A New and Unique Prediction for Cue-search in a Parallel-constraint Satisfaction Network Model: The Attraction Search Effect

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Abstract

A common assumption of many established models for decision making is that information is searched according to some pre-specified search rule. While the content of the information influences the termination of search, usually specified as a stopping rule, the direction of search is viewed as being independent of the valence of the retrieved information. We propose an extension to the parallel constraint satisfaction network model (iCodes: *i*ntegrated *co*herence-based *de*cision and *s*earch), which assumes—in contrast to pre-specified search rules—that the valence of available information influences search of concealed information. Specifically, the model predicts an attraction search effect in that information search is directed towards the more attractive alternative given the available information. In three studies with participants choosing between two options based on partially revealed probabilistic information, the attraction search effect was consistently observed for environments with varying costs for information search although the magnitude of the effect decreased with decreasing monetary search costs. We also find the effect in reanalyses of five published studies. With iCodes, we propose a fully specified formal model and discuss implications for theory development within competing modeling frameworks.

Keywords: Search in probabilistic decision making, attraction search effect, parallel-constraint satisfaction network model, fast-and-frugal heuristics

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The accuracy of inferences clearly depends on the quality of available information. If valid information is not conveniently presented at a glance—as it is often the case in real-world environments—people need to search for information before making a decision. Doctors need to look for symptoms, educated consumers need to retrieve product-information, police needs to search for evidence, etc. While there exist many accounts on how people integrate probabilistic information, a “puzzling preference for theories that ignore search and stopping” (Gigerenzer, Dieckmann, & Gaissmaier, 2012, p. 243; Todd, Hills, & Robbins, 2012) has been lamented recently. In the current article, we compare fixed search rules as formulated in the research-program on the adaptive toolbox (Gigerenzer et al., 2012) or the adaptive decision maker (Payne, Bettman, & Johnson, 1988) to a new theory of coherence-based search that emerges from parallel-constraint satisfaction processes (Glöckner & Betsch, 2008a; Glöckner, Hilbig, & Jekel, 2014; McClelland, Mirman, Bolger, & Khaitan, 2014).

Fixed Search Rules

Formalized heuristics include search-, stop-, and decision-rules (Payne et al., 1988; Todd, Hills, & Robbins, 2012): According to the non-compensatory heuristic Take-the-best (TTB), for example, people search cues in the order of their predictive validity, stop when the first cue discriminates between choice-options, and decide in line with this first discriminating cue (Gigerenzer & Goldstein, 1996). As a consequence, information is searched and compared within each cue, which is referred to as cue-wise search and constitutes a typical property of the class of non-compensatory strategies (Payne et al., 1988). In contrast, people applying a compensatory strategy (in which less valid cues can compensate more valid cues) such as the Weighted Additive Rule (WADD) are often assumed to tend to search all cues option-wise, that is by searching and integrating information mainly within options.

More recent refinements of heuristic search assume that the order of cue-values inspected is not exclusively dependent on cue-validities but also driven by other properties of cues such as cue-discrimination (Lee & Newell, 2011; Lee, Newell, & Vandekerckhove, 2014; Martignon & Hoffrage, 1999; Newell, Rakow, Weston, & Shanks, 2004; Ravenzwaaij, Moore, Lee, & Newell, 2014), the gain in the probability of a correct decision (Nelson, 2005; Nelson, McKenzie, Cottrell, & Sejnowski, 2010), or cue-outcome correlation (Rakow, Newell, Fayers, & Hersby, 2005). Furthermore, strategies for search have been formulated that involve learning in that they are contingent on the experienced accuracy of decisions resulting from search-orders (Todd & Dieckmann, 2004; Dieckmann & Todd, 2012) or the expected reward from search (McNamara & Fawcett, 2012).

There is a solid body of evidence supporting the view that information search (cue-wise vs. option-wise) changes adaptively contingent on the structure of the environment (e.g., Bröder, 2003; Payne et al., 1988; Rieskamp, 2006; Rieskamp & Otto, 2006) and many other factors such as task-complexity (Payne, 1976; Böckenholt, Albert, Aschenbrenner, & Schmalhofer, 1991), information-costs (Bröder & Schiffer, 2006), time pressure (Rieskamp & Hoffrage, 1999, 2008; Payne et al., 1988; Edland, 1994; Edland & Svenson, 1993), stress (Glöckner & Moritz, 2008), and age (Mata, Schooler, & Rieskamp, 2007; Mata, von Helversen, & Rieskamp, 2011). These adaptive changes have mainly been interpreted as resulting from the selection of different strategies that are composed of search-, stopping-, and decision rules.

However, other evidence puts into question whether modeling information search as fixed search rules within heuristics is appropriate. Many studies show that people search by default more information than would be necessary to apply the respective heuristics (e.g., Bröder, 2000, 2003; Hausmann & Läge, 2008; Newell & Shanks, 2003; Newell, Weston, & Shanks, 2003) leading to the conclusion that “[o]nly if search costs are explicit are stricter stopping (and decision) rules employed” (Newell & Bröder, 2008, p. 211). Further research shows that the stopping rule for information search is not fixed but dependent on already revealed evidence (Söllner & Bröder, 2016; Söllner, Bröder, Glöckner, & Betsch, 2014). These findings concerning search and stopping are difficult to reconcile within a simple heuristics framework and indicate that there is a need for alternative conceptualizations.

Coherence-based Search

An alternative view of information-processing assumes that a fundamental property of the cognitive system includes forming coherent interpretations by interactive neuronal activation (Clark, 2013; Rumelhart, McClelland, & The PDP Research Group, 1986, see also Wertheimer, 1938; Festinger, 1957; Pennington & Hastie, 1981). This approach has also been applied to decision making (Thagard & Millgram, 1995; Glöckner & Betsch, 2008a; Betsch & Glöckner, 2010; Kunda & Thagard, 1996), which has led to the development of the parallel constraint satisfaction model for decision making (PCS-DM; Glöckner et al., 2014), a fully specified decision model with one free person parameter that captures inter-individual differences in sensitivity to differences in cue validities. According to PCS-DM, decisions are achieved by automatically integrating decision-relevant information through spreading activation in a network. As one core limitation, PCS-DM does not model search for new information (Marewski, 2010). Previous empirical investigations of PCS-DM therefore intentionally simplified the decision situation in that participants did not need to acquire information.

Rather, all pieces of information were presented in an open information-board and could be directly inspected (cf. Glöckner & Betsch, 2008b). Although this setup simplifies the decision situation (and thus also modeling of this situation), it also neglects search as a crucial aspect for making good decisions. In the current article, we propose a straightforward extension of the PCS-DM model that includes modeling of search for information. To avoid cumbersome acronym extensions of PCS-DM with additional letters, we refer to the new model by the name “iCodes” meaning “integrated coherence-based decision and search". In the first part of the article, we introduce iCodes conceptually: We derive a qualitative prediction from the model capturing a critical property that diverges from competing models—the attraction search effect.

We present three empirical studies testing this prediction. First, we analyze the first information acquisition in each trial, testing the qualitative prediction of the model under varying conditions in two studies. Second, we conduct overall analyses for the first two studies in which we compare differences in the restriction of search and information costs between conditions and extend the test to quantitative predictions for choice and information search. Third, we extend the joint analyses to investigate further aspects such as whether the hypothesized effect also holds for whole sequences of search and whether it results from deliberate or intuitive processes. Fourth, we discuss the "rationality" of the attraction search effect and present a third empirical study showing that it depends on the environmental structure, although it can be found regardless whether it is beneficial or detrimental. Fifth, we present a comprehensive re-analysis of previously published studies to test the generality of our findings. In the concluding section, we discuss our findings and their implications for decision theory.

Modeling Heuristic and Coherence-based Search for Cues

Consider, for illustration, the example that a person decides between two stocks in a hypothetical stock-market game (Bröder, 2000) in which information from two binary probabilistic experts (i.e., cues) can be retrieved. The first expert (cue 1) has a higher predictive validity than the second expert (cue 2). Both provide information whether investing in stock A or stock B would be recommendable (+) or not (–). Now let us assume that one piece of information—the prediction of cue 1 for stock A—is already available but all other information is still concealed (Figure 1, upper left display). Which predictions concerning the next step of information search can be derived from standard heuristic models? A user of the non-compensatory TTB heuristic would search for the second cue-value of the most valid cue 1 next. In contrast, a user of a compensatory WADD strategy is expected to open the cue-value of cue 2 for stock A next. Importantly, both predictions are independent of the valence of the available cue-value. That is, the direction of search is independent of whether the already available piece of information from cue 1 speaks for or against stock A (Figure 1, upper left display, value in parenthesis). This prediction concerning the independence of the direction of search from the specific valence of already available information results from the more general assumption of fixed search rules, which is typical for strategies suggested in the tradition of the adaptive decision maker and shared by all of them.

In contrast to this prediction, in iCodes cue-search is dependent on the current evidence of already revealed cue-values. iCodes assumes that people form an initial preference for one of the options based on the available cue-value(s), as already described by PCS-DM (Glöckner et al., 2014). As the pivotal extension, we propose that the resulting preliminary impression then influences which cue-value is opened next such that concealed cue-values of currently preferred options are more likely opened next than cue information concerning less preferred options. In line with the general idea of interactive activation models, this important property of the iCodes model developed in this paper proposes that the more highly activated (attractive) option receives more attention which governs cue search in addition to the validities of cues. Specifically, for allowing to model cue-search we extend the original PCS-DM model (Glöckner & Betsch, 2008a; Glöckner et al., 2014) in two respects: (1) each cue-value (+ or –) is represented by a separate node in the network that is connected to a cue-node for modeling interdependence between cue-values from the same cue and (2) the original PCS-DM network consisting of options and open cue-values is extended by a subnet consisting of concealed cue-values.

Open cue-value(s; unshaded rectangle C1A for cue 1 concerning stock A; Figure 1, upper right panel) are connected to cue-nodes and to option-node(s) (i.e., positive connection as indicated by the black line from C1A to A). Connections between options are inhibitory—as indicated by a dashed line between A and B—because participants can only choose one of the options. The strength of connections between source node and cue-nodes is proportional to the cue-validities as indicated by thicker lines for the more valid cue 1 as compared to cue 2. The process of forming an initial preference for one of the options is simulated as activation spreading from the source-node to the cues and single cue-value(s) and to the options in an iterative process of updating activations of cues. In the example provided in the upper right part of Figure 1 involving a positive value of Cue 1 for option A (i.e., C1A), option A receives high activation. The positively activated option A inhibits option B, which results in a highly activated option A and a less activated option B as indicated by differences in box-sizes.

Concealed cue-values form a subnet: Activation flows from the cue-nodes and the option-nodes (Figure 1, lower left display) to the concealed cue-values. Note that connections between option-nodes and cue-nodes to concealed cue-value nodes are only uni-directional (as indicated by grey single-arrowed connections), since we assume that yet unknown cue-values cannot influence the activation of options. Activation flowing from the source node to the cue-nodes is proportional to cue-validities as in the original PCS-DM model.

For information search, this leads to two core predictions: First, the probability of opening a cue-value increases with its validity (keeping everything else constant). This prediction has already received ample support (e.g., Glöckner & Betsch, 2008b; Glöckner et al., 2014, Exp. 4) but since it is shared with several alternative models (e.g., evidence accumulation models: Busemeyer & Townsend, 1993; Krajbich & Rangel, 2011; adaptive strategy selection models: Payne et al., 1988; Payne, Bettman, & Johnson, 1993; Gigerenzer & Goldstein, 1996; Todd, Gigerenzer, & The ABC Research Group, 2012), it is not particularly useful for testing models comparatively. Second, activation flowing from the options to the nodes representing concealed cue-values leads to the prediction of an increased tendency to search cue-values of the currently preferred option (i.e., higher activated option-node). This should lead to an attraction search effect, which is not predicted by alternative models (heuristics as well as diffusion/evidence accumulation models). According to this model-inherent prediction, information will be mainly searched within an option if it is attractive but that the direction of information search tends to switch to the other option if the searched alternative appears to be unattractive.

In line with the well supported concept of interactive activation and parallel constraint satisfaction (McClelland et al., 2014), iCodes predicts that both sources of activation (i.e., validity of the cue and attractiveness of the option) are additive (as also encoded in the activation function, see section on the formalization of the model below) and jointly determine the activation of concealed cue-value nodes and thereby the likelihood of opening it derived from those activations. Specifically, iCodes predicts that the likelihood for each cue-value to be opened increases with the activation of the respective cue-value node (as compared to the overall activation of all concealed cue-value nodes). In case the initial evidence is positive for option A and the difference in validities between cues is small, iCodes predicts that it is more likely that participants inspect the cue-value of cue 2 for option A instead of the more valid cue-value of cue 1 for option B. In case the initial evidence is negative for option A, participants are predicted to search evidence for option B more likely instead.

In sum, based on its core property of interactive activation, iCodes predicts an attraction search effect in that the next step of information search should tend to be more option-wise in case there is a current tendency to prefer option A and more cue-wise in case there is a current tendency to prefer option B.[1] This effect allows for a critical property testing against the most prominent classes of competing models. Adaptive strategy selection models (Gigerenzer, Todd, & The ABC Research Group, 1999; Payne et al., 1993) assume as a core property that people use fixed rules for information search. For such rules, the valence of the information cannot influence the direction of search. Also, the class of evidence accumulation models (Busemeyer & Townsend, 1993; Krajbich & Rangel, 2011; Lee & Cummins, 2004) does not predict such an effect. These models assume that attention switches probabilistically between cues (or attributes) and evidence is accumulated until a decision threshold for one of the options is reached. The random distribution of attention to cues is influenced by validity or other factors (e.g., perceptual salience) of cues and the decision environment but is independent of the initial evidence resulting from the interplay of already available cues. The crucial difference to PCS models is that backward activation processes from options to search are precluded. Hence, evidence accumulation models do not predict the attraction search effect either.

Studies that directly compare the adequacy of heuristic search-rules to alternative accounts are still largely missing mainly because alternative models (such as PCS-DM) were so far underspecified with respect to information search (but see Glöckner & Herbold, 2011, for describing first steps towards a network model of attention and integration in risky choice). We aim to close this gap by comparing the predictions from an extended PCS model for search against predictions from heuristic search-rules and evidence accumulation models using a critical property testing account with a focus on the attraction search effect in three experimental studies.

Related Evidence: Pseudodiagnosticity in Hypothesis Testing

In research on information search for conditional probabilities in reasoning and hypothesis testing, a phenomenon similar to the attraction search effect has been demonstrated, which is referred to as pseudodiagnostic search (Doherty, Mynatt, Tweney, & Schiavo, 1979; Kern & Doherty, 1982; Mynatt, Doherty, & Dragan, 1993). It is shown that individuals do not look up both relevant conditional probabilities for considering whether a piece of information (e.g., the patient has fever) speaks for a hypothesis (e.g., the patient has flu) or an alternative (e.g., the patient has a sepsis). This is usually explained by peoples' inability "to think about one datum in relation to two hypotheses" (Mynatt et al., 1993, p. 119) and a default attentional shift in focus on the information about a single hypothesis (Evans, Venn, & Feeney, 2002). Since only the comparison of both conditional probabilities between hypotheses (e.g., is the probability of fever given a flu higher than the probability of fever given sepsis?) allows to evaluate whether this piece of information speaks for one of the hypotheses (i.e., by calculating the ratio of likelihoods), not looking up the other relevant information has to be considered suboptimal.[2]

In hypothesis testing, pseudodiagnostic search is consistently observed. Providing an initial information (e.g., conditional probability of fever given flu = .80) that seems to speak for the hypothesis due to a probability larger than .50 leads to an increased search for a next piece of information that relates to the same hypothesis (e.g., the conditional probability of headache given flu), whereas the relevant other piece of information (e.g., conditional probability of fever given sepsis) is ignored. If—in contrast—the first information seems to speak against the hypothesis (e.g., conditional probability of fever given flu = .20), search switches to information concerning the other option (Mynatt et al., 1993). Hence, pseudodiagnostic information search in hypothesis testing describes a phenomenon similar to the attraction search effect predicted by iCodes for multiple-cue decision making in that information search is dependent on the valence of the already revealed information. Given the differences between the pseudodiagnosticity paradigm and typical multi-attribute decision tasks, it is, however, unclear whether the effect generalizes, which we investigated in the current research. Furthermore, while explanations of the phenomenon in pseudodiagnosticity research include mainly broad framework models (Evans, 2007, 2008; Evans et al., 2002), iCodes provides a fully specified computational formal model for predicting the magnitude of the attraction search effect.

Study 1

In Study 1, we test for the existence of an attraction search effect that is uniquely predicted by iCodes but not predicted by competitors such as adaptive decision making and evidence accumulation models. Instead of comparative model fitting, we thereby rely on a critical property when testing a qualitative hypothesis that can only be accounted for by one model but not by the others. This approach avoids the problem of potential over-fitting (Gigerenzer & Brighton, 2009; Marewski & Olsson, 2009; Roberts & Pashler, 2000) since the prediction of the attraction search effect does not depend on parametric constellations.

Methods

Participants. Thirty-three participants (17 male; mean age = 25 years, $SD = 4$, mainly students from the University of Göttingen) were recruited using the database ORSEE (Greiner, 2004). Participants received a show-up fee of 2€ (≈ 2.2 USD) and performance-contingent payment for each correct choice of up to 3.20€ (≈ 3.6 USD).

Material. Participants played a hypothetical stock-market game in which they were asked to choose the more profitable of two stocks (Figure 2). They could use the advice from four experts that varied in predictive power with cue validities v = {.90, .80, .70, .60}, which was introduced as the number of correct predictions of the respective cue/expert in the past one-hundred rounds prior to the study. Participants were also made aware of the fact that cues with fifty out of one-hundred predictions correct are no better than chance. Each expert made a binary prediction ("+" = good, "–" = bad) concerning the performance of each stock. Some of these cue-values were directly available, other cue-values were concealed. From the concealed cue-values, some were potentially available, as indicated by "?", or unavailable as indicated by "x" (Figure 2).

Participants were asked to open one additional available information only (i.e., "?") before deciding which option to choose. The cue-value they opened before making a decision was the dependent variable. The more likely option according to naïve Bayes (Jekel, Glöckner, Fiedler, & Bröder, 2012; Lee & Cummins, 2004) given validities and all cue-values (i.e., open and concealed) of a trial was reinforced with 2.5 Cents for each correct decision and participants were informed about their performance (i.e., number of correct decisions) at the end of the study.

Participants were told that experts generated their predictions independently and that the resulting recommendations were thus independent from each other. Names of the stocks and experts changed for each new trial to further stress that trials were independent of each other and no information of prior trials could be used to infer concealed cue-values in subsequent trials (Jekel, Glöckner, Bröder, & Maydych, 2014). Overall, eight cue-patterns (i.e., all cue-values concerning option A and B) with two different versions each were presented. Each of them was repeated eight times resulting in 8 (cue-patterns) $\times$ 2 (versions: stock A attractive vs. stock B attractive) $\times$ 8 (repetitions) = 128 rounds in total (Table 1). The factor "version" contained the critical within-subjects manipulation of options' attractiveness that should induce differences in information search according to the attractive search effect. For manipulating version, the cue-pattern was held constant except for one or two directly available cue-values that were varied so that option A was more attractive in the first version and option B was more attractive in the second version according to iCodes.

It was expected that the manipulation of attractiveness implemented in the factor version leads to respective changes in information search, that is, increased search for cue-values from stock A than stock B in version 1 and vice versa for version 2. For each cue-pattern, we calculated an attraction search score as the dependent variable that equals 1 if all participants search for stock A in version 1 and for stock B in version 2 and that equals 0 if no switches in search are induced by the manipulation of attractiveness (i.e., score = p(search stock A|version 1) - p(search stock A|version 2)). The factors cue-patterns and repetitions test the generality and robustness of the effect. For each cue-pattern, evidence of concealed cue-values was randomly set positive or negative.[3] The order of patterns was randomized between participants.

Procedure. Participants received a paper-and-pencil instruction of the stock-market game. After clarifying potential questions individually to assure understanding, they completed 64 trials of the game. After a short self-paced break, they then completed the second half of the trials and indicated demographic data. Finally, participants were debriefed, and paid according to their performance.

Results

R-scripts and data from Study 1, Study 2, and Study 3 can be downloaded from the Open Science Framework at http://doi.org/10.17605/OSF.IO/Q6C5Y. Participants made on average 78% ($SD = 3\%$) correct decisions according to naïve Bayes standards, which is significantly higher than the 50% chance-level ($t(32) = 46.23, p < .001$). This indicates that people made informed decisions, taking into account the information provided. More importantly, we descriptively found the predicted attraction search effect for all cue-patterns (Figure 3). The average attraction search score is $M = .30$ ($SD = .14$) and significantly larger than zero ($t(32) = 12.37, p < .001$). This means that participants searched in 30% of all trials more often cues of option A when option A was more attractive than option B than vice versa (i.e., version 1 vs. version 2) according to iCodes. See Appendix A for a complete display of the observed proportions of cue-values opened first. The attraction search effect is also consistently found in separate analyses for all cue-patterns (all paired $ts(32) > 2.39, p < .05$) and thus does not seem to depend on specifics of the cue-patterns (Wells & Windschitl, 1999; Westfall, Judd, & Kenny, 2015) although its size varies across patterns.

The overall effect size of the attraction search effect is Cohen's $d = 2.15$ and the effect sizes per pattern range from $d = 0.42$ (cue-pattern 3) to $d = 2.66$ (cue-pattern 7). Importantly, differences in the size of the effect are in line with model predictions: iCodes predicts the strongest attraction search effect ceteris paribus for cue-patterns 6 and 7. Specifically, the model predicts that search is determined both by validity and top-down activation generated by the attractiveness of options. Hence, the attraction search effect should be weaker (but still present) in patterns where top-down activation by the attractive option is in conflict with tendencies generated by validity, such as in cue-patterns

1, 2, 3, 4 and 5, but not 6, 7, and 8.

Analyses at the level of individuals revealed that 76% of the participants showed a significant attraction search score (all ts(7) > 2.00, ps < .05; t-tests based on eight attraction search scores) and nearly all participants (i.e., 97%) showed a positive attraction search score, indicating that the effect is not only driven by a small subset of participants.

Discussion

We find strong support for the attraction search effect predicted by iCodes. The effect is consistently found for all cue-patterns and for the majority of participants supporting the critical property prediction of the model. Neither fixed strategies, as formulated in the adaptive toolbox program, nor standard evidence accumulation models can account for this effect that follows from interactive activation.

One limitation of Study 1 is that the decision task was restricted by the fact that participants were only allowed to open one additional cue-value before making a decision. This might reduce the generality of our findings since information search in natural environments is rarely restricted in this way. We address this issue in Study 2 by investigating the prevalence of the attraction search effect in a less restricted and thus potentially more natural environment.

Study 2

Study 2 tested whether the attraction search effect generalizes to situations where participants could search for more than one additional cue-value. Furthermore, we investigated the effect of monetary costs of search, which has been shown to crucially influence information search in previous studies (Bröder & Schiffer, 2006).

Methods

Participants and Design. One-hundred-eleven new participants (73 female; mean age = 25 years, $SD = 5$, two participants did not indicate their age) were recruited from the same database used in Study 1. Participants again received a show-up fee of 2€ ($\approx$ 2.2 USD) and performance contingent payment for each correct choice of up to 3.20€ ($\approx$ 3.6 USD). We manipulated information costs between participants who were randomly assigned to either a condition with or without monetary costs for information search.

Materials and Procedure. We used the same materials and procedure as in Study 1 except for that people were free to choose how many cue-values to open before making a choice. In the information cost condition, participants could open one cue-value for free. For every additional cue, participants were told that a fee of .25 Cents was applied (i.e., 10% of the potential reward). In the condition without information costs, participants were asked to open one cue-value and could open as many additional values as they wanted without any costs.

Results

Participants made on average 87% (SD = 4%) correct decisions in the condition with information search costs but only 81% (SD= 7%) in the condition without information search costs. Both are significantly different from chance-level (both ts > 33, $p < .001$) and they are different from each other ($t(109) = -5.49$, $p < .001$). In the information cost condition, participants inspected on average only freq = 0.25 costly cues (i.e., cues beyond the first cue opened) per decision, whereas freq = 2.1 additional cue-values were inspected in the condition without information cost ($t(109) = -19.43$, $p < .001$). Less inspection thus led to more correct decisions. This is likely due to the non-compensatory structure of the decision environment given validities and the naïve Bayesian incentive scheme[4] and participants who tended to integrate information in a more compensatory fashion as suggested by fits of the P-Parameter in iCodes (i.e. $P < 1.9$, see below for details).

In accordance with Study 1, we calculated the attraction search score based on the first cue-value opened for both conditions by comparing search between versions of cue-patterns. We observe the predicted attraction search effect in both conditions (Figure 3). For the information cost condition, the average attraction search score is $M = .32$ ($SD = .22$). The attraction search effect is significantly smaller for the condition without costs $M = .11$ ($SD = .14$) ($t(109) = 5.91$, $p < .001$), but both are again significantly larger than zero (both ts > 6.38, $p < .001$).

The overall effect size of the attraction search effect is Cohen's $d = 1.50$ for the information-cost condition and Cohen's $d = 0.86$ for the no-cost condition. Overall, we find that the attraction search effect is present in both conditions but letting participants search for cues without monetary costs reduces the size of the effect considerably. On the individual level, 75% of the participants show a significant attraction search effect (all ts$(7) > 1.97$, $p < .05$; t-tests based on eight attraction search scores) and nearly all participants (i.e., 91%) show a positive attraction search score in the information cost condition. In the no-cost condition, a considerably lower 25% of participants (all ts$(7) > 2.00$, $p < .05$) show a significant attraction search effect but the majority of participants (i.e., 82%) shows at least a positive attraction search score overall.

Discussion

We find again strong support for the attraction search effect predicted by iCodes under more realistic conditions of unrestricted search. The size of the effect appears to depend on the type of search as analyzed next.

Comparison of Studies and Analysis of Psychometric Properties

Comparison between Studies

In the first study, participants were only allowed to search for one additional cue. In the second study, participants could either search additional cues with or without any monetary costs. All other aspects (i.e., cue-patterns and procedure) were identical in both studies.

A comparison within and between studies reveals that the attraction search effect is similar for restricted search and unrestricted search with costs and lower for all cue-patterns in the condition with unrestricted search without costs as shown in Figure 3. A multi-level regression (Table 2) predicting the attraction search score with random intercepts and random slopes for participants and two Helmert contrasts comparing conditions confirmed this impression (unrestricted search without costs < restricted search & unrestricted search with costs; $t(133.31) = -7.27$, $p < .001$; restricted search vs. unrestricted search with costs; $t(86.05) = -0.56$, $p = .58$).

There are various factors that could cause the attraction search effect to be lower in the unrestricted search condition without costs. One factor is that participants in the condition might search information less systematically. Furthermore, they might be less likely to form a preliminary assessment of the options concerning their attractiveness before searching, which is required for the attraction search effect to evolve. Both potential explanations are indirectly supported by the fact that search time (i.e. time before an information is opened) is lower in the unrestricted search condition (i.e., 4506ms for restricted search versus 3153ms and 2140ms for unrestricted search with or without costs; see section on the automaticity of the attraction search effect below for details).

A third further factor that is likely to reduce the attraction search effect in the unrestricted search condition without information costs is the effect of reading direction, which is more likely to overwrite the systematic attraction search effect in the unrestricted search condition without costs. Specifically, in decision tasks without restrictions of search (and particularly in open displays), individuals tend to focus initially more on the information provided on the upper left side of the screen (e.g., Fiedler & Glöckner, 2012). In line with this explanation, there are strong reading biases in the unrestricted search condition without costs as compared to the other conditions. For cue-patterns in which the most valid cue-values for both options are the same (i.e., patterns 6 to 8; Table 1), for example, participants looked up a piece of information displayed on the left in 73% of the trials, whereas this bias was much weaker (58% of the trials) in the two other conditions, $t(142) = 6.10, p < .001$, Cohens's $d = 1.05$. Similarly, for remaining cue-patterns 1 to 5, in which the most valid cue is different for both options, there is a stronger top/bottom reading bias for unrestricted search without costs than in the other two search conditions. Participants in the unrestricted search condition without costs focus more on the information presented on the top as compared to participants in the other conditions (average ranks: unrestricted without costs = 2.86 vs. other = 3.20, $t(142) = -4.70, p < .001$, Cohen's $d = 0.81$). Note, however, that this analysis has to be interpreted cautiously since presentation order is confounded with cue validity in our paradigm.

In summary, there is evidence from multiple process measures that the observed lower attraction search scores in the condition with unrestricted search without costs as compared to the other conditions might be driven by the fact that under unrestricted search without costs (i) participants look up information less systematically, (ii) they might be less likely to take the time to generate a required preliminary attractiveness rating before search, and (iii) they show stronger reading biases by preferring information on the left and on the top of the display that overwrite effects of attraction search.

Inter- and Intraindividual Stability of the Attraction Search Effect

Next, we investigated whether the attraction search effect is stable within each person. This seems to be the case since individuals' search across eight cue-patterns is reliably affected by the attractiveness of choice-options (Cronbach's $\alpha = .80$; eight items; 144 participants). To further investigate the stability of attraction search over time, we analyzed how consistently participants looked up information from the more (=1) or less (=0) attractive option over eight repetitions of sixteen cue-patterns. Overall, individuals show very stable search strategies in that for 32% of the cases (i.e., 16 cue-patterns $\times$ 144 persons) behavior was perfectly consistent (i.e. variance of zero). That is, participants inspect consistently over eight repetitions cue-values from the same option.

To counter a possible objection that repeating the patterns artificially inflated the effect, we also calculated the attraction search score for the first occurrence of each cue-pattern per person only. The magnitude of the effect does not differ from the attraction search effect calculated for all repetitions: The average difference between scores for each cue-pattern averaged over all participants per condition and for each participant averaged over all cue-patterns is low ($\text{diff}_{\text{pattern}} = 0.001$, $t(23) = 0.048$, $p = .96$; $\text{diff}_{\text{participant}} = -0.01$, $t(143) = -0.53$, $p = .59$). Correlations between scores are also high for cue-patterns ($r = .89$, $p < .001$; Figure 4, left display) and participants ($r = .63$, $p < .001$; right display). Hence, the size of the attraction search effect is stable within persons and independent of the number of repetitions of cue-patterns.

Quantitative Predictions of Choice and Search with a Fully Specified iCodes Model

In this section, we introduce a fully specified iCodes model and test how accurately the model can predict choice of options in comparison to the noncompensatory strategy TTB and the compensatory strategy WADD. We further analyze if the new model can predict which concealed cue-value participants first opened in both studies.

Formalization of iCodes

The decision situation is encoded in a symbolic network (Figure 5) with nodes representing elements of the decision situation (cues and options) and links between nodes representing constraints between elements. The new model iCodes retains all core aspects of the former version PCS-DM (Glöckner et al., 2014; Glöckner & Betsch, 2008a; Glöckner & Betsch, 2012) including a layer of option nodes (opt_1 and opt_2), a layer of cue nodes (cue_1, cue_2, cue_3, cue_4) and a general validity node. Note that an extension of the model to more options and more or less cues is, however, of course straightforward. The network structure depicted illustrates the representation of the decision situation of cue-pattern 2 version 1, in which the first most valid cue favors option 1 and all other cues are concealed (Table 1).

The original model is extended in two important respects. First, an additional layer of cue-value nodes is included ($cue_{1,1}$, $cue_{2,1}$, ..., $cue_{4,2}$) that allows the model to take into account single cue-values by individual nodes that are connected to a shared cue-node. Hence, each prediction of a cue for an option is now represented by a separate node (i.e., cue_1 makes a positive prediction for option 1, represented by node $cue_{1,1}$ which is connected by a facilitating link to option 1). This new layer contains nodes that represent cue-values that are already available (unshaded rectangles) and nodes that represent cue-values that have not been inspected (shaded rectangles) by the decision maker yet. Thus, single nodes for cue-values (e.g., $cue_{1,1}$ and $cue_{1,2}$) represent the pieces of open or concealed information in the decision situation while nodes for cues (i.e., cue_1) model the interdependence of cue-values that stem from the same cue. Second, activations of cues and the activation of options impact the activation of concealed cue-values. Thus, activations of cue-values is driven by cue-validity and the current attractiveness of options. In the model, concealed cue-values do not impact the decision situation of already available cues (i.e., $cue_{1,1}$ in the example) and thus links to concealed cue-values are uni-directional only (i.e., concealed cue-values form a subnet).

The impact of open positive cue-values on options and from options to cue-values is encoded as bi-directional positive links with a weight of .01 (e.g., link between cue-value $\mathrm{cue}_{1,1}$ and first option opt_1) whereas open negative cue-values are encoded as bi-directional negative links (i.e., $-.01$). The impact of options on concealed cue-values (i.e., modeling of the attraction search effect) is encoded as positive links of size .01 (e.g., link between option opt_1 and concealed cue-value $cue_{2,1}$). The impact of cues on cue-values is encoded as positive links of size .1. Thus, the impact of cue-validities versus attractiveness of options on search was set to a ratio of 10 to 1 in the simulations.[5]

Like in the original PCS-DM model, cue-validities $v = \{.90, .80, .70, .60\}$ are transformed into net weights for validities between the validity-node and cues according to the function $W_{v(i)} = (v_i - .5)^P$ (Glöckner et al., 2014). P is a free parameter fitted individually to participants. A high P results in high ratios between cues which leads to non-compensatory decision making. A low P results in compensatory decision making. Thus P represents the participant's sensitivity to differences in validities.

The decision-making process is simulated as weighted activation flowing iteratively between nodes. At each iteration $i = \{1, 2, \ldots, I\}$, constant activation flows from the validity node into the network at $a_{\text{validity}} = 1$. Each node receives input from all connected nodes according to a simple linear weighted additive rule $input_i = \sum w \times a$. Input is transformed into activation a according to a sigmoid function with $a_{t+1} = (1 - decay) \times a_t + input \times (1 - a_t)$ if $input_i \geq 0$ or $a_{t+1} = (1 - decay) \times a_t + input \times (a_t + 1)$ if $input_i < 0$. In accordance with prior studies, the parameter $decay$ was set to .1. The overall coherence is defined as the negative Hopfield energy over all q nodes with $-energy = -\sum_{q=1}^{Q} \sum_{r=1, r\neq q}^{R} w_{q,r} \times a_q \times a_r$ (Glöckner & Betsch, 2008a; Read, Vanman, & Miller, 1997). Iterative updating is stopped when the change in negative energy per iteration does not supersede an arbitrary low threshold at 10^{-6} for ten iterations.

For transforming node-activations into choice probabilities, we used the node-activations of the option a_p^O preferred by participants and options a_{np}^O not preferred by participants and calculated choice-probabilities for trials $t = \{1, \ldots, T\}$ according to a softmax choice rule with $p(O_p|P, \lambda_c, t) = e^{\lambda_c \times a_{p(t)}^O} / \sum_{k=\{p(t), np(t)\}} e^{\lambda_c \times a_k^O}$ (cf. Glöckner et al., 2014, p. 662, equation B2). The individually fitted parameter λ_c determines the steepness of the choice-function: A participant with a high versus low λ_c is more or less sensitive to the differences in activations of options. For modeling search, activations for concealed cue-values Z are similarly transformed into probabilities of inspecting a concealed cue-value i of option j according to the same softmax choice rule with $p(cue_{i,j}|P, \lambda_s, t) = e^{\lambda_s \times a_{i,j}(t)} / \sum_{z=1}^{Z} e^{\lambda_s \times a_z(t)}$. As before, the individually fitted parameter λ_s

determines the steepness of the choice-function. Thus, in total the model consists of one individual parameter P for modeling sensitivity to differences in validities and two individual parameters λ_c and λ_s for transforming activations of options or concealed cue-values into choice probabilities and probabilities for inspecting a cue value, respectively.

Predicting Choices

Model Fitting. To test whether iCodes can describe participants' choices of options better than the strategies TTB and WADD and to test how search relates to decision making, we fitted all three models to participants' choices taking cue-patterns into account after participants had searched for information.

For iCodes, we used a maximum-likelihood method to identify individual level parameters P and λ_c (both in the range $[0, 5]$) that maximize the sum of the log-likelihoods of the choices of all trials T according to $\sum_{t=1}^{T} ln(p[O_p|P, \lambda_c, t])$.

For the single strategies WADD and TTB, participants are assumed to apply the strategy with a trembling-hand application error ϵ in the range of $[0, .5]$ (i.e., from perfect strategy application to chance-application). Based on the number of strategy consistent choices c, strategy inconsistent choices nc and the number of predicted guesses g (i.e., probability of .5 for choices between two options), the maximum sum of log-likelihoods of participant's choices is calculated by finding the parameter ϵ that maximizes $ln[(1-\epsilon)^c \times \epsilon^{nc} \times .5^g]$. From the maximum sum of log-likelihoods, the Bayesian information criterion BIC is calculated for each model $m \in \{\text{iCodes}, \text{WADD}, \text{TTB}\}$ and all trials T according to $-2 \times ln(L_m) + ln(T) \times p_m$ (Glöckner et al., 2014, equation B10). The number of parameters p_m is set to 2 for iCodes (i.e., P and λ_c) and 1 for strategies (i.e., ϵ) to adjust fit for model-flexibility.

The estimated best-fitting parameters for participants (Figure 6, two upper left displays) show a similar mean of 1.66 for the iCodes-parameter P and a slightly lower mean of 2.34 for sensitivity λ_c in comparison to previous studies from our lab (cf., Glöckner et al., 2014, p. 663, Table B 1). Strategy application errors ϵ are considerably higher with means .15 and .18 for TTB and WADD than in prior studies (cf., Glöckner et al., 2014, p. 663, Table B 1; ϵ between .03 and .09).

Adherence with Choice Predictions. Considering all participants in both studies, iCodes can account for 89% of all decisions correctly (Figure 7). The proportion of choices in line with the theory predictions was considerably and significantly lower for the alternative strategies with WADD reaching 84% ($t(143)$ = -12.80, $p < .001$) and TTB 77% ($t(143)$ = -22.77, $p < .001$). iCodes could account better for the data in the condition with unrestricted search without information costs (Study 2) than in the condition with information costs in the same study ($t(109) = 2.99$, $p < .01$) and in Study 1 with restricted search ($t(86) = 5.87$, $p < .001$). The overall Bayesian Information Criterion for all $I = 144$ participants in Study 1 and Study 2 (i.e., $-2 \times \sum_{i=1}^{I=144} ln(L_{m(i)}) + 144 \times ln(144 \times T) \times p_m$) indicates strong support for iCodes in comparison to WADD and TTB (both Bayes factors for iCodes at least $e^{1250} > 10^{308}$). Classifying each participant according to individual BICs results in 79.8% of participants best described by iCodes, 14.6% best described by WADD, and 5.6% by TTB.

Cross-prediction. To test how well models are able to predict choices, we did a cross-prediction analysis where we fitted individual model-parameters to odd numbered cue-patterns (i.e., pattern 1 versions 1 and 2, pattern 3 versions 1 and 2, etc.) and predicted choices with fixed parameters for even numbered cue-patterns (i.e., pattern 2 versions 1 and 2, pattern 4 versions 1 and 2, etc.). Results are overall similar to fitting choices: iCodes makes 88% correct predictions for choices whereas WADD and TTB make 84% and 77% correct predictions, respectively (both paired ts(143) > 7.38, $p < .001$). The percentage of participants best described by iCodes based on the individual sum of maximum log-likelihood scores is slightly lower in cross-prediction than in fitting: iCodes predicts 59.0% of participants best, whereas WADD and TTB account best for 27.8% and 13.2% of participants, respectively. Overall, iCodes is at least $e^{320} > 10^{138}$ more likely the data-generating model than TTB or WADD.

Impact of Search on Choices. Although we cannot measure the impact of searching cues on the final choice directly since we did not assess participants' preference for choices prior to cue-search, we can proxy the impact of search on choice indirectly. If additional search does not have any impact on choice, iCodes-predictions based on the initially concealed cue-patterns should be equally accurate in accounting for choices as iCodes-predictions based on observed cue-patterns after search. To allow such a comparison, we fitted iCodes to choices for all participants based on concealed cue-patterns: iCodes fitted to initial available cue-values only accounts for 79.8% of choices, which is significantly lower than 89.1% overlap for iCodes-predictions based on available cue-values after search ($t(143)$ = -19.52, $p < .001$). When considering only the trials in which the two versions of iCodes make distinct predictions (approx. 20% of the trials), the advantage of iCodes taking into account all available pieces of information after search becomes considerably more pronounced: 75% of choices in these trials are in line with iCodes.

Finally, the data indicated that participants who can be best described by iCodes based on choices for options show a tendency, although not statistically significant ($t(142) = 1.89$, $p = .06$), for a higher attraction-search effect (.26 versus .18 overall attraction search score) than participants classified as users of the strategies WADD or TTB. In summary, we find that iCodes can account for participants' choices best and we show that choices can be related to cue-search in a meaningful way providing some converging evidence for the choice-based model-classification.

Predicting Search of Cue-values

Model Fitting. To investigate how well iCodes can account for search, we correlated the mean predicted probability of inspecting a concealed cue-value with the observed proportion of participants indeed inspecting this cue-value. For doing so, we ran simulations of iCodes with individual parameters for participants and all cue-patterns as exemplified in Figure 5. For each participant, we re-used sensitivity parameter P from fitting choices and fitted λ_s for transforming activations of concealed cue-values into probabilities for inspecting cue-values in the range [0, 1000] by maximizing the sum of log-likelihoods of concealed cue-values inspected (see Figure 6 upper right panel for distribution of λ_s).[6] From these simulations, we derived for each participant and concealed cue-value the probability of opening the cue-value according to iCodes. We then averaged predicted probabilities over participants per concealed cue-value and correlated those with the observed proportions of search.

Adherence with Search Predictions. For the 55 concealed cue-values included in all studies, the predicted probabilities and observed proportions of inspecting them correlate almost perfectly with $r = .95$ ($p < .001$) (Figure 8, left display). Since proportions of the same trial are dependent (i.e., predicted probabilities and observed proportions of opening cue-values add up to 1 in each trial), we also compared the predicted probabilities and the observed proportions for the most likely cue-value opened first for each cue-pattern according to the model (black dots in Figure 8, left display). Predicted probabilities and observed proportions correlate with $r_{\text{black}} = .81$ ($p < .001$). We also assessed how often participants chose the cue-value with the highest probability predicted by the model (i.e., overlap between choice and prediction of cue-value opened first). Overall, predictions by the model and participants' choices of first cue-value opened overlap in 67% of all trials. As a lower benchmark, note that random prediction (i.e., choosing a cue-value to be opened next randomly) would lead to 37% correct predictions on average only.

One notable difference to fixed search rules is the proposed attraction search effect. In iCodes, the effect results from the connections between option-nodes and cue-values. To test whether this aspect of the model adds to its accuracy in predicting search, we re-ran all simulations using a reduced version of iCodes with all connections between options and concealed cue-values removed (i.e., no direct impact of options on concealed cue-values).[7] The correlation between predicted probabilities and observed mean rates of the first cue-value opened is lower for the reduced model with $r = .87$ and $r_{\text{black}} = .51$ (both ps $< .01$).[8]

We also assessed the overall model fit as a comprehensive measure for comparison by calculating the log-likelihoods from the predicted search-probabilities of cue-values participants actually uncovered first for both versions of the iCodes model. According to the maximum log-likelihood values of the models, the overall observed data is $e^{186} > 10^{80}$ more likely under iCodes than under the reduced iCodes model thus supporting the use of coherence-based principles in modeling search. Comparing model-fits for single participants, 55% of all participants can be accounted better by iCodes than the reduced iCodes model. Percentage of participants best described by iCodes by condition matches the strength of the attraction search score reported before: In the first study with restricted information search, 85% of participants can be best described by iCodes. In the second study with unrestricted search with costs, the percentage decreases to 54%. In the condition with unrestricted search without information costs, the percentage further decreases to 38%. Thus, for unrestrictive search without search costs, the majority of participants' search can be better described without assuming coherence-effects in search.

Cross-prediction. To test how accurately models predict search, we did a cross-prediction analysis where we again fitted the free model-parameter λ_s to odd numbered cue-patterns (i.e., pattern 1 versions 1 and 2, pattern 3 versions 1 and 2, etc.) and predicted search with λ_s fixed for even numbered cue-patterns (i.e., pattern 2 versions 1 and 2, pattern 4 versions 1 and 2, etc.). Overall, results replicate when applying cross-prediction and are therefore only briefly summarized: iCodes is $e^{590} > 10^{256}$ more likely than the reduced iCodes-model and 63% of all participants can be best described by iCodes (separated for conditions: 91%, 59%, 49% of participants when search is restricted, unrestricted with costs, or unrestricted without costs, respectively). Overall correlations between predicted mean probabilities of cue values searched and observed proportions of cue-values for cross-prediction trials with fixed parameter λ_s differ by a value less or equal to .01 in comparison to correlations reported above. Correlations between predicted probabilities and observed proportions for cue-values per cue-pattern that are most likely opened next according to the model are lower with $r_{\text{black}} = .77$ for iCodes and $r_{\text{black}} = .33$ for iCodes with no impact of options on concealed cue-values (cf. Figure 8).

Joint Analyses of Properties of Attraction Search

Generalizability of the Attraction-search Effect beyond the First Cue-value Opened

The aforementioned analyses examined the predicted attraction search effect relative to the experimental design comparing different cue information patterns. In the upcoming section, we test whether the attraction search effect also shows in absolute terms (and not only when comparing two versions of cue-patterns) and whether the effect generalizes to search beyond the first cue-value opened. For each acquisition of a cue-value, we simulated iCodes's search prediction with sensitivity parameter P fitted from choices for each participant. We then assessed whether the cue-value of the more attractive option according to iCodes (i.e., a cue-value of the option with the highest activation) was also opened by the participant. The mean overlap of trials in which a participant behaved according to the model, $p(\text{agree})$, was subtracted from the complementary mean number of trials in which a participant behaved in disagreement to the model (i.e., searching a cue-value of the less attractive option), $p(\text{disagree}) = 1 - p(\text{agree})$. Hence, we can define an absolute attraction search score ASSc $= p(\text{agree}) - p(\text{disagree})$ with the same properties as the score above: The minimum is -1, the maximum is +1. A value of 1 signifies a perfect attraction search effect. The index is zero if there is no correlation between search direction and the content of revealed information.[9]

Figure 9 shows the mean values of the absolute ASSc for the first to sixth cue-value opened together with the 95% confidence intervals and Cohen's d effect size measures. The attraction search effect as predicted by iCodes was observed for the first, second, third and fifth cue-value opened with all Cohen's $d > 0.28$ and all ps $< .05$ as evaluated by t-tests. Overall, results suggest that the attraction search effect also shows in absolute terms and generalizes to up to at least three cues searched.

Automaticity of the Attraction Search Process

The Parallel Constraint Satisfaction Model of Decision Making has been proposed as a dual process model for intuitive (i.e., effortless and automatic) and deliberate decision making (Glöckner & Betsch, 2008a; see also Glöckner & Witteman, 2010). The core process of cue integration is assumed to be based on intuitive-automatic processing. This assumption has been supported by studies showing that participants are able to integrate multiple pieces of information in a compensatory fashion rapidly and in much less time than would be required for deliberate calculations (e.g., Glöckner & Betsch, 2008b, 2012). To explore whether information search and in particular the attraction search effect rests mainly on deliberate or intuitive processes, we analyzed individuals' average time for deciding which information to search first (search-decision time) and its correlation with interindividual differences in the magnitude of the attraction search effects. If attraction search would result mainly from slow and time-consuming deliberation, a positive correlation would be expected and slower participants should show larger attraction search effects. If (more) careful deliberation concerning search reduces the effect, a negative correlation would be expected.

Search-decision time was measured as the time participants took to open the first concealed cue-value for the first occurrence of each of the 16 cue-patterns, to rule out learning effects due to pattern repetition. The overall median search-decision time is 3134 milliseconds, which indicates that some deliberation might be involved, considering that the overall decision time including search and integration in previous studies was in a similar range (cf. Glöckner & Betsch, 2008b). In a similar vein, there is an overall positive correlation between individuals' median search time and their attraction search score, Pearson's $r = .18$ ($t(142) = 2.13$, $p < .05$).[10] This correlation is, however, mainly driven by differences between studies and conditions, and disappears when controlling for conditions (partial correlation $r = .08$, $p = .36$). Specifically, median search-decision times were longer for restricted search (Md = 4506ms) than for unrestricted search with costs (Md = 3153ms) and unrestricted search without costs (Md= 2140ms) and corresponding differences were found for effect sizes of the attraction search score (see Figure 3). Hence, scarcity and costs for information search seem to increase the degree of deliberation about search and this is associated with an increasing attraction search score. Overall, this indicates that attraction search effects are driven by more time-consuming top-down activation processes that might involve increased deliberation. If this hint to rather deliberative processes extends to information integration in tasks involving search is an interesting question for further research.

Study 3: Search Bias and Accuracy

Search for cue-values of the more attractive option may lead to better or worse decisions depending on the decision environment. For the cue-patterns used in studies 1 and 2, search according to the attraction search effect did not relate to choice accuracy (see Appendix B for details). In the third study, we tested cue-patterns that are—according to iCodes—predicted to either mislead or support participants showing the attraction effect in finding the better option. If choice depends on search, participants' tendency to search for cue-values of the more attractive option is predicted to correlate negatively or positively with accuracy depending on the specific pattern of cue values that are hidden and yet to be uncovered.

Methods

We replicated the same methodology from Study 2 for the condition with unrestricted search with costs. 44 participants (26 female, mean age = 25, $SD = 6$, mainly students from the University of Bonn) were recruited and received a fixed amount of

4€ (≈ 4.8 USD) and 2.5 Cents for each correct decision using the same 128 trials as in studies 1 and 2 (Table 1). In each trial, participants had to open one additional cue-value for free and were allowed to open as many additional cue-values as desired with a cost of 0.25 Cents for each uncovered cue-value, replicating the condition unrestricted search with costs from Study 2. In difference to prior studies, we included four repetitions of four new cue-patterns (i.e., 16 additional trials in total). For two beneficial cue-patterns, search for cue-values of the more attractive option is predicted to result in more correct decisions (Table 3, top row). For the other two detrimental cue-patterns, search for cue-values of the more attractive option is predicted to result in fewer correct decisions (Table 3, bottom row). For example, for the detrimental cue-pattern 1, a positive cue-value speaks for option B with all other cue-values concealed before search. Following the attraction search effect would lead to search for cue 2 of option B. Opening this positive cue-value renders option B even more positive. Doing this, however, is detrimental because option A dominates option B when considering all cues. Not following the attractions search effect would lead to search of cue 1 of option A showing indifference of cue 1 between options. Thus, in case participants do not search cue-values of the more attractive option, they are more likely to make a correct decision for option A.

Results

Concerning the attraction search effect, results are very similar to the condition with unrestricted search with costs in Study 2. The overall attraction search score based on 128 trials is of almost identical size and significantly different from zero (mean of ASSc = .34; $t(43) = 11.98$, $p < .001$). Attraction search scores for single cue-patterns are all significantly different from zero ($t(43) > 2.80$). The size of the attraction search scores for single cue-patterns is almost perfectly correlated between studies ($r = .99$, $t(6) = 25.10$, $p < .001$) indicating a high reliability of the findings.

For the beneficial cue-patterns (Table 3, top row), almost all participants chose the better option after search (mean performance $M = .97, SD = .05$). For the detrimental cue-patterns (Table 3, bottom row), mean performance was low with $M = .30$ ($SD = .32$) for cue-pattern 1 and $M = .18$ ($SD = .22$) for cue-pattern 2. Mean performances for beneficial and for detrimental cue-patterns are significantly different from each other ($t(43) = 26.92$, $p < .001$) and different from chance performance of .50 (detrimental: $t(43) = -10.32$, $p < .001$; beneficial: $t(43) = 61.70$, $p < .001$).

We calculated individual attraction search scores based on 128 trials as a measure of participants' individual tendency to search cue-values of the more attractive option to predict average performance for the sixteen additional trials. As predicted, we found a negative correlation between the individual attraction search score and average performance in the detrimental cue-patterns ($r = -.44$, $t(42) = -3.14$, $p < .01$). That is, participants showing the attraction search effect in the 128 trials more strongly are also more likely to choose the inferior option for the detrimental cue-patterns. Almost all participants answered the beneficial cue-patterns correctly which probably generated a ceiling effect. For the beneficial cue-patterns, we therefore find a positive although statistically insignificant correlation between the individual attraction search score and average performance ($r = .15$, $t(42) = 0.99$, $p = .33$).

Discussion

Overall, results of Study 3 show that search for cue-values of the more attractive option can lead to lower or higher accuracy in choices dependent on the type of cue-patterns available in the environment. Thus, bias in search can be linked to accuracy in choices in a meaningful way as predicted by iCodes.

Re-analyses of Published Data Sets

The unique iCodes prediction of the attraction search effect was confirmed in three experimental studies, and it turned out surprisingly large. However, all studies reported so far were designed in a restrictive fashion to demonstrate this effect, and hence, one might suspect that its size might be exaggerated (Wells & Windschitl, 1999; Westfall et al., 2015). If the tendency to prefer information search about the currently most attractive option is a general feature of information search as predicted by iCodes, it should also show in typical MouseLab studies without these artificial restrictions. Therefore, we re-analyzed five published studies by one of the authors (AB) that had been conducted for different purposes. The studies are described in Bröder and Schiffer (2003, here: Study 1), Bröder (2003, Exp. 2, here: Study 2), Bröder (2005, Exp. 4a, here: Study 3), and Bröder and Schiffer (2006, both experiments, here: Studies 4 and 5). The sample sizes in the five studies were 60, 120, 60, 120, and 120, respectively, resulting in 480 participants altogether.

Methods

All experiments also employed hypothetical stock market games with three options described by four cues. For half of the participants in Study 5, the stock market game changed to a structurally equivalent real estate investment game in the second half of the trials. Cue-values were concealed, and participants had the opportunity to learn the cue validities through feedback. In each of 80 trials (160 trials in Studies 4 and 5), participants saw an empty cue-by-option matrix, and they could acquire new information by clicking on the respective fields. All experiments used binary cues like the experiments described above. We refer the reader to the original sources for details of the experiments that varied payoff structures and other independent variables that are not of interest in the current context.

Second Information Purchase

The simplest analysis in order to test for the existence of an attraction search effect is to examine the second information acquisition after one of the 12 information boxes had been opened. If the first cue revealed is positive, then the respective option would become the most attractive one relative to the other two. If the cue-value was negative, however, then the respective option would be the currently least attractive option. Hence, according to the attraction search effect, the probability of switching search to another option when the revealed cue-value is negative $p(\text{switch option}|\text{negative value})$ should exceed the tendency $p(\text{switch option}|\text{positive value})$ to switch the option if the revealed information is positive. Hence, we can define an attraction search score as $p(\text{switch option}|\text{negative value}) - p(\text{switch option}|\text{positive value})$ which is identical to the absolute attraction search score ASSc introduced above. This index is independent of any general tendency to search more option-wise or more cue-wise: Any general tendency to show a certain search direction would not be influenced by the content of the information opened in the first search step. This index was computed for each participant across all trials of the experiment. Figure 10 shows the mean values of the ASSc for the five reanalyzed studies together with the 95% confidence intervals and Cohen's d effect size measures. The attraction search effect predicted by iCodes was observed in all experiments with all Cohen's ds > 1.00 and all ps $< .001$ as evaluated by one-sample t-tests.

Information Purchases Beyond the Second Purchase

Analyzing the second purchase after one piece of information was revealed gives the most unequivocal evidence of an attraction search effect as demonstrated above. However, it is also of interest if the attraction search effect can be found in later purchases. Since the re-analyzed studies had three options, a different scoring had to be used in order to deal with the fact that options' attractiveness values may be tied occasionally. For example, after opening the most valid cue for options A and B, they might both have positive cue-values. Hence, they have the same current attractiveness which is higher than option C's. In these cases, continuing search on either option A or B was scored "+0.5" whereas continuing with option C was scored "-1". If both cue values were negative, the scoring would have been "-0.5", "-0.5", and "+1" for options A, B, and C, respectively.

Attractiveness of all options in each trial was approximated by a strictly compensatory linear rule integrating the hitherto revealed cue-values. Note that this modified index has similar properties to the indices above: Its expected value is zero if there is no dependency of search on the attractiveness of options, and it is positive (negative) if the choice conforms to (contradicts) the attraction search effect prediction. Note, however, that it may not reach the "+/- 1" boundaries. Also, the later the purchasing step analyzed, the smaller is the number of trials on which its calculation is based since in many trials, participants stopped search quite early. Hence, we only analyzed the 3rd up to the 6th information purchase in each trial. The score was computed for each participant in each trial, and Figure 11 reports the overall means of these individual means together with 95% confidence intervals and effect sizes.

Figure 11 indicates that the prediction of an attraction search effect was corroborated for 17 of the 20 analyses. In the three remaining cases (all in Studies 1 and 2), the score did not significantly deviate from zero. Note, however, that the modified score for later information purchases beyond the second purchase need not provide unequivocal support for iCodes since the predictions are not completely unique for the model. The effect for the fourth information purchase, for example, would also be predicted by an elimination by aspects heuristic (EBA, Tversky, 1972) when people exclude the least attractive option from consideration after they have inspected the most valid cue for all options.

Discussion

Whereas the experiments reported in the first part of this article were explicitly intended to test for the new prediction of the extended model, the re-analyzed data sets were collected before iCodes was even formulated. They comprise usual MouseLab studies on information search that were originally analyzed with the standard parameters characterizing search introduced by Payne et al. (1988). However, this general characterization of the search process obviously obscured the powerful attraction search effect that could be revealed now by a second look at the same data. The second information purchase after opening one cue-value provides unequivocal evidence: if the cue-value opened is negative, participants are more likely to switch to another option than if it is positive. This is clearly in line with the predicted attraction search effect, but it cannot be explained by fixed search strategies as assumed by heuristics. The prediction of an attraction search effect was also confirmed by analyzing the purchases beyond the second acquisition, but note that this evidence is weaker since the predictions for positive scores may not be unique to iCodes.

These overall large effects in the data had been overlooked by the former analyses that aimed at describing general characteristics of the search process, such as Payne's (1976) strategy index that quantifies whether search is more cue-wise or option-wise without considering the content of the revealed information. Given these surprising confirmations of the attraction search effect in our re-analyses, we encourage researches to scrutinize their old MouseLab studies to test for a potential attraction search effect in their data.

Overall Discussion

In this article, we propose a model of integrated coherence-based decision and search (iCodes) as a comprehensive process model for decision making. Furthermore, we tested the attraction search effect as a new qualitative prediction derived from the model as well as the model's overall capability to predict choices and search in decision making.

We showed that participants tend to increasingly search for cue-values of attractive as compared to less attractive options in three studies. The effect was present when search was restricted (Study 1), unrestricted with costs (Study 2), or unrestricted without costs (Study 2). Unrestricted search with costs and restricted search doubled the size of the effect relative to unrestricted search without costs. We showed (Study 3) that biased search can result in higher or lower choice accuracy depending on the cue-patterns in the decision environment.

Participants consistently (over cue-patterns) differed in the extent that they were affected by the initial attraction for options suggesting that size of the attraction search effect depends on individual properties of participants. The attraction search effect could be demonstrated for the first, second and third cue-value searched. iCodes, a fully specified coherence-based network-model of decision making and search, could explain the data very well and better than a network model that did not involve interactive activation of concealed cue-values and options. Extensive reanalyses of data from five published studies could also demonstrate the attraction search effect showing that the effect is not restricted to the cue-patterns and settings used in the three studies of the article.

Attraction Search Effect in Prior Studies

One may wonder why this strong attraction search effect was not observed in prior studies on cue-search in probabilistic decision making. There are at least two reasons: First, since theories did not predict an effect of already revealed cue values on search direction, standard analyses did not include respective conditional analyses and the effect was considered to be part of a largely noisy information search process. Second, some research paradigms precluded the effect by artificially restricting information search. A closer inspection of the literature on search for cues in probabilistic decision making reveals that our task differed in one crucial aspect from the task used in many key-studies on cue-search (Bröder, 2000; Dieckmann & Todd, 2012; Lee et al., 2014; Mata, von Helversen, & Rieskamp, 2010; Newell & Lee, 2011; Newell et al., 2004; Newell & Shanks, 2003; Newell et al., 2003; Rakow et al., 2005; Rieskamp, 2006; Rieskamp & Otto, 2006; Ravenzwaaij et al., 2014; Söllner & Bröder, 2016): The task used in those former studies allowed participants to uncover all values of a cue at once and not single cue-values for options separately.[11] This artificial restriction of information-search in the lab may not be representative of the real-world (Brunswik, 1955): By gathering a cue-value about one decision-option, one does not automatically receive all cue-values from this cue for all other options. More importantly for our research question, this restriction leads to a non-diagnostic task for the attraction search effect (Jekel, Fiedler, & Glöckner, 2011). This is problematic insofar that these studies thereby lent unjustified support for theories of search based on properties of cues such as validities only.

Alternative Theoretical Accounts

At first glance, the newly predicted attraction search effect shares similarities with both confirmatory search as well as the win stay/lose shift heuristic. However, the phenomenon is conceptually different, and these two accounts cannot readily explain our experimental results.

Confirmatory Search. The attraction search effect is distinct from confirmatory search (also known as selective exposure), which describes people's tendency to "avoid information likely to challenge them and seeking information likely to support them" (Hart et al., 2009, p. 556). While confirmatory search effects require a priori information of whether the cue-value is in line with the preferred hypothesis or require a type of search that makes confirmatory evidence more likely, the attraction search effect follows merely from interactive activation of available evidence and a piece of concealed information belonging to an option. Since we did not provide a hint on the valence of the concealed information in the studies reported in this paper, confirmatory search was by design precluded.

One might, however, argue that participants infer the valence of concealed cue-values from the values of available cues. For example, if the two most valid cues are positive for option A and all other cue-values are concealed (i.e., version 1 of cue-pattern 5; Table 1), the third most valid cue is also likely to speak for option A since all cues probabilistically reveal the same true state.[12] Thus, confirmatory search and the attraction search effect do not differ in their prediction of search for cue-values of option A for this trial.

Note, however, that even with this additional assumption confirmatory search and the attraction search effect differ in predictions for some of the cue-patterns included in our studies. If the initial choice tendency (or hypothesis) favors an option, confirmatory search predicts search of additional positive information for this option. If, instead, the initial hypothesis disfavors an option, confirmatory search—in a strict interpretation—predicts search of additional negative information for this option. Thus, confirmatory search for the task used in our study predicts that the valence of the information of an option searched matches the initial valence of the option. In contrast, iCodes predicts that search is always directed towards the favored option. Thus, for example, confirmatory search also predicts inspection of a further cue-value of option A in case the first two cue-values are of negative valence for option A as it is for example the case in version 2 of pattern 5 (Table 1). Our data show that this prediction does not hold empirically, since individuals tend to look up information for the other option. To account for this finding, it is possible to relax the predictions of confirmatory search further by also allowing the possibility for looking up information from the other option that might support the hypothesis that the currently considered option is inferior. This is problematic since predictions of confirmatory search then become rather unspecific: Both search for option A and option B are in line with the theory. Hence, nothing is forbidden, the theory loses its ability to predict behavior and its empirical content by becoming overly flexible (Roberts & Pashler, 2000; Glöckner & Betsch, 2011). Therefore, iCodes has the comparative advantage to provide a fully specified alternative model for the same behavior that makes more precise predictions.

One potential further alternative explanation for the attraction search effect related to confirmatory search is that people might use the information that cue-values more often are different between both options than not (i.e., the discrimination rate of cues, see also footnote 3) to infer the value of a cue without opening it (Jekel et al., 2014). This would mean that, for example, after seeing a negative cue value for option A, participants would not look up the value of the same cue for option B but infer it and look up the information of other less valid cues instead. If this tendency for inferring cues would be related to the value (positive / negative) of a cue due to confirmatory search, this could potentially lead to observing behavior in line with the attraction search effect as well. Inspection of the data, however, speaks against the hypothesis that participants infer cues based on such a strategy (see Tables A1 to A3 in Appendix A). For cue-pattern 2, for example, for the majority of trials (i.e., 60%, 64%, and 80% for the three conditions) participants search the first cue-value of option B when the initial evidence of the first cue for option A is negative instead of inferring it. Switching to one of the other less valid cues is only rarely selected (aggregated probability for searching cues 2 to 4 for option B: 12%, 12%, 5%). Similar results are observed for other cue patterns (e.g., cue-pattern 5).

Win-Stay/Lose-shift Heuristic. The attraction search effect has conceptual similarities with the win-stay/lose-shift heuristic in reinforcement learning (Nowak & Sigmund, 1993; Worthy & Maddox, 2014). The heuristic describes participants' tendency to repeat an action if rewarded and to switch to an alternative action if punished. Participants in our study did not receive feedback on their accuracy of decisions for options and therefore also did not receive feedback on the efficiency of their search. Therefore, the win-stay/lose-shift heuristic does not apply to the search task of the studies. Nonetheless, participants might have experienced uncovering a positive cue-value as "reward" and uncovering a negative cue-value as "punishment". If this was true, uncovering a positive cue-value might have pushed participants continuing search for additional information of the same option whereas uncovering a negative cue-value might have pushed participants towards shifting search to the information of the alternative option. Note, however, that we presented partially uncovered cue-patterns at the beginning of each trial (Table 1) and participants tended to search cue-values of the more attractive option in accordance to a compensatory integration of available cue-values such as described by iCodes. Thus, since opening the first cue-value does not involve prior experience of search in the trial, the win-stay/lose-shift heuristic cannot explain the strong effect of attraction on search for the first cue-value opened (Figure 3) but might add to the observed effect for search beyond the first cue-value opened.

Stable Individual Differences of the Attraction Search Effect

Since participants differed consistently over cue-patterns in the size of the attraction search effect, an individual parameter modeling the relative impact of the initial preference of an option and other influences of the decision situation (i.e., cue-validity or cue-salience) might add to the modeling of information search in iCodes. Additionally, modeling stopping of cue-search (Lee et al., 2014) is still missing in the current implementation of the model. Recent evidence shows that stopping can be best modelled with a flexible evidence-threshold that needs to be surpassed by evidence from available cues before search is terminated (Söllner & Bröder, 2016; Hausmann & Läge, 2008; Lee et al., 2014). In a similar vein, one potential implementation of a flexible threshold in iCodes is to let activation of nodes representing concealed cue-values surpass a threshold before being considered.

Situational and Individual Moderators and Generalizations of the Attraction Search Effect

In the current research we show that the magnitude of the attraction search effect is moderated by situational factors (e.g., information costs) and that it is likely that it is moderated by individual factors as well due to the observed reliable interindividual differences. Promising factors for future investigations might be whether feedback on the accuracy of decisions is provided (cf. Rieskamp, 2006; Rieskamp & Otto, 2006) that might be used to correct search as well, or differences in cognitive development between age groups (cf. Betsch, Lang, Lehmann, & Axmann, 2014). Although we show that the effect is strong and can be found in various studies, it is an open question to what extent the effect also applies to more natural representations of information in a search task. It is furthermore an open question whether the attraction search effect also generalizes to search for cue-values inside the memory of the decision maker (Gigerenzer et al., 2012). The attraction search effect predicts that participants are more likely to recall cue-values for options that are favored when making decisions from memory. This hypothesis could be easily tested in a modified standard paradigm for decision making from memory (e.g., Bröder, Newell, & Platzer, 2010; Platzer & Bröder, 2012; Persson & Rieskamp, 2009).

Conclusion

With the attraction search effect we have demonstrated a new empirical phenomenon that is not predicted by current toolbox or evidence accumulation models, but follows naturally from an interactive coherence maximizing view. A precise computational instantiation of the latter approach has been provided with iCodes. We conjecture that the attraction search effect offers a wealth of possibilities for testing its individual and situational moderators that will eventually advance theoretical development targeting at an integrative theory of information search and information integration in decision making.

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Notes

1. Note that the exact sizes of boxes—i.e., the distribution of likelihoods for opening cue-values—is dependent on the relative impact of cue-validities and the attraction search effect that might differ individually.

2. Note, however, that a recently proposed alternative expected utility framework questions the validity of this normative evaluation (Crupi, Tentori, & Lombardi, 2009; but see response from Tweney, Doherty, & Kleiter, 2010).

3. Given the constraint for the entire set of trials that cue-validities—when recalculated for the naïve Bayesian incentive scheme—were above .5 and in the ordering told to participants. The Bayesian incentive scheme led to noncompensatory environment with validities of .86, .69. .59, and .56 for cue 1 to 4. Specifically, after chance correction (subtracting .5) the first cue was more valid than the sum of the remaining (chance corrected) cues. Note that differences in validities cannot influence choice behavior because participants did not receive feedback about their choice accuracy before the end of the study. The discrimination rate for cues 1 to 4 was .74, .50, .71, and .63, respectively.

4. That is, the two least valid cues cannot overrule the first or the second cue since $\log(.7/.3) + \log(.6/.4)$ is below $\log(.9/.1)$ or $\log(.8/.2)$.

5. We fixed this ratio for all participants to keep the model simple. The impact of the attraction of options on search varied consistently for cue-patterns between participants in the studies. Thus, the ratio could potentially be implemented as a free parameter in the model.

6. Note that specific values of parameters P and λ_c that were fitted using choices do not necessarily imply a specific search behavior; both parameters can be independent of search. To test this, we correlated individual model-parameters with the individual attraction search score and find correlations close to zero ($r = .05$ for P and $r = -.05$ for λ_c) that are statistically non-significant (all ps $> .55$).

7. Note that weights for links between options and concealed cue-nodes are fixed with a value of .01 in iCodes and thus a model with zero weights is not a submodel of iCodes. Thus, the model without connections from options to concealed cue-values does not necessarily lead to a worse account of the data.

8. The good comparative performance in predicting search of the reduced iCodes model without connections to options is mainly driven by "easy trials" in which the predicted probability for search is extreme. It drops to $r = .65$ ($r = .10$) for "harder trials" with predicted search probabilities in the range .2 to .8 (.3 to

.7), respectively. The predictive performance of the full model, in contrast, remains relatively constant also for harder trials ($r = .83$ and $r = .73$).

9. Note that the attraction search score for the second to sixth cue-value opened excludes participants from Study 1 who could only acquire one additional cue-value and cue-patterns 1, 3, 4, and 6 with only two concealed cue-values.

10. The pattern of results is stable when including search times of all 128 trials: differences in search time are statistically significant between Study 1 and Study 2 and statistically not significant between conditions in Study 2. We also find a statistically significant positive correlation between individual attraction search scores and search time of similar size ($r = .19$) when including all 128 trials in all studies. The only difference are much lower search times with an overall median search time of only 1354ms and a higher, albeit statistically not significant, partial correlation when controlling for conditions ($r = .15$, $p = .08$, two-sided test).

11. For exceptions see Bröder (2003, 2000); Bröder and Schiffer (2003, 2006); Glöckner and Betsch (2008b); Mata et al. (2007); Payne et al. (1988); Reisen, Hoffrage, and Mast (2008); Rieskamp and Hoffrage (1999). Note that studies using the Payne-Index of cue-search (Payne et al., 1988) or similar measures (Böckenholt & Hynan, 1994) need to allow for search of single cue-values.

12. To give an intuition for this fact: Assume all cues are perfectly reliable, that is, assume cues always give a correct prediction. Inspecting one cue is sufficient to infer the values of all other cues since cues are perfectly correlated in this case.

Table 1

Cue-patterns used in Studies 1, 2, and 3. ? = concealed information, x = unavailable information, + = positive advice, – = negative advice. For each trial, value/s in parenthesis/es represent the second versions of cue-patterns. The attraction search effect as predicted by iCodes states that participants search cue-values for option A for version 1 and more likely for option B in version 2 in parentheses.

Cues	Pattern 1		Pattern 2		Pattern 3		Pattern 4	
	A	B	A	B	A	B	A	B
Cue 1	+	−	+ (−)	?	x	−	?	− (+)
Cue 2	+ (x)	+	?	?	x	− (+)	−	?
Cue 3	?	+	?	?	?	+	+	−
Cue 4	−	?	?	?	−	?	−	+
	Pattern 5		Pattern 6		Pattern 7		Pattern 8	
	A	B	A	B	A	B	A	B
Cue 1	+ (−)	?	+ (−)	− (+)	+ (−)	− (+)	−	+
Cue 2	+ (−)	?	?	?	?	?	+	−
Cue 3	?	?	+	−	+	−	?	?
Cue 4	?	?	−	+	−	?	+ (?)	?

Table 2

Differences of the attraction search score between study conditions predicted by a multilevel regression with random intercepts and random slopes for participants.

Variables	*b*	*se*	*t*	*df*	*p*
Intercept	0.25***	0.01	17.67	121.75	<.001
Unrestricted without costs vs. others	-0.19***	0.03	-7.27	133.31	<.001
Restricted vs. unrestricted with costs	-0.02	0.04	-0.56	86.05	.58

Note. Contrast "Unrestricted without costs vs. others" is coded as 2/3 for condition with unrestricted information search without costs and -1/3 for the other two conditions. Contrast "Restricted vs. unrestricted with costs" is coded 1/2 for the condition with restricted information search (i.e., Study 1) and -1/2 for unrestricted information search with costs. $^{***}p < .001$.

Table 3

Four additional cue-patterns in Study 3 (repeated four times) for which attraction search is predicted to increase (beneficial) vs. decrease (detrimental) the likelihood of accurate choice.

Cues	Pattern 1		Pattern 2	
	A	B	A	B
Beneficial task structure				
Cue 1	$\boxed{+}$	−	+	$\boxed{-}$
Cue 2	+	−	−	+
Cue 3	−	+	+	−
Cue 4	−	+	+	−
Detrimental task structure				
Cue 1	+	$\boxed{+}$	$\boxed{-}$	+
Cue 2	+	+	+	−
Cue 3	−	−	+	−
Cue 4	+	−	+	−

Note. All cue-values except for cue-values in rectangles are concealed (i.e., the cue-patterns are identical to cue-pattern 2 version 1 and 2 in Table 1 in studies 1 and 2). Cue-patterns are sorted in the table such that option A is the better option (according to naïve Bayes). In the study, the order of columns of cue-patterns was set randomly and cue-patterns were included in the remaining 128 trials at random positions.

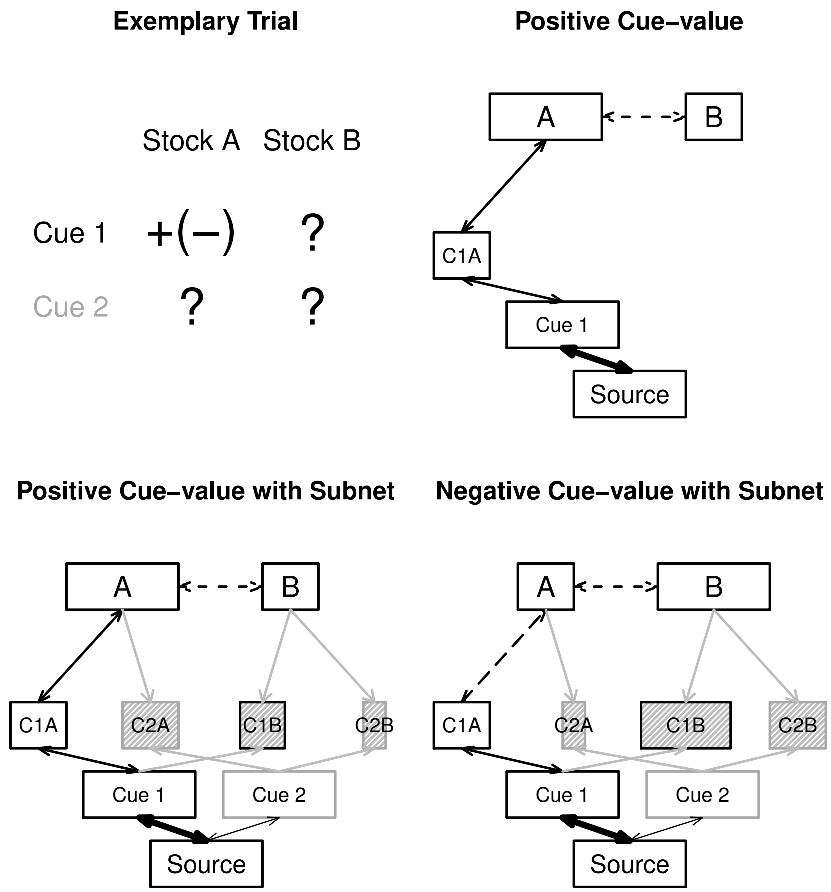

Figure 1. Modeling cue-search in a model of *i*ntegrated *co*herence-based *de*cision and *s*earch (iCodes). Continuous and dashed lines indicate excitatory and inhibiting connections, respectively. Black and grey lines indicate bi-directional and uni-directional links, respectively. The open cue-value (either positive or negative) that is already available in the decision situation (upper left display) forms a network resulting in an initial preference for option A as indicated by a larger box-size for option A (upper right display) in case the cue-value is positive (or an initial preference for option B in case the cue-value is negative, not shown). Concealed cue-values (shaded rectangles) form a subnet: The current preference for options (lower left or right display for positive or negative evidence for option A) as well as cue-validities influence search for cues. Larger box-sizes indicate the increased likelihood (i.e., preference) for each concealed cue to be opened next (see text for more explanations).

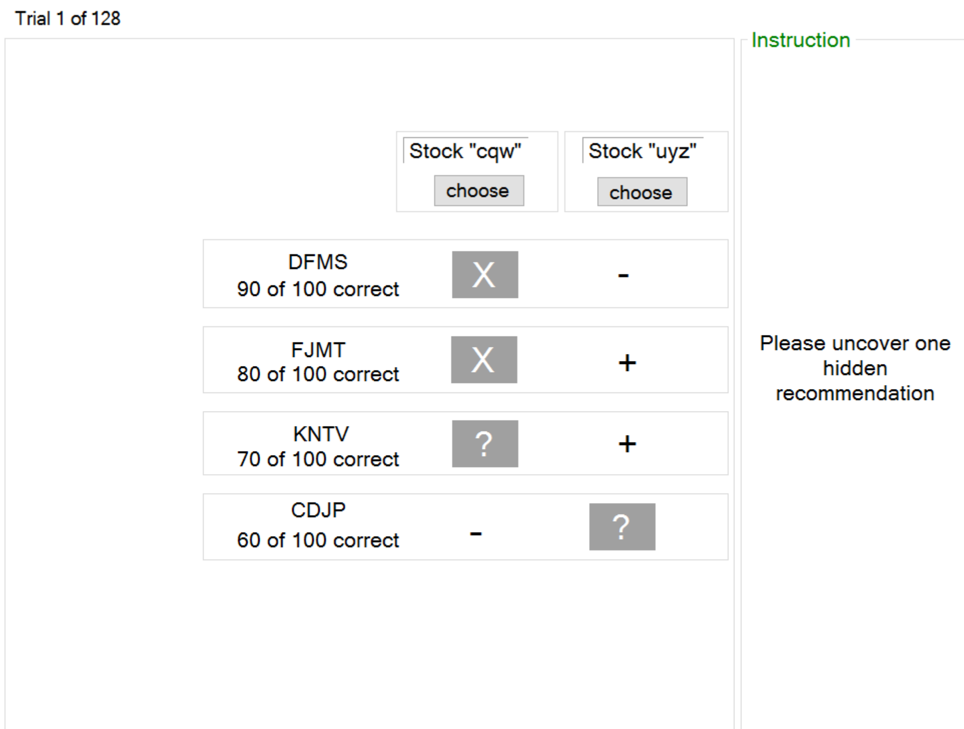

Figure 2. Screenshot of the stock-market game (translated from German) of cue-pattern 3 in version 2 (Table 1). Expert DFMS speaks against stock "uyz" ("-"); information on stock "cqw" is not available ("X") for experts DFMS and FJMT. The participant can either uncover the recommendation of expert KNTV on stock "cqw" or expert CDJP on stock "uyz" ("?"). After uncovering one concealed recommendation, the participant is asked to choose between stocks. Names and order of options were randomly generated for each participant.

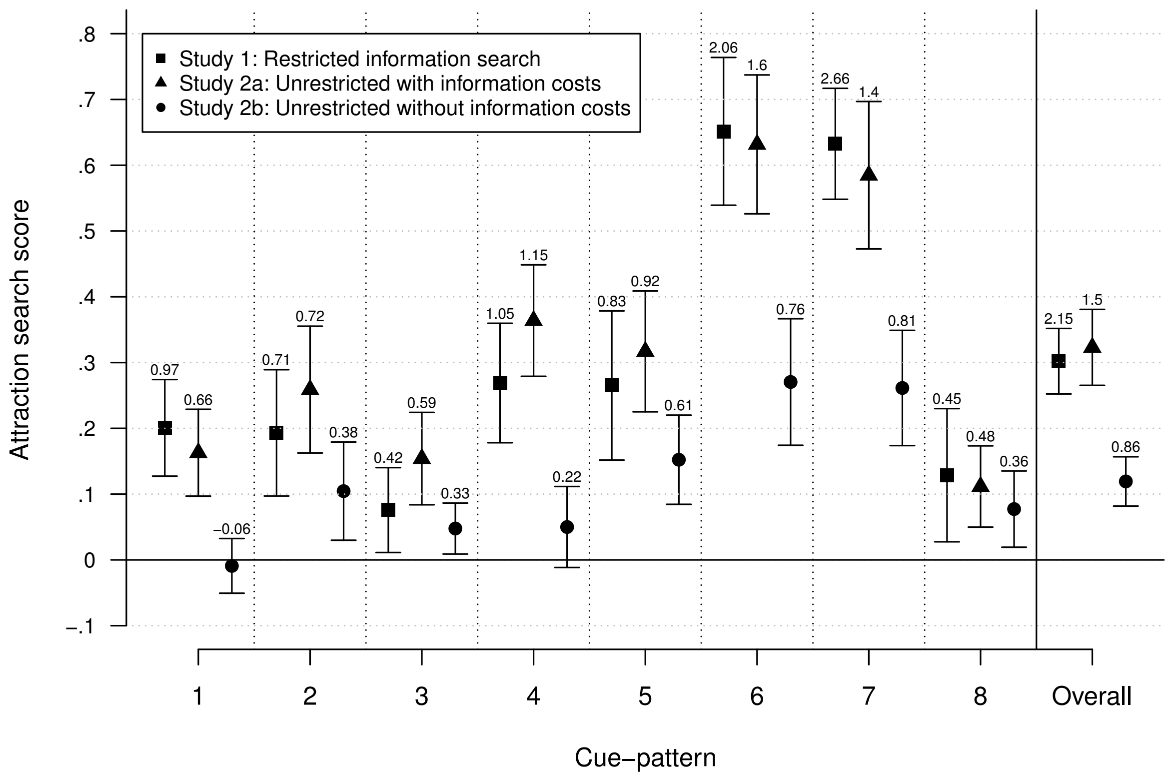

Figure 3. Mean attraction search score with 95%-confidence intervals by cue-pattern and overall for Study 1 and Study 2. Numbers above upper confidence intervals indicate the effect size (Cohen's *d*) of the attraction search score for each pattern or overall in both studies. An additional interactive boxplot of the data showing also the distribution of individual scores can be accessed at http://coherence-based-reasoning-and-rationality.de/materialASE/interactiveASE.html.

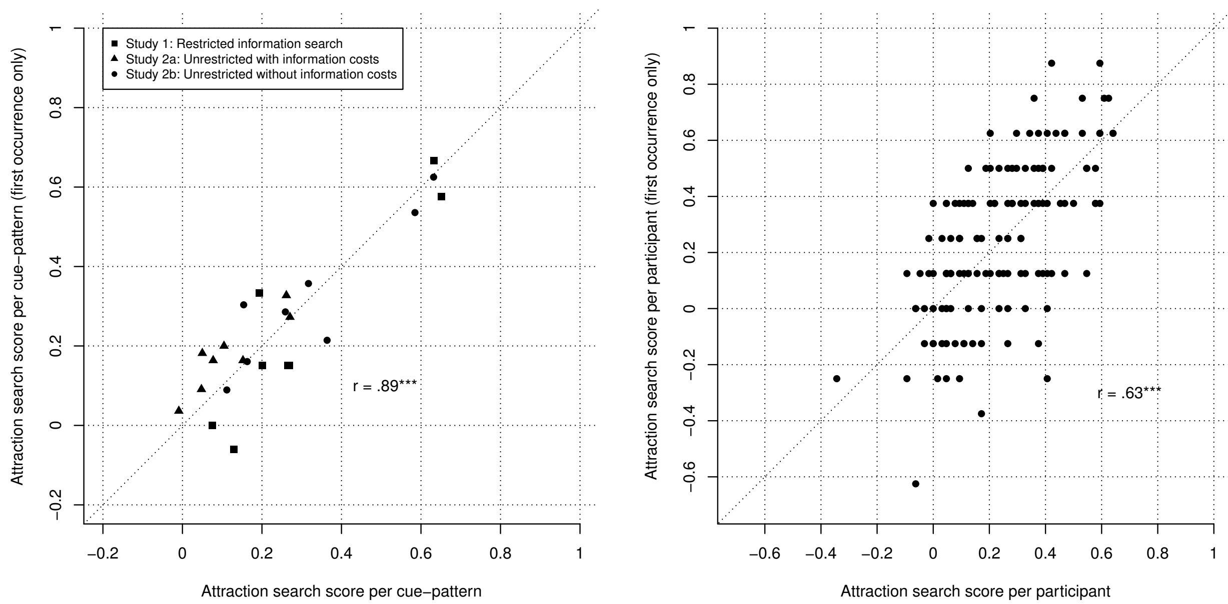

Figure 4. Mean attraction search score for all eight repetitions (cf. Figure 3) plotted against the mean attraction search score based on the first occurrence of each cue-pattern per pattern (left display) and per participant (right display). The dotted diagonals indicate the identity line. $^{***}p < .001$

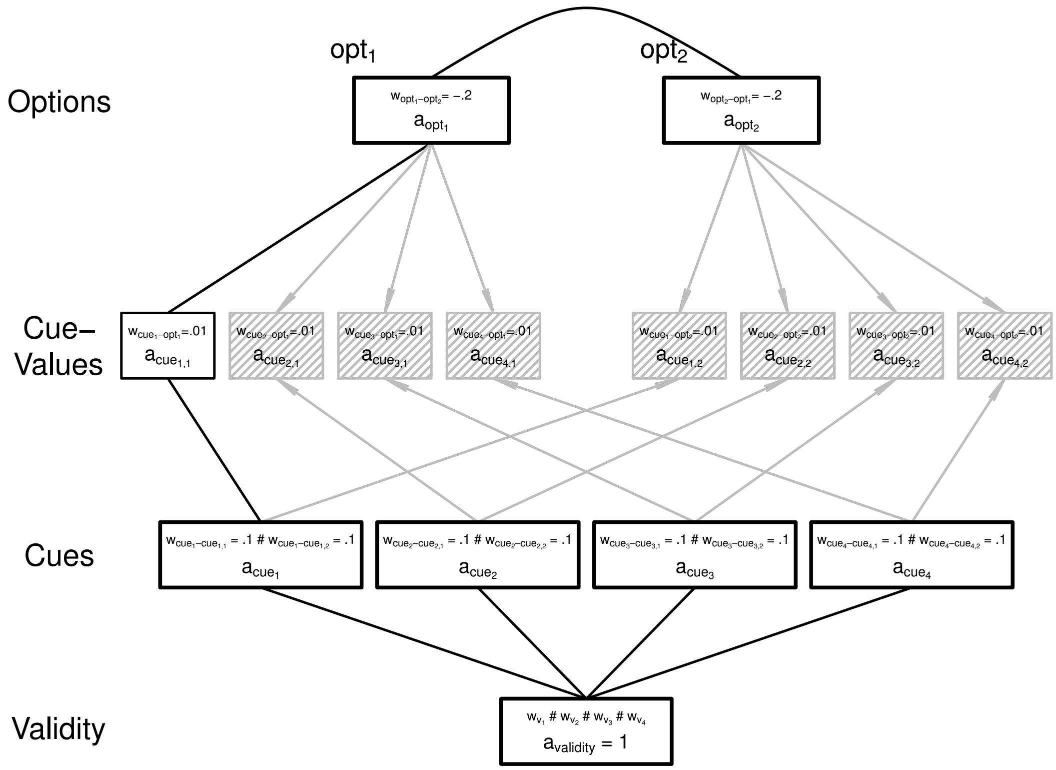

Figure 5. Depiction of the model of integrated coherence-based decision and search (iCodes) for cue-pattern 2 version 1 (i.e., all cue-values except for the most valid cue-value of option 1 are concealed, Table 1). Grey shaded rectangles indicate concealed cue-values. Grey lines indicate uni-directional links, all other links are bi-directional. Within each rectangle, weights for links (i.e., w) are provided (e.g., strong inhibitory link $w_{opt_1-opt_2} = -.2$ between options). Animations of the process of iterative updating of node-activations in iCodes can be accessed at http://coherence-based-reasoning-and-rationality.de/materialASE/pos/iCodes_pos.html in case the first cue-value speaks *for* option 1 and http://coherence-based-reasoning-and-rationality.de/materialASE/neg/iCodes_neg.html in case the first cue-value speaks *against* option 1.

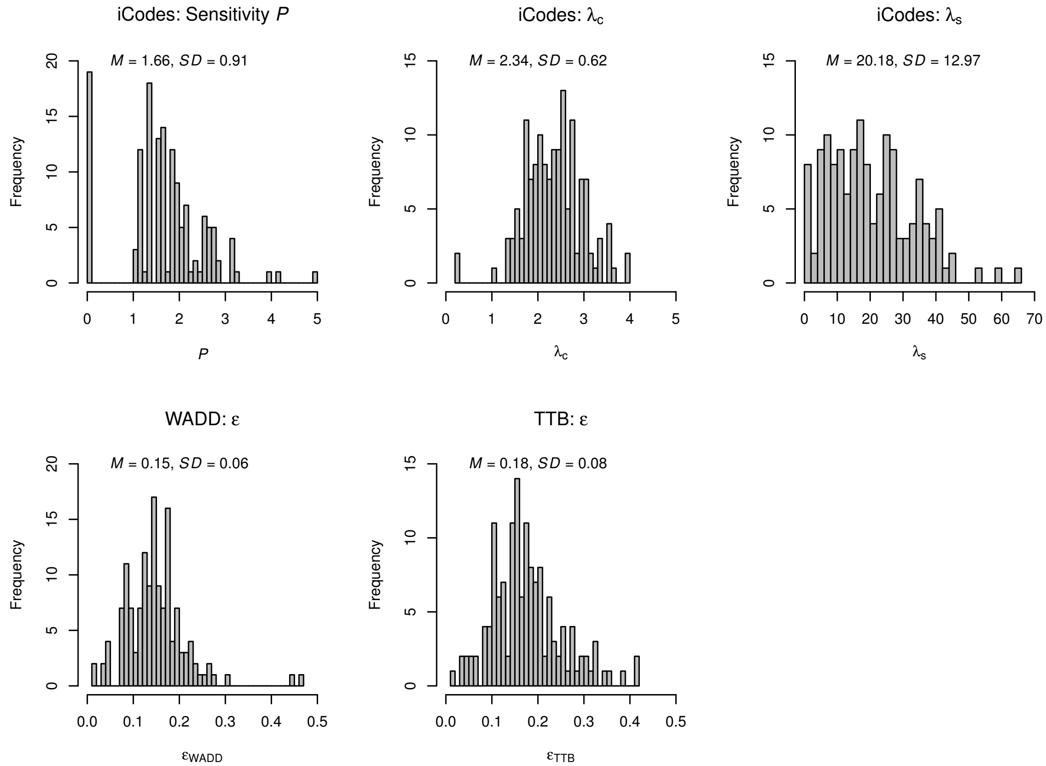

Figure 6. Frequency of fitted parameters P (extent of non-compensatory net-weights), λ_c (sensitivity to differences in activations for options A or B), and λ_s (sensitivity to differences in activations of concealed cue-values that can be searched) for iCodes and ϵ (strategy application error) for WADD and TTB. Note that 19 participants have a P parameter close to or exactly 0. When we remove those participants from the analysis, the overall attraction search score is still statistically significant in all conditions (all ts > 6.1, $p < .001$) and the effect is still strong with Cohen's d ranging from 0.88 to 2.12.

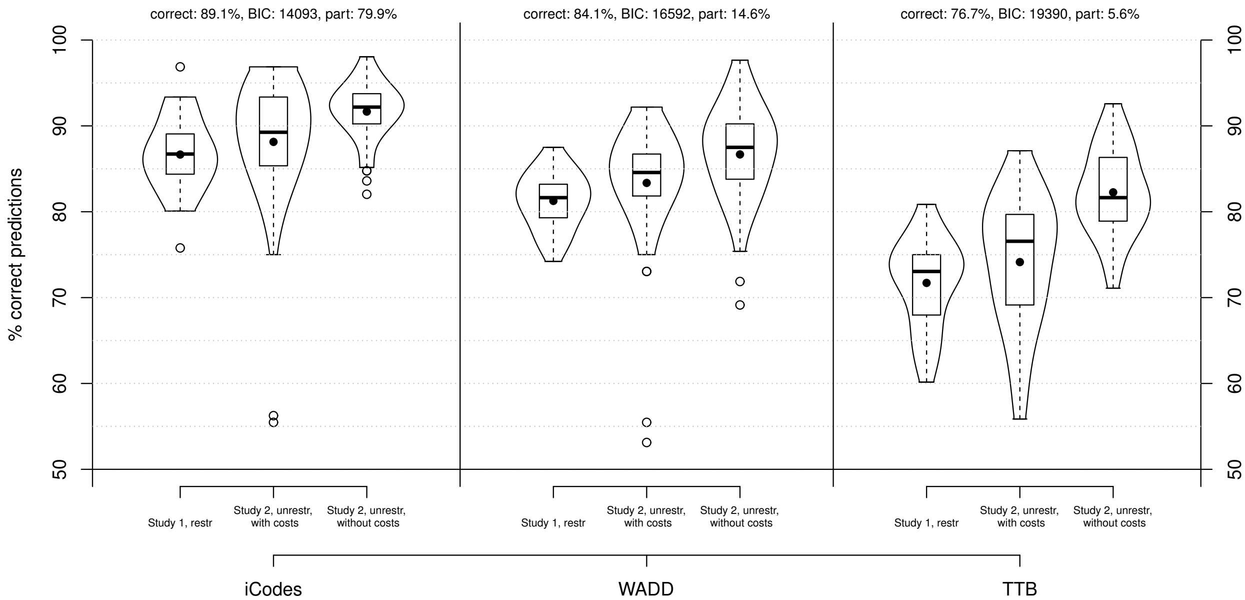

Figure 7. Percentage of correct predictions for each model (iCodes, WADD, TTB) and each experimental condition (restricted search in Study 1, unrestricted search with or without costs in Study 2). Overall percentage of correct predictions, Bayesian Information Criterion, and percentage of participants classified for each model are plotted in the header. Violin plots are displayed: Means are black dots, medians are black thick lines, the borders of the box indicate the lower or upper quartile (i.e., middle 50% of all data), whiskers indicate the minimum or maximum data point within 1.5× the interquartile range, white dots indicate outliers, and shapes around the boxplots indicate the density distribution of the data.

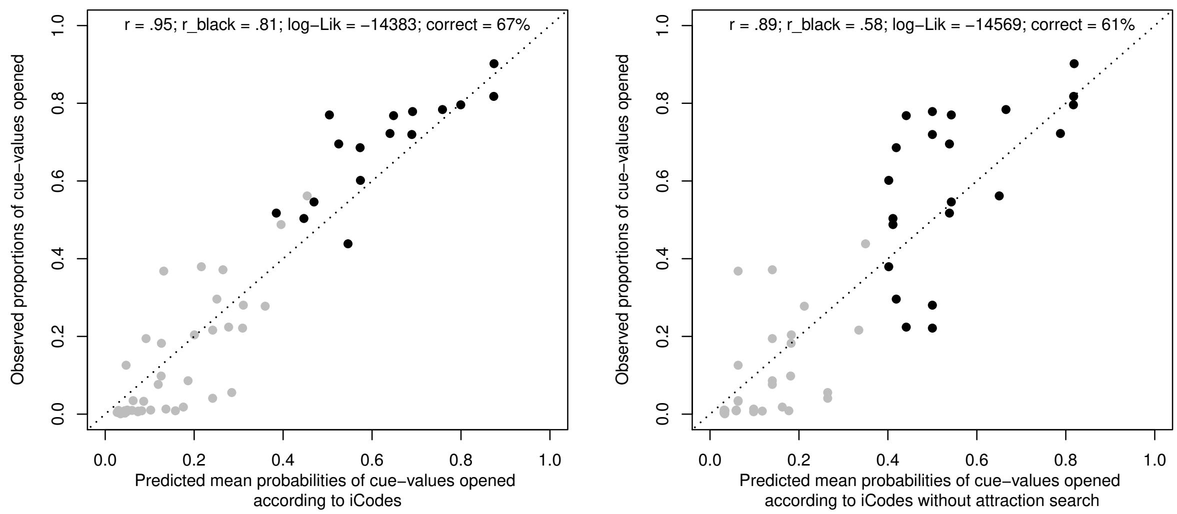

Figure 8. Observed participants' proportions of cue-values opened plotted against predicted mean probabilities of cue-values opened for all 55 concealed cue-values in all 16 cue-patterns (black and grey dots). The left display shows predictions based on iCodes with the attraction-search effect implemented (i.e., links from option-nodes to concealed cue-values) and the right display shows iCodes with no direct impact of options on concealed cue-values (i.e., links between nodes and concealed cue-values removed). Black dots indicate for each cue-pattern the concealed cue-value with the highest probability of being searched next based on iCodes. In the headers, correlations between predicted probabilities and observed proportions are shown for all concealed cue-values ("r"; i.e., black and grey dots) or for cue-values per cue-pattern that are most likely opened next according to the model ("r_{black}"; i.e., black dots only). Headers also show overall log-likelihoods of the fit between iCodes and observed cue-values searched for ("log-Lik") and the percentage of correctly predicted cue-values searched for by participants ("correct").

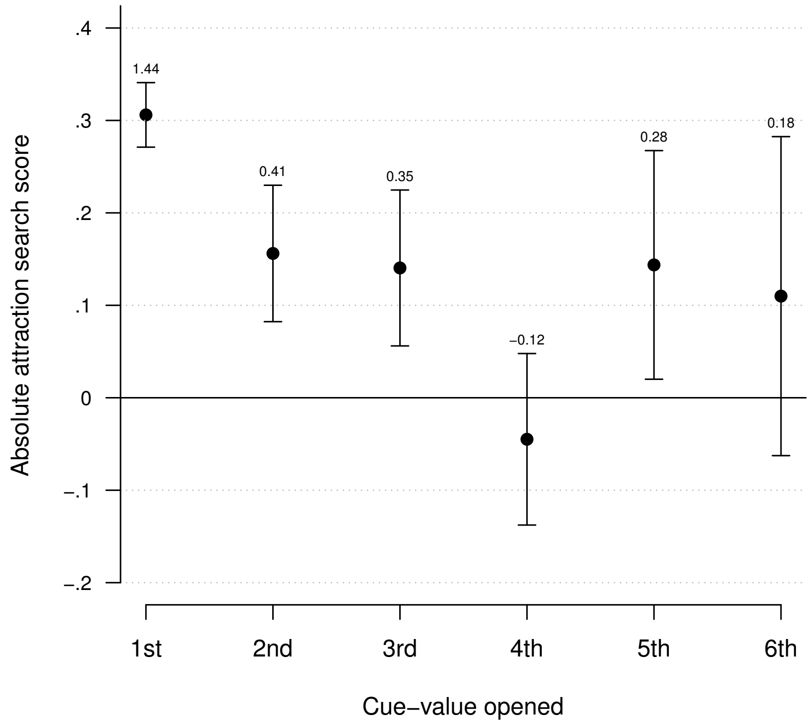

Figure 9. Absolute attraction search score with 95%-confidence intervals for first to sixth cue-value opened. Numbers above upper confidence intervals indicate the effect size (Cohen's *d*) of the attraction search score for each pattern or overall in both studies. An additional interactive boxplot of the data also showing the distribution of individual scores can be accessed at http://coherence-based-reasoning-and-rationality.de/materialASE/interactiveASE_absolute.html.

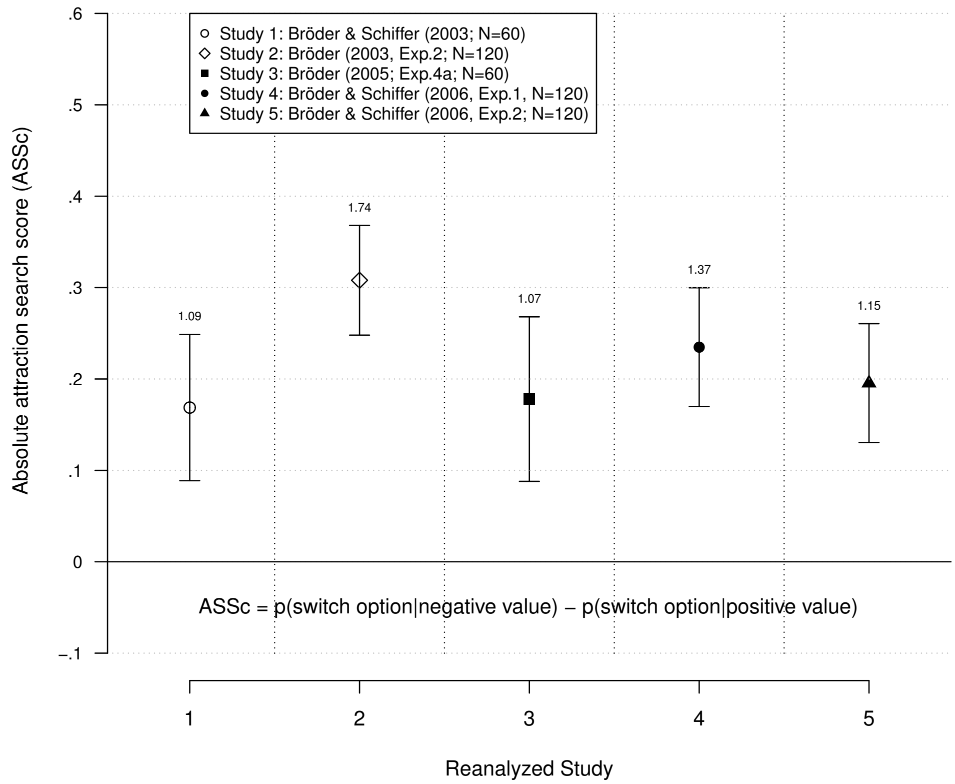

Figure 10. Absolute attraction search score (ASSc) for the second information purchase in five re- analyzed studies with 95%-confidence intervals and effect sizes Cohen's d (numbers above confidence intervals).

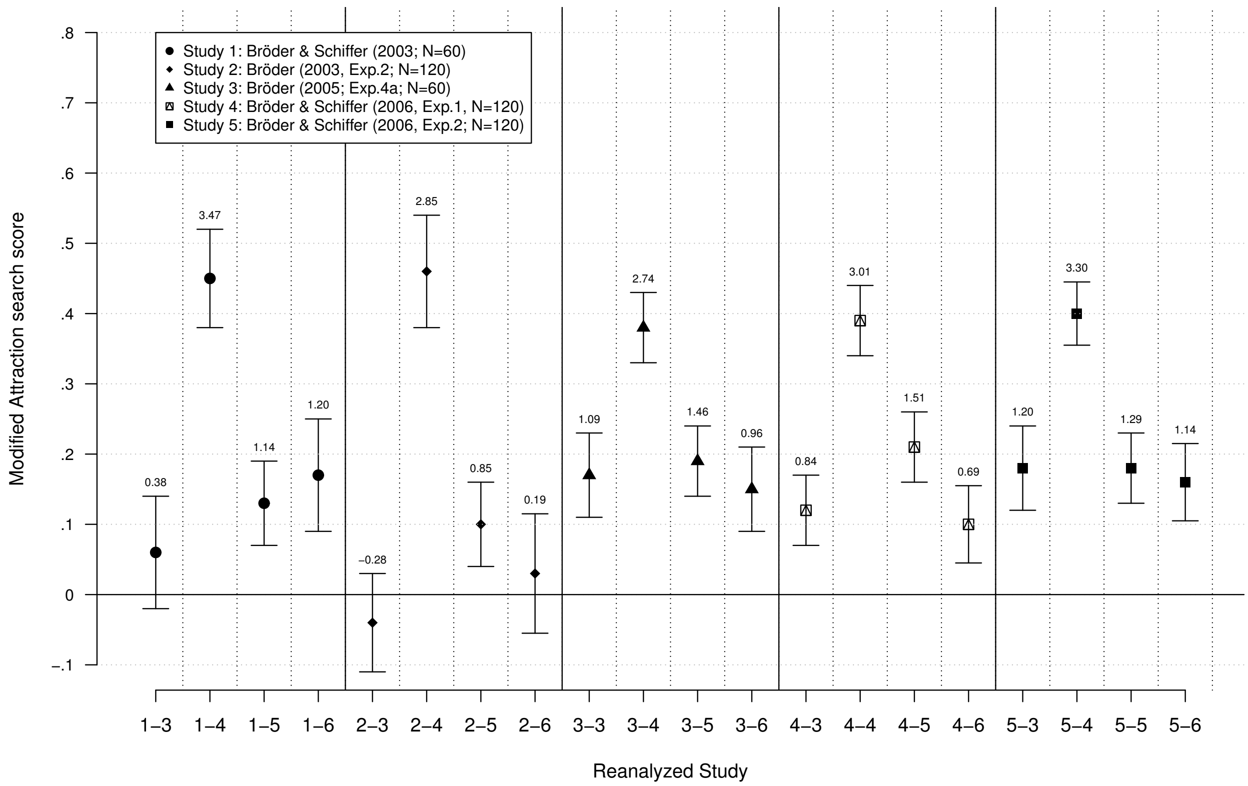

Figure 11. Modified attraction search scores for the 3rd to 6th information purchases in re-analyzed Studies 1 to 5 (Bröder & Schiffer, 2003; Bröder, 2003, 2005; Bröder & Schiffer, 2006) with 95%-confidence intervals and effect sizes Cohen's d (numbers above confidence intervals). In the labels for the x-axis, the first number indicates the experiment and the second number the number of the information purchase.

Appendix A

Search-rates for All Cue-values in All Conditions

In the following Appendix C, Appendix D, and Appendix E, observed proportions of cue-values opened first by participants for each cue-pattern and version are displayed. For example in Study 2 pattern 4, in 83% of all cases participants chose to open cue 1 for option A and in the remaining 17% cases participants chose to open cue 2 for option B when the first cue for option B was negative. When the first cue for option B was positive instead, participants chose to search for the less valid cue 2 for option B in 54% of all cases which results in an attraction search score of the size $.83 - .46 = .37$.

Appendix B

Rationality of the Attraction Search Effect in Study 1 and Study 2

In this Appendix, we discuss whether search of evidence for the more attractive option is rational or irrational in that it leads to better or worse decisions for the cue-patterns used in Study 1 and Study 2. To test whether making a correct decision is related to the magnitude of an individuals' attraction search effect, we ran a logistic multilevel-regression with making a correct decision as dependent binary variable (1 = correct, 0 = incorrect) and the centered individual attraction search score as predictor. The regression includes random intercepts for participants and types of cue-pattern as well as two dummy variables to control for the (three) experimental conditions. We find no significant relation between the size of the attraction search score and the odds of making a correct decision ($b = 1.02$, $p = .24$).

In a next step, we analyzed potential relations between attraction search and correct decisions in more detail for each of the cue-patterns. However, no significant differences between patterns were observed. In detail, for some cue-patterns, searching the cue-value of the more attractive option coincides with searching a more valid cue-value (i.e., cue-patterns 1, 3 and 4 version 1 and cue-pattern 2 and 5 version 2 in Table 1). For those "beneficial" cue-patterns, one would expect that odds for a correct decision increase when the attraction search score increases. For "detrimental" cue-patterns where search for the cue-value of the more attractive option leads to inspection of a less valid cue-value (i.e., cue-patterns 1, 3 and 4 version 2 and cue-pattern 2 and 5 version 1 in Table 1), one would expect higher attraction search scores resulting in lower odds of making a correct decision. There should be no relation in cases where the type of search is not correlated with cue validity (i.e., cue-patterns 6, 7, and 8 for both versions). To test these relations statistically, we added to the multilevel model reported above two centered dummy-variables comparing either beneficial ($\text{dummy}_{\text{ben}}$) or detrimental patterns ($\text{dummy}_{\text{det}}$) to neutral patterns. We included two 2-way interaction terms for testing the proposed relation between the attraction search score and the type of cue-pattern (i.e., $\text{dummy}_{\text{ben}} \times \text{ASSc}$ and $\text{dummy}_{\text{det}} \times \text{ASSc}$). Both interactions did not reach significance (ps $> .18$). Hence, based on our data we conclude that search for cue-values of the more attractive option does not lead to higher odds of making a correct decision.

The rationality of information search can also be assessed by testing whether looking up a piece of information maximally increases the probability of making a correct decision in case persons would apply a rational or approximately rational strategy for information integration (Baron, Beattie, & Hershey, 1988; Nelson, 2005; Nelson et al., 2010). For the analysis, we calculated for each of the 128 trials the probability of choosing the better option after searching either the most valid available information from the more attractive or the less attractive option according to the naïve Bayesian solution. Search of cue-values for the more attractive option would lead to an average probability of .84 of making a correct decision whereas search for cue-values of the less attractive option would lead to an average probability of .83. This difference of 1% more correct decisions is not statistically significant ($t(254) = 0.43$, $p = .66$). This indicates that the cue-patterns used in studies 1 and 2—that were well suited for demonstrating attraction search effects—cannot be used to demonstrate its detrimental (i.e. biasing) or beneficial effects on the rationality of choice.

More generally, these analyses show by example that attraction-based search does not necessarily lead to better or worse outcomes. They leave open the broader question whether it is in general appropriate to show this attraction-based search or not. This would be the question of the ecological rationality of this search principle which would require an analysis of the structural properties of “typical” or “modal” decision environments.

Appendix C

Observed Proportions of Cue-values Searched for All Eight Cue-patterns in Study 1.

Cues	Pattern 1		Pattern 2		Pattern 3		Pattern 4	
	A	B	A	B	A	B	A	B
Cue 1	+	–	+ (–)	41% (60%)	x	–	78% (51%)	– (+)
Cue 2	+ (x)	+	45% (27%)	9% (10%)	x	– (+)	–	22% (49%)
Cue 3	92% (72%)	+	2% (1%)	2% (2%)	73% (66%)	+	+	–
Cue 4	–	8% (28%)	1% (0%)	1% (0%)	–	27% (34%)	–	+
	Pattern 5		Pattern 6		Pattern 7		Pattern 8	
	A	B	A	B	A	B	A	B
Cue 1	+ (–)	43% (65%)	+ (–)	– (+)	+ (–)	– (+)	–	+
Cue 2	+ (–)	5% (8%)	86% (20%)	14% (80%)	86% (23%)	13% (74%)	+	–
Cue 3	49% (21%)	3% (3%)	+	–	+	–	49% (36%)	51% (63%)
Cue 4	0% (1%)	0% (1%)	–	+	–	0% (3%)	+ (0%)	0% (1%)

Appendix D

Observed Proportions of Cue-values Searched for All Eight Cue-patterns in Study 2 With Information Costs.

Cues	Pattern 1		Pattern 2		Pattern 3		Pattern 4	
	A	B	A	B	A	B	A	B
Cue 1	+	–	+ (–)	38% (64%)	x	–	83% (46%)	– (+)
Cue 2	+ (x)	+	46% (21%)	11% (11%)	x	– (+)	–	17% (54%)
Cue 3	90% (74%)	+	1% (1%)	1% (1%)	76% (60%)	+	+	–
Cue 4	–	10% (26%)	2% (1%)	0% (0%)	–	24% (40%)	–	+
	Pattern 5		Pattern 6		Pattern 7		Pattern 8	
	A	B	A	B	A	B	A	B
Cue 1	+ (–)	41% (72%)	+ (–)	– (+)	+ (–)	– (+)	–	+
Cue 2	+ (–)	4% (5%)	85% (22%)	15% (78%)	82% (24%)	17% (74%)	+	–
Cue 3	46% (15%)	7% (6%)	+	–	+	–	47% (35%)	51% (62%)
Cue 4	2% (2%)	0% (1%)	–	+	–	1% (2%)	+ (1%)	2% (2%)

Appendix E

Observed Proportions of Cue-values Searched for All Eight Cue-patterns in Study 2 Without Information Costs.

Cues	Pattern 1		Pattern 2		Pattern 3		Pattern 4	
	A	B	A	B	A	B	A	B
Cue 1	+	–	+ (–)	72% (80%)	x	–	74% (69%)	– (+)
Cue 2	+ (x)	+	23% (13%)	3% (5%)	x	– (+)	–	26% (31%)
Cue 3	90% (90%)	+	1% (0%)	1% (0%)	93% (88%)	+	+	–
Cue 4	–	10% (10%)	0% (0%)	0% (0%)	–	7% (12%)	–	+
	Pattern 5		Pattern 6		Pattern 7		Pattern 8	
	A	B	A	B	A	B	A	B
Cue 1	+ (–)	76% (89%)	+ (–)	– (+)	+ (–)	– (+)	–	+
Cue 2	+ (–)	3% (4%)	66% (39%)	34% (61%)	65% (39%)	34% (60%)	+	–
Cue 3	20% (5%)	0% (1%)	+	–	+	–	50% (42%)	50% (57%)
Cue 4	1% (0%)	0% (0%)	–	+	–	1% (1%)	+ (0%)	0% (0%)