analyses.

In addition to the levels of given information, we observed in both Experiments 1 and 2 a second factor that seemed to systematically influence the stopping behavior of the participants: the validity of hidden information. Within our paradigm, it is not possible to deconfound both factors entirely because the former restricts the possible combinations of the latter. In Experiments 1 and 2, we maximized and minimized the validity of hidden information for each level of given evidence, respectively. In Experiment 3, we systematically varied the validity of hidden information within the levels factor to investigate the impact of both factors separately.

5.1 Method

5.1.1 Design and procedure

The design and procedure of Experiment 3 closely resembled the one of Experiment 2. We manipulated information costs (high versus low) between subjects. Within subjects we manipulated, as in Experiments 1 and 2, the levels of given information (8 levels) and, additionally, the validity of hidden information (7 levels) in any feasible combination. Appendix 1 shows the resulting 24 combinations of the two factors administered in the test phase.

We again employed the oil drilling task (Rieskamp, 2006; Rieskamp & Otto, 2006), but in the *low cost* condition participants were informed that each analysis cost 2 % of the potential bonus of 400 Penunzen, whereas in the *high cost* condition the information costs were set to 8 %. Accordingly, well-calibrated compensatory decision strategies yielded a higher payoff than TTB in the *low cost* condition, whereas in the *high cost* condition TTB yielded the highest payoff (see Table 3). Participants were informed that the end balance in Penunzen would be converted to real money at a rate of 100 Penunzen = 0.01 Euro. This information was additionally displayed on the screen during all calibration and test phase trials. The participants received their reward according to their performance immediately after the experiment.

The 90 calibration phase trials were identical to the ones employed in Experiments 1 and 2, but the test phase trials were adjusted to allow for a systematic manipulation of the second factor of interest, the validity of hidden information. To sustain a manageable number of test trials, we employed different numbers of trials per combination, resulting in 94 test trials of interest for further analyses, and added in sum 20 distractors. Therefore, each test phase consisted of 57 trials, leading to 114 test phase trials in sum.

5.1.2 Participants

Sixty students of the University of Mannheim (55 female, mean age 20.9) took part in this experiment. They received course credit for their participation and were rewarded in accordance to their performance (mean reward: 6.01 Euro).

5.2 Hypotheses

For Experiment 3, we again tested the hypotheses depicted in Table 2. Additionally, we predicted that the second within-subject factor validity of hidden information should also influence the stopping behavior. In particular, a higher validity of hidden information should lower the probability of immediate stopping. The information cost manipulation should lead to more noncompensatory decision making (TTB) in the *high cost* condition than in the *low cost* condition. This difference in strategy usage should be mirrored in lower evidence thresholds in the *high cost* condition than in the *low cost* condition.

5.3 Results and discussion

5.3.1 Strategy classification

As for Experiments 1 and 2, decision strategies were classified with the outcome-based classification method (Bröder & Schiffer, 2003b; Bröder, 2010) on the basis of the calibration phase data. In the high information cost condition, we classified 19 participants to have most probably adhered to TTB and eleven participants were classified as users of a compensatory strategy. In line with our hypothesis, we found more users of a compensatory strategy (16 participants) and less TTB consistent participants (14 participants) in the low information cost condition. However, this descriptive difference was only marginally significant ($\chi^2(1, N = 60) = 1.68$, $p = .097$, directional test). Nevertheless, we included the between subjects factor *information cost condition* in the further analyses to illustrate the basic idea that a factor (i.e., information costs) influencing the distribution between TTB and compensatory decision strategies should also impact the mean estimated evidence accumulation threshold as MSMs and EAMs mimic each other.

5.3.2 Stop of information search

For Hypotheses 1.a to 1.c we analyzed the dichotomous dependent variable whether information search was immediately abandoned when a certain level of evidence was presented. Figure 6 shows the mean percentage of immediate stopping across all participants and additionally for the sub-groups TTB and COMP participants.

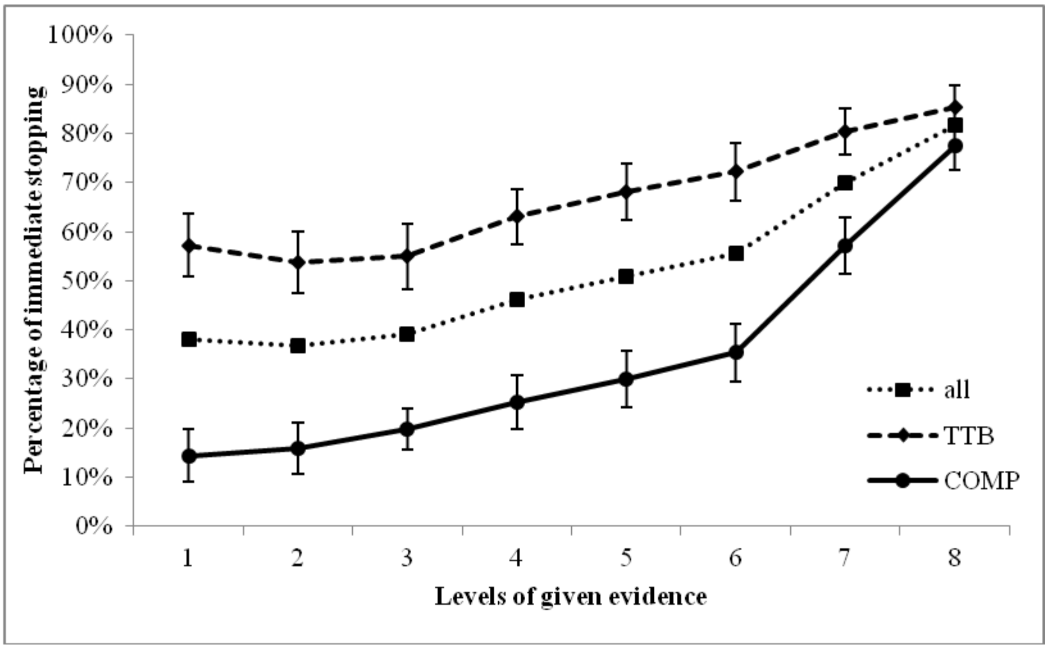

Figure 6: Percentage of immediate stopping of information search in Experiment 3 (error bars represent standard errors).

Testing Hypothesis 1.a on the group level of all participants, we found a significant effect of the within-subject factor levels of given evidence ($F(3.25, 191.66) = 61.62$, $p < .001$, $\eta^2 = .51$) on the stopping behavior. The significant linear trend ($F(1, 59) = 117.77$, $p < .001$, $\eta^2 = .67$) indicated that with increasing levels of given evidence the percentage of immediate stopping also increased. This finding was predicted by the EAM view.

Based on the strategy classification results of the calibration phase data, we analyzed TTB participants and COMP participants separately for Hypothesis 1.b. For both sub-groups we observed the effect predicted by EAMs (TTB: $F(2.85, 91.20) = 20.01$, $p < .001$, $\eta^2 = .39$; COMP: $F(3.58, 93.11) = 57.86$, $p < .001$, $\eta^2 = .69$): With increasing levels of given evidence an increase in the percentage of immediate stopping was associated (linear contrast TTB: $F(1, 32) = 35.21$, $p < .001$, $\eta^2 = .52$; linear contrast COMP: $F(1, 26) = 141.64$, $p < .001$, $\eta^2 = .85$). Except for the highest level of given evidence (level 8), the mean percentage of immediate stopping on each level was higher for TTB participants than for COMP participants (independent samples one-sided t-tests: all p's $\leq .001$; for level 8: $p = .121$).

Hypothesis 1.c referred to the individual stopping behavior of the participants. Running a binary logistic regression for each participant, we found a significant positive slope parameter (Wald-test, $p < .05$) for 44 of our 60 participants. Thus, these 73 % of our participants showed stopping behavior that was well in line with the EAM prediction, but deviated from the MSM prediction. For 15 participants (25 %) we found a slope that did not significantly differ from zero. This pattern complied with the MSM prediction, but could also be interpreted as EAM-consistent with a very high or very low evidence threshold (cf. Experiment 1). For one participant we found a significant negative slope parameter – a finding that is neither predicted by EAMs nor by MSMs.

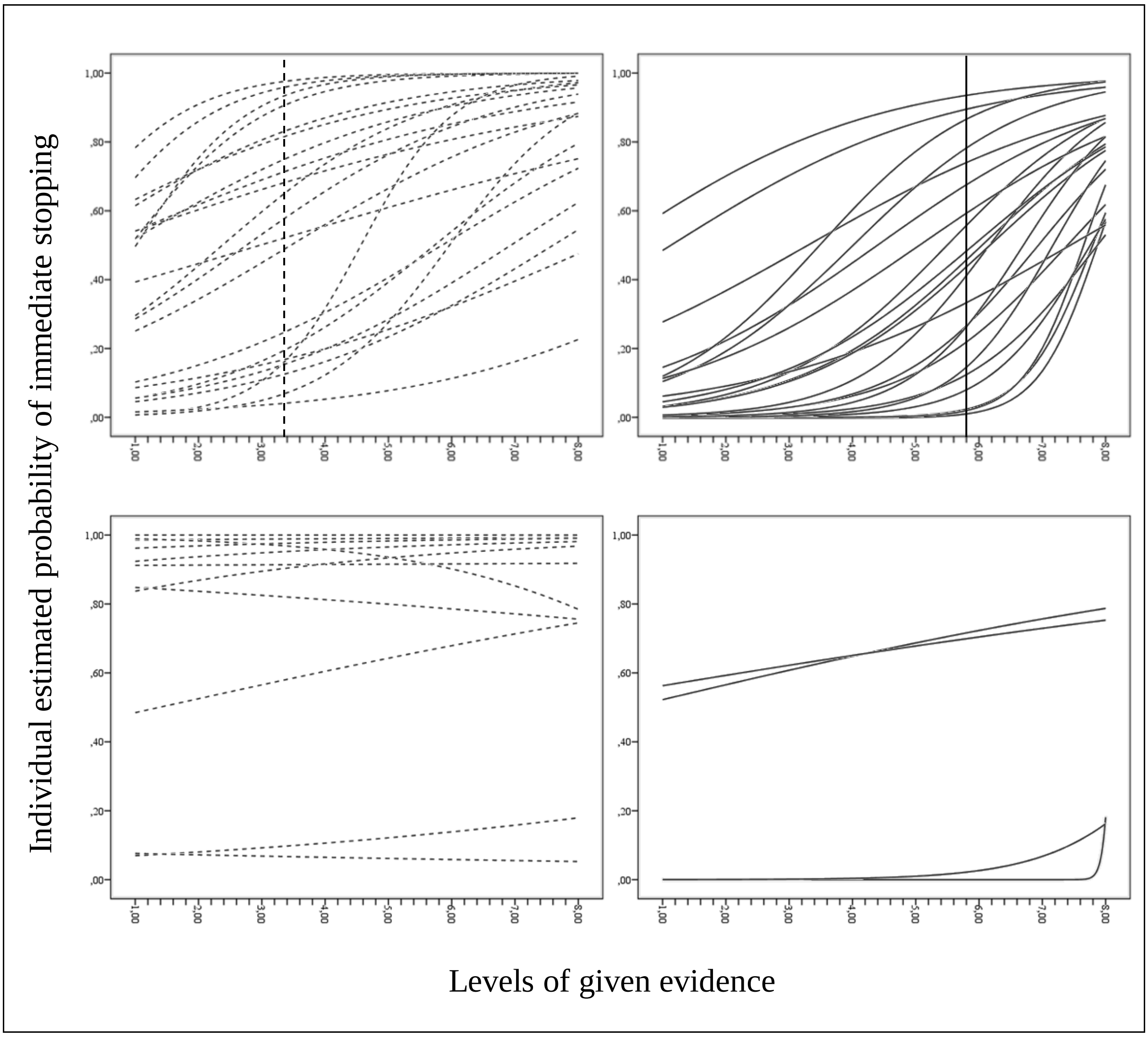

Figure 7: Individual estimated logistic functions for TTB (left part) and COMP (right part) participants in line with EAMs (upper part) or MSMs (lower part) in Experiment 3.

Note: For TTB and COMP participants compatible with EAMs (upper part) the mean estimated evidence threshold is displayed.

Figure 7 shows the individual estimated logistic functions. Estimating the individual evidence thresholds for the 44 participants that were best described by the EAM prediction, we found that the mean estimated threshold was lower for TTB participants (3.36) than for COMP participants (5.80; one-sided $t(33.94) = 2.87$, $p = .004$).

In Experiment 3, we manipulated information costs between subjects. For the strategy classification in the *high cost* condition we found descriptively more TTB-consistent and fewer COMP-consistent participants than in the *low cost* condition. Comparing the individual estimated evidence thresholds for the participants that had a significant positive slope parameter in the binary logistic regression (Wald-test: $p < .05$), we found a significantly lower evidence threshold for the *high cost* condition (3.64) than for the *low cost* condition (5.63; one-sided $t(42) = 2.32$, $p = .013$).

As discussed before, in Experiments 1 and 2 we observed a drop in the mean percentage of immediate stopping contingent on the validity of hidden information chosen in the respective experiments. Thus, in Experiment 3 we systematically manipulated this second factor in addition to the levels of given evidence (see Appendix 1). As stated above, despite this different validity of hidden information for each level of given evidence, we replicated the basic finding that with increasing levels of given evidence the percentage of immediate stopping increases – on the group level as well as on the sub-group levels of TTB and COMP participants. We could, however, also analyze the stopping behavior by running repeated measures ANOVAs separately for each validity of hidden information level. The resulting iso-validity-curves are depicted in Figure 8 (left part). For each validity of hidden information level a significant effect of the levels of given information on the stopping behavior was found (all p's $< .001$) and a linear trend was observed (all p's $< .001$). To assess the relevance of the second factor *validity of hidden information*, we could apply the same logic. Figure 8 (right part) shows the iso-level-curves. Except for levels 1 and 8, we found a significant effect of the validity of hidden information on the stopping behavior (all p's $\leq .040$) and a linear trend was observed (all p's $\leq .043$). For level 1 we had only one validity of hidden information level and therefore no test could be run. For level 8 we observed a ceiling effect as the percentage of immediate stopping was high – irrespective of the validity of hidden information.

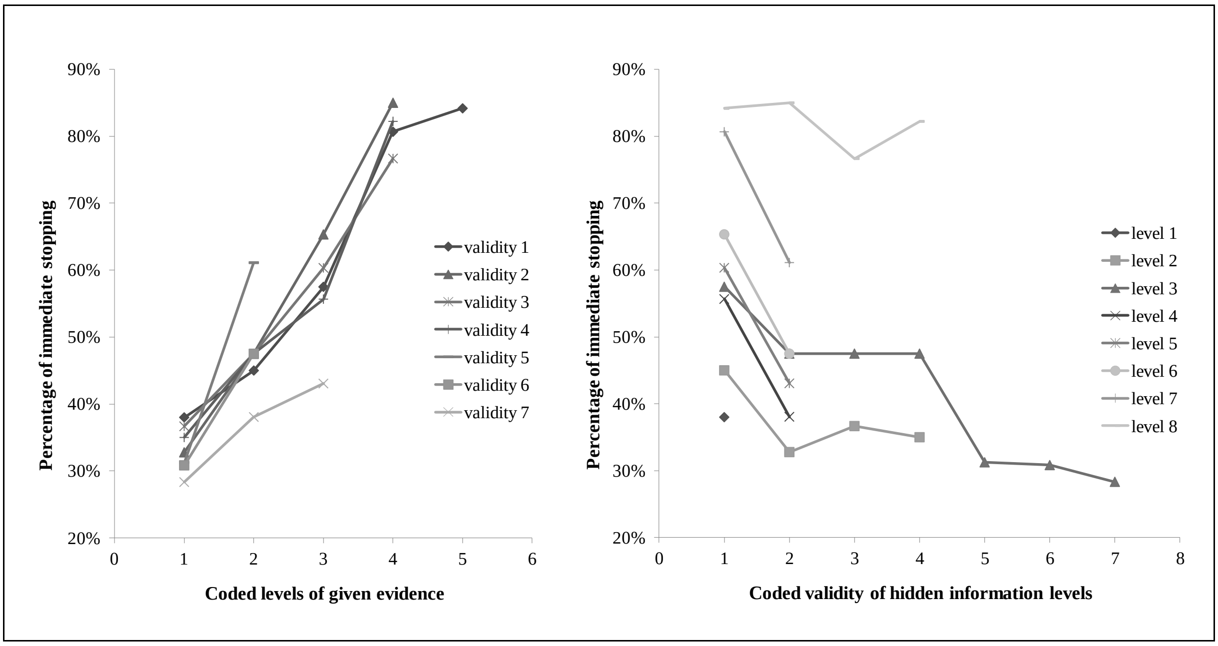

Figure 8: Iso-validity-curves (left part) and iso-level-curves for the immediate stopping behavior in Experiment 3.

Note: For the left part the levels of given evidence were coded to level 1 being the lowest level of evidence tested for the respective validity of hidden information level, level 2 being the second lowest level of evidence tested for the respective validity of hidden information level and so on. For the right part the validity of hidden information was coded in the same way.

To summarize: The important effect of level of given evidence as predicted by EAMs was observed at each single level of the second factor (validity of hidden information). Furthermore, the latter factor had an effect at almost all levels of given evidence if these were held constant.

5.3.3 Further information search

The information search behavior could further be analyzed by concentrating on trials where participants chose to purchase at least one further piece of information. To test Hypothesis 2, we compared trials of the same level of evidence (and with equal validity of hidden information) that differed in respect to their compatibility with the initially open information. Two trials for each level were pre-selected to constitute the incompatible trials and two further pre-selected trials formed the compatible trials. Table 8 displays the mean number of additionally purchased cues.

Table 8: Mean number of additionally purchased cues in case of no immediate stopping in Experiment 3.

	Mean number of additionally purchased cues (N)								
	level 1	level 2	level 3	level 4	level 5	level 6	level 7	level 8	all
incompatible	2.43 (70)	2.31 (74)	2.22 (81)	2.40 (65)	2.16 (55)	2.06 (53)	1.67 (39)	1.54 (24)	2.18 (461)
compatible	1.05 (75)	1.08 (77)	1.13 (85)	1.14 (59)	1.07 (59)	1.08 (53)	1.06 (32)	1.11 (28)	1.09 (468)

Running a repeated measures ANOVA, we found a significant effect of the factor compatibility ($F(1, 53) = 126.76$, $p < .001$; $\eta^2 = .71$): After purchasing one piece of information, participants purchased more information when incompatible information was found than when the information was compatible with the initially open information. This finding was confirmed for each level of given information by running independent samples t-tests (all p's $\leq .014$, directional tests).

5.3.4 Discussion

In Experiment 3, we were able to replicate the systematic effect of the levels of given evidence on the stopping behavior that was shown in Experiments 1 and 2, despite the additional manipulation of a second factor (validity of hidden information). These findings unanimously favored the EAM stopping prediction over the MSM prediction.

The adequacy of the employed paradigm was tested by imposing different levels of information costs. If the frameworks (MSMs and EAMs) actually mimic each other and our paradigm allows for valid threshold estimation, a variable influencing the decision strategy distribution (MSM view) should also influence the height of the evidence accumulation threshold (EAM). Although the influence of this manipulation was only descriptively observable in the decision strategy classification, it was mirrored in the estimated evidence accumulation thresholds.

In addition to the levels of given evidence, we manipulated a second factor in Experiment 3 that descriptively influenced the stopping behavior of the participants in Experiments 1 and 2. This *validity of hidden information* factor captured how much value (in our experiments in terms of validity and discrimination rate) a participant could receive when continuing information acquisition. Our analyses showed that this factor actually systematically influenced the stopping behavior: The more valuable the hidden information was, the higher was the probability that information acquisition continued.

6 Summary and General Discussion

In multi-attribute decision making two frameworks coexist that make considerably different assumptions about the process underlying people's adaptation to different environments. Multiple-strategy models (MSMs) assume that people choose from a toolbox of different decision strategies the one that fits best to the current problem. Single-process models (SPMs), however, hold that people employ the same uniform mechanism and merely adapt its parameters. For example, evidence accumulation models (EAMs), a class of SPMs that makes distinct assumptions about the process of information acquisition, assume that decision makers sample information until the accumulated evidence reaches the proposed evidence accumulation threshold whose height can be adapted to different environments.

In the present paper, we aimed to contrast these two frameworks by concentrating on their basic assumptions about the information acquisition stopping behavior. We introduced a novel paradigm that allowed us to contrast MSMs' and EAMs' predictions by systematically varying the levels of given evidence in a half-open-half-closed information board. We found in each of our three experiments that the observed stopping behavior was well described by the EAM prediction, but for most participants did not comply with the MSM prediction. In particular, we discovered the following: (1) On the group level, the probability of immediate stopping increased with increasing levels of given evidence – a finding, that also held when participants classified as TTB users and compensatory strategy users were analyzed separately. (2) For the majority of our participants the individual stopping behavior was well captured by assuming an individual evidence threshold; only a minority of participants showed no significant increase of the probability of immediate stopping with increasing levels of given evidence. Importantly, this minority did not necessarily contradict the EAM prediction: Although their stopping behavior could be interpreted as confirming to one of the investigated decision strategies (TTB or a compensatory strategy, MSM view), it could also result from a particularly high or low evidence threshold (EAM view). Hence, an EAM-friendly interpretation would be that all participants followed this model, but some thresholds were outside the observed range. Viewed from the most MSM-friendly perspective possible, one might argue that a minority of participants conformed to decision strategies (22 %, 35 %, and 25 % in Experiments 1 - 3, respectively), whereas the majority was best described by some EAM model. (3) Confirming the results of our work within a different paradigm (Söllner et al., 2014), we found that the compatibility of additionally purchased information with the initially displayed information influenced the subsequent stopping behavior – a finding that neither TTB nor compensatory decision strategies would predict.

The work presented herein tackled two potentially critical issues relating to our previous work (Söllner et al., 2014): (1) possible demand effects and (2) the concentration on TTB-consistent behavior. Regarding the first issue, no incompatible information was “forced” upon the participants by displaying it for free (cf. Söllner et al., 2014) in the three experiments presented herein. Instead, participants could intentionally purchase additional information. Therefore, demand effects cannot account for our EAM-consistent finding that participants adapt their information search to the compatibility of this additional information. To account for the second issue, we based our MSM predictions on all the routinely investigated decision strategies (TTB and compensatory ones). Thus, the reported EAM-consistent findings do not rely on a strategy-specific induction procedure and are based on the whole sample of participants. Employing our novel paradigm, we found further support that the content (compatibility) of additional information is not irrelevant for the termination of information search (MSM prediction), but systematically affects subsequent behavior as predicted by EAMs. This finding holds for intruding information (Söllner et al., 2014), but also for intentionally purchased information (present work).

The adequacy of our approach is supported by its capability to reproduce the aforementioned mimicking relationship between the two frameworks: (1) In each of the three reported experiments, we found a higher mean percentage of immediate stopping for participants classified as TTB users than for compensatory strategy (COMP) users. (2) Concentrating on participants that showed a significant increase in their stopping behavior across the levels of given evidence (confirming the EAM prediction), we observed a lower mean estimated threshold for participants classified as TTB users than for COMP users in all three reported experiments. (3) In Experiment 3, we showed that an information cost manipulation causing a descriptive shift in the strategy classification (MSM) was mirrored in a statistically significant difference in the mean estimated evidence thresholds between the two information cost conditions. Note that these findings are not trivial as the decision strategy classification was based on the calibration phase data, whereas the stopping behavior observation and the subsequent threshold estimation relied on the test phase data of the participants.

Proponents of the MSM could argue that the concentration on TTB and compensatory decision strategies (e.g., WADD and EQW) in our approach might be common practice (e.g., Bergert & Nosofsky, 2007; Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b, 2006a, 2006b; Dieckmann et al., 2009; Gigerenzer & Goldstein, 1999; Lee & Cummins, 2004; Newell & Lee, 2011; Rieskamp, 2006; Rieskamp & Otto, 2006), but does not do justice to the complexity of the MSM framework. The adaptive toolbox (Gigerenzer & Todd, 1999), for example, includes further heuristics (e.g., “Take Two” heuristic, Dieckmann & Rieskamp, 2007) and stopping rules (cf. Gigerenzer et al., 2012) that have not been addressed in our considerations. However, we argue that our findings concerning the immediate stopping behavior in our paradigm cannot be accounted for by any of these: A stopping rule that relies on the mere number (m) of uncovered cues, would predict uniform stopping behavior across all levels (immediate stopping for $m \leq 3$, continued acquisition for $m > 3$). Heuristics with a stopping rule that relates to the number of reasons (n) in favor of one option (i.e., compatible discriminating cues) might, however, be more successful candidates. As the paradigm was tailored to have TTB ($n = 1$) give uniform predictions and no level openly displayed more than two reasons (forcing all stopping rules with $n > 2$ to predict continued acquisition for all levels), the Take Two heuristic ($n = 2$) deserves a closer look: This heuristic would indeed predict continued information acquisition for levels 1 to 3 and immediate stopping for levels 4 to 8. In contrast to this prediction, we (1) observed a wide range of individual evidence thresholds in all reported experiments and (2) still found the reported effect of the levels of given evidence on the immediate stopping behavior when including only levels 4 to 8 in the analyses[10].

Another potential criticism could relate to our deterministic interpretation of the decision strategies’ stopping rules. Of course, we agree that a probabilistic stopping rule that allows for random errors might give a more realistic view on human decision making. However, our findings are not invalidated by such an extension of the MSM view as a probabilistic stopping rule should merely result in random errors around the

[10] For example, reanalyses for Hypothesis 1.a (group level) yielded the following results: Experiment 1: $F(2.52, 156.48) = 88.09$, $p < .001$, $\eta^2 = .59$; linear trend: $F(1, 62) = 161.69$, $p < .001$, $\eta^2 = .72$; Experiment 2: $F(2.10, 129.93) = 52.50$, $p < .001$, $\eta^2 = .46$; linear trend: $F(1, 62) = 73.97$, $p < .001$, $\eta^2 = .54$; Experiment 3: $F(2.10, 124.09) = 62.63$, $p < .001$, $\eta^2 = .52$; linear trend: $F(1, 59) = 103.12$, $p < .001$, $\eta^2 = .64$.

predicted flat slope. In particular, the repeatedly observed strong linear increase in the immediate stopping behavior cannot be explained by assuming probabilistic rather than deterministic stopping for the decision strategies.

Finally, we base our considerations on two essential, but potentially critical assumptions: We assume that participants do not switch strategies (1) between calibration and test phases and (2) within the test phases in accordance to the different information patterns. We deem the first assumption plausible for several reasons: During the test phases, participants did not receive feedback on their choices that could teach them how to adjust their behavior (cf. Newell & Lee, 2009). Moreover, previous work has reported routine effects in decision strategy use (cf. Bröder & Schiffer, 2006a; Rieskamp, 2006) – even when feedback was given. Also, we explicitly (and veridically) told participants in the instructions that calibration and test phases were similar to each other, except for only two modifications – the absence of choice feedback and the circumstance that already three cues had been opened. Finally, we actually observed the expected mimicking relationship between strategy use (MSM view, determined based on calibration phase data) and estimated evidence thresholds (EAM view, based on test phase data) that builds on the assumption that participants do not switch strategies between calibration and test phases.

The second assumption, that participants do not switch decision strategies contingent on the specific information pattern encountered, is even more crucial for our conclusions. We discussed this potential objection before (cf. Söllner et al., 2014) and remain confident that questioning this assumption is neither supported by previous work on strategy classification (e.g., Bröder & Schiffer, 2003b; Glöckner, 2009; Payne et al., 1993) and routine effects (Bröder & Schiffer, 2006a; Rieskamp, 2006) nor by the basic idea of a "strategy" as an ordered set of processes to solve a task.

To conclude, the reported experiments demonstrate that participants' stopping behavior in multi-attribute decision tasks is influenced by two factors: (1) the value of the uninspected cues (validity of hidden information) and (2) the levels of given evidence. The effect of the validity of hidden information (1) on the stopping behavior emerged across the three experiments as an unexpected byproduct of our main interest in the levels of given information. It seems that the participants consider not only the information costs attached to a cue, but the value (in terms of validity and discrimination rate) they gain by investing these costs. Thus, their stopping behavior seems to depend on cost-benefit-considerations that include several factors. To our knowledge, no EAM or MSM exists, that models stopping behavior accordingly. Indeed, stopping behavior regularly depends on the so-far sampled information, but not on the potentially further available information. Busemeyer and Rapoport (1988) discuss an optimal stopping rule and a ("myopic") stopping rule that require planning several steps (i.e., *m* cues) ahead to determine whether "the expected loss [or gain] of making a terminal decision on the basis of the current information is less [or more] than the expected loss [or gain] of making a terminal decision after purchasing at most *m* more observations" (p. 117; brackets added). Although, for example, Gigerenzer and Todd (1999, p. 10) reject this "optimization under constraints" for being computationally intractable and therefore "demonic", our results show that participants actually employ a rather complex stopping rule. Therefore, we believe that future research should focus on *how* this can be done – instead of assuming that it *cannot* be done.

The main finding from our experiments, however, is that the levels of given evidence consistently affect the stopping behavior in a multi-attribute decision task. The unanimous findings clearly favor the EAM prediction over the MSM prediction. We are not aware of any decision strategy that would predict these highly systematic findings that are clearly in line with a basic prediction of EAMs. Of course, the MSM framework could potentially include an "evidence-accumulation" decision strategy that can account for our findings as the set of decision strategies is theoretically not restricted (e.g., Glöckner & Betsch, 2011; Newell & Lee, 2011; Newell, 2005, but see Marewski, 2010). However, we believe that such absorption of additional decision strategies that are able to account for certain empirical findings is not warranted as it results in an untestable and therefore invulnerable framework (Glöckner & Betsch, 2011). Instead, we advocate to noncommittedly investigate which framework's metaphor describes decision making best. The results presented in this article clearly favor the evidence accumulation models' adjustable spanner metaphor over the toolbox metaphor of the multiple-strategy models.

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Appendix

Appendix 1: Levels of given evidence (level 1: minimum evidence; level 8: maximum evidence) - and validity of hidden information- manipulation in Experiment 3.

Validity combination 1	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1	- -	- -	+ -				+ -	+ -
Cue 2	- -	+ -	- -				- -	+ -
Cue 3	+ -	- -	- -				+ -	- -
Cue 4	? ?	? ?	? ?				? ?	? ?
Cue 5	? ?	? ?	? ?				? ?	? ?
Cue 6	? ?	? ?	? ?				? ?	? ?
Validity combination 2	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1		- -	+ -			+ -		+ -
Cue 2		+ -	- -			- -		+ -
Cue 3		? ?	? ?			? ?		? ?
Cue 4		- -	- -			+ -		- -
Cue 5		? ?	? ?			? ?		? ?
Cue 6		? ?	? ?			? ?		? ?
Validity combination 3	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1		- -	+ -		+ -			+ -
Cue 2		+ -	- -		- -			+ -
Cue 3		? ?	? ?		? ?			? ?
Cue 4		? ?	? ?		? ?			? ?
Cue 5		- -	- -		+ -			- -
Cue 6		? ?	? ?		? ?			? ?
Validity combination 4	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1		- -	+ -	+ -				+ -
Cue 2		+ -	- -	- -				+ -
Cue 3		? ?	? ?	? ?				? ?
Cue 4		? ?	? ?	? ?				? ?
Cue 5		? ?	? ?	? ?				? ?
Cue 6		- -	- -	+ -				- -
Validity combination 5	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1			+ -				+ -	
Cue 2			? ?				? ?	
Cue 3			- -				+ -	
Cue 4			? ?				? ?	
Cue 5			? ?				? ?	
Cue 6			- -				- -	
Validity combination 6	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1			+ -			+ -		
Cue 2			? ?			? ?		
Cue 3			? ?			? ?		
Cue 4			- -			+ -		
Cue 5			? ?			? ?		
Cue 6			- -			- -		
Validity combination 7	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Cue 1			+ -	+ -	+ -			
Cue 2			? ?	? ?	? ?			
Cue 3			? ?	? ?	? ?			
Cue 4			? ?	? ?	? ?			
Cue 5			- -	- -	+ -			
Cue 6			- -	+ -	- -			