Judgment and Decision Making, Vol. 14, No. 4, July, 2019, pp. 488–512

Information search in everyday decisions: The generalizability of the attraction search effect

Sophie E. Scharf*† Monika Wiegelmann‡ Arndt Bröder‡

Abstract

The recently proposed *integrated coherence-based decisions and search model* (iCodes) makes predictions for search behavior in multi-attribute decision tasks beyond those of classic decision-making heuristics. More precisely, it predicts the *Attraction Search Effect* that describes a tendency to search for information for the option that is already attractive given the available evidence. To date, the Attraction Search Effect has been successfully tested using a hypothetical stock-market game that was highly stylized and specifically designed to be highly diagnostic. In three experiments, we tested whether the Attraction Search Effect generalizes to different semantic contexts, different cue-value patterns, and a different presentation format than the classic matrix format. Across all experiments, we find evidence for information-search behavior that matches iCodes's information-search prediction. Therefore, our results corroborate not only the generalizability of the Attraction Search Effect in various contexts but also the inherent process assumptions of iCodes.

Keywords: attraction search effect, information search, generalizability

1 Introduction

When faced with a decision, we often have to search for information that enables us to weigh the advantages and disadvantages of each option against each other. Information search is especially important, if the decision at hand has non-trivial consequences, such as when buying a car, deciding on a job offer, or taking out insurance. Despite the importance of information search for decision making, psychological decision-making models have usually focused more on the processes of integrating information rather than the processes behind searching for information (Gigerenzer et al., 2014).

Aware of this lack of specified information-search process models, Jekel et al. (2018) recently extended the parallel constraint satisfaction model for decision making (PCS-DM; Glöckner et al., 2014) to include information search in multi-attribute decision tasks. The new integrated coherence-based decision and search model (iCodes) makes detailed predictions for the information-search process in multi-attribute decisions (Jekel et al., 2018). One core prediction of iCodes is the *Attraction Search Effect*, which states that people tend to search for information about the option that is currently supported by the already available evidence. The Attraction Search Effect and iCodes itself have received initial support from three experiments and the reanalyses of five already published experiments (Jekel et al., 2018).

The original experiments by Jekel et al. (2018) used a probabilistic-inference task presented as a hypothetical stock-market game with cue-value patterns that were specifically designed to be highly diagnostic for the Attraction Search Effect. In our view, it is essential to demonstrate that the support for the Attraction Search Effect found by Jekel et al. (2018) was not due to arbitrary design choices in their studies. The goal of the present work is to test the generalizability of the Attraction Search Effect to different settings. With data from three online experiments, we test whether the Attraction Search Effect replicates in different, more diverse semantic context settings. As a next step, we investigate whether the Attraction Search Effect can be found with randomized cue-value patterns as well. Finally, we evaluate whether the Attraction Search Effect also emerges when information is not presented in a classic mouselab-type setting (first introduced by Johnson et al., 1989, referred to as mouselab in the following) but in a more realistic, simulated online shop. Since iCodes is a new model, demonstrating that its core prediction generalizes to different settings strengthens the relevance and reach of the model.

In the following paragraphs, we will first take a closer look at iCodes's prediction of information search in general and

This work was supported by the University of Mannheim's Graduate School of Economic and Social Sciences funded by the German Research Foundation (DFG). The authors thank Laura Büche, Daniela Kauschke, and Luca Pier for their support in creating stimulus materials for Experiment 3, Yury Shevchenko for his support in programming Experiment 2, two anonymous reviewers for their helpful comments in the revision process, and Marc Jekel for helpful comments on earlier versions of this manuscript.

*School of Social Sciences, University of Mannheim, L13, 17, 68161 Mannheim, Germany. Email: sophie.scharf@gess.uni-mannheim.de.

†Social Cognition Center Cologne, University of Cologne, Germany

‡School of Social Sciences, University of Mannheim, Germany.

the Attraction Search Effect specifically. After presenting already existing evidence for iCodes's core prediction, we will argue why generalizability is an important issue and present data from three experiments that test exactly this generalizability of the Attraction Search Effect. In these three studies, we gradually move away from the original study setup by (a) demonstrating the Attraction Search Effect in other semantic domains, (b) extending the range of domains and relaxing the cue-value patterns, and (c) moving away from the matrix format in a simulated online-shop setting.

2 The integrated, coherence-based decision and search model

The original PCS-DM is a network model that successfully predicts choices, decision times, and decision confidence for multi-attribute decisions in different contexts (Glöckner et al., 2012, 2014; Glöckner & Betsch, 2012; Glöckner & Hodges, 2010; Glöckner et al., 2010). However, one shortcoming of PCS-DM is that it models information integration only and is thus applicable only to decision situations that do not require information search (Marewski, 2010). Therefore, Jekel et al. (2018) have recently extended PCS-DM to include information-search processes. This new model shares in principle the same basic network structure and the same assumptions regarding the underlying decision process with its predecessor PCS-DM. The crucial extension is an additional layer of nodes that is included in the network structure. This layer represents the cue values present in the decision situation. In the following paragraphs, we will introduce how iCodes specifies the information-search process and how it predicts the Attraction Search Effect. For the exact model specification and formalization, please refer to Jekel et al. (2018).

2.1 The prediction of information search in iCodes

In a multi-attribute decision task, the decision maker is presented with at least two options for which information is provided in the form of attributes or cues (Harte & Koele, 2001). Depending on the specific task, the goal of the decision maker is to either choose the option that maximizes an objective criterion value (Glöckner et al., 2010), such as buying the most successful stock, or to choose the option that maximizes a subjective criterion value (Payne et al., 1993), such as buying the preferred sweater. The cues provide information about the options in form of cue values that can be positive evaluations of the respective option, often represented by a "+", or negative evaluations, often represented by a "−". In probabilistic-inference tasks, the cues usually differ in their validity, that is, they differ in how often they correctly evaluate an option as better than the other option(s) on the objective criterion (Gigerenzer & Goldstein, 1996). Besides positive and negative evaluations, cue values can also be hidden and have to be searched for, which is represented by a "?". An example trial of such a multi-attribute decision task with two options and two cues is shown in Figure 1.

The information in such a multi-attribute decision task is represented in iCodes as a network (Jekel et al., 2018). There are nodes for the options, cues, and cue values that are connected via links as depicted in Figure 1. The information-search process of iCodes is modeled as a spread of activation through this network that is initiated by the source node at the bottom of the network. Activation is spread between nodes via the connecting links. The spread of activation continues until the activation of each node has stabilized and, therefore, does not change substantially anymore. At this point, the network as a whole is stable and the model predicts that the concealed cue value whose node received the most activation during this process is opened next. The activation, that concealed cue-value nodes receive, stems from two sources in the network (Jekel et al., 2018). These sources are the option and cue nodes that are connected to searchable cue values via unidirectional links. Thus, nodes of concealed cue values receive activation only but do not continue the spread of activation further. These links are unidirectional to represent that concealed cue values do not carry any information with regard to the options or cues. Note that once a concealed cue value is opened the unidirectional links become bidirectional indicating that the information of this cue value is now available. The amount of activation that nodes of searchable cue values receive from cue nodes is proportional to their respective validities. Thus, the higher the validity of a cue, the more activation the corresponding cue-value nodes receive. The activation received from the option nodes depends on the current evidence for the options. Thus, the more the current evidence favors one option over another, the more activation the corresponding cue-value nodes receive - via the links between cue-value nodes and options. Both sources of activation are assumed to influence search in an additive manner. Therefore, both the respective cue's validity and the respective option's evidence determine iCodes's search prediction for a concealed cue value.

2.1.1 The Attraction Search Effect

Formal models that predict information search in multi-attribute decision tasks often assume that information is searched for cue-wise or option-wise and most often following the order of cues' validities (Payne et al., 1988; Lee & Cummins, 2004; Gigerenzer & Goldstein, 1996). These search directions are assumed to be independent of the already available evidence. In the example trial in Figure 1, in which one cue value is already available, these models would therefore predict that the valence of this cue

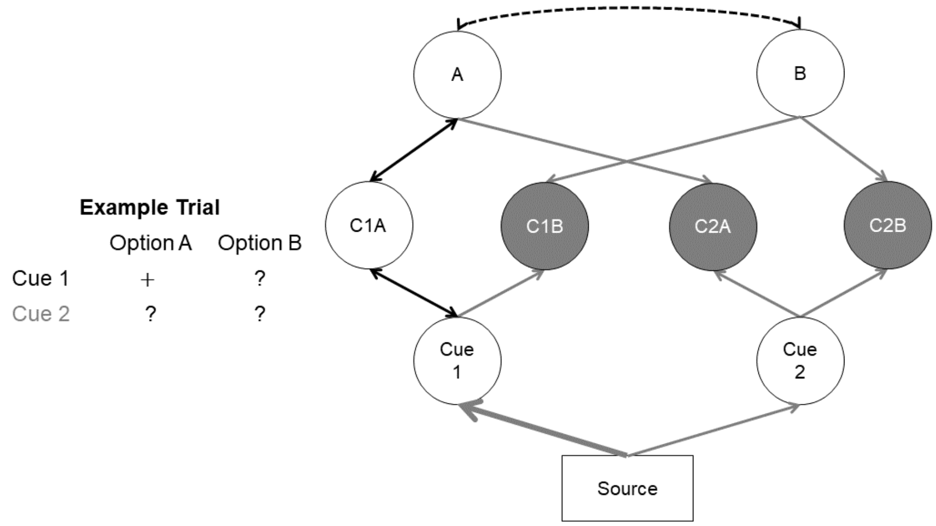

FIGURE 1: The translation of a probabilistic-inference task into the network structure of iCodes. In this example task, the first cue, which is more valid than the second cue, makes a positive statement regarding Option A and all other information is still hidden. The options are represented by the option nodes in the top layer of the network and are connected by an inhibitory, bidirectional link (dashed line). The cue values are included in the next layer of nodes where the white node represents the already available information and the gray nodes represent still concealed information. Below the layer of cue-value nodes is the layer of cue nodes. The source node on the bottom of the network initializes the spread of activation. The activation the cue nodes receive is proportional to their respective validities, as indicated here by the thickness of the link. The black arrows in the network represent bidirectional links, whereas gray arrows represent unidirectional links. Adapted from "A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect," by M. Jekel, A. Glöckner, and A. Bröder, 2018, *Psychological Review, 125*, p. 746. Copyright 2018 by the American Psychological Association.

value would not matter for whether information is searched cue-wise or option-wise. ICodes, however, predicts that the already available evidence influences information search (Jekel et al., 2018). This is due to the fact that iCodes assumes a joint influence of the cues' validities and the options' current attractiveness on information search. The influence of the cues' validities leads to iCodes's prediction that, all things being equal, cue values from highly valid cues are more likely to be searched for than cue values from less valid cues. The influence of the current evidence on information search in the formalized iCodes model also leads to an additional qualitative search prediction: Cue values with information on the currently preferred option are more likely to be searched for than cue values with information on the less attractive option. This prediction has been coined as the Attraction Search Effect by Jekel et al. (2018).

Searching information on the currently attractive option has also been shown in information-search paradigms outside the realm of probabilistic-inference tasks. One common observation is information-search behavior consistent with selective exposure (Frey, 1986; Hart et al., 2009; Fischer & Greitemeyer, 2010). Selective exposure is the tendency to search for information that supports the currently preferred option. In the literature, this pattern of information search is often considered to mainly stem from the motivation to defend one's prior beliefs or prior position (Hart et al., 2009; Fischer & Greitemeyer, 2010).[1] In the standard paradigm of selective exposure subjects, therefore, know the valence of the searchable information a priori (Fischer et al., 2011). This a priori knowledge constitutes the key difference of selective exposure and the Attraction Search Effect. The Attraction Search Effect cannot be driven merely by the motivation to defend one's preferred option since this would require knowing beforehand whether the concealed information supports or contradicts the currently attractive option. Rather, the mechanism of information search in iCodes is to find information that potentially increases the coherence of the decision situation.[2]

Two other phenomena that have been described in the literature predict search behavior similar to the Attraction Search Effect: pseudodiagnostic search in hypothesis testing (Do-

[1]Both, Hart et al. (2009) and Fischer & Greitemeyer (2010) also discuss the role of accuracy motivation for selective exposure in their articles. Accuracy motivation is defined as the goal to search for information that leads to the objectively best choice. As the effect of accuracy motivation on selective exposure is at least somewhat inconsistent, Fischer & Greitemeyer (2010) put forward an integrative model that explains the combined influence of accuracy and defense motivation on selective exposure.

[2]The role of coherence for selective exposure has also been investigated by Fraser-Mackenzie & Dror (2009).

herty et al., 1979; Mynatt et al., 1993) and leader-focused search (Carlson & Guha, 2011). Pseudodiagnostic search describes that individuals tend to search for information about their current hypothesis only and fail to test the alternative hypothesis. This behavior is particularly observed when the first piece of found information supports the currently tested hypothesis (Mynatt et al., 1993). The aforementioned failure to test alternative hypotheses is problematic as a cue is only diagnostic for a hypothesis test when its values are known for both hypotheses.

In the case of leader-focused search, information-search behavior is also characterized as searching for information on the currently preferred option (the leader) independently of the expected valence of this information (Carlson & Guha, 2011). Carlson & Guha (2011) could show that this preference for information on the leader is so strong that subjects preferred negative information on the leader compared to negative information on the trailer (the currently less preferred option).

Similar cognitive explanations have been proposed for both pseudodiagnostic and leader-focused search. Evans et al. (2002) proposed that pseudodiagnostic search results from a habitual focus on one hypothesis only and individuals tend to ignore other, alternative hypotheses. Similarly, Carlson & Guha (2011) refer to *focalism* (Wilson et al., 2000) as a possible underlying mechanism for leader-focused search in that individuals focus on the current leader and subsequently ignore other options. Thus, besides different theoretical underpinnings, the only difference between leader-focused search and the Attraction Search Effect is that for the former effect subjects are asked which option is more attractive whereas for the latter effect the attractiveness of the options is manipulated via cue-value patterns. Both phenomena, pseudo-diagnostic and leader-focused search, are similar to the search pattern predicted by iCodes but lack an explicit theoretical model formalizing the underlying processes of this type of search behavior. With iCodes, there is now a computational, formal model that allows precise predictions of when and how strong the information search direction should be biased towards the currently more attractive option. Hence, our explanation does not contradict the theories mentioned above, but the observed focalism may be the result of an underlying coherence-maximizing mechanism.

When focusing on probabilistic-inference tasks, different models have been proposed that predict information search, such as heuristics as part of the adaptive toolbox (e.g., Gigerenzer & Todd, 1999; Payne et al., 1988) and models of the class of evidence accumulation models (e.g., Hausmann & Läge, 2008; Lee & Cummins, 2004). However, the prediction of the Attraction Search Effect is unique compared to these formalized models as they base only their prediction of the stopping of information search on the available information. The predicted direction of information search, however, in these types of models relies solely on external criteria such as the cues' validities. Yet, in iCodes, the information-search prediction depends on the additive effects of validity-driven cue-node activations and attractiveness-driven option-node activations on the activations of concealed cue-value nodes (Jekel et al., 2018). Thus, the Attraction Search Effect follows from the joint effects of validity and the current attractiveness of the options.

2.1.2 Evidence for the Attraction Search Effect

The Attraction Search Effect was tested by Jekel et al. (2018) in two experiments. In both experiments, they used an artificial stock-market game in which subjects had to choose the more successful of two stocks based on expert judgments that differed in their respective validities. For this stock-market game, the authors specifically designed half-open cue-value patterns that were highly diagnostic for the Attraction Search Effect. The diagnosticity of the patterns was achieved by creating two versions of each cue-value pattern such that in the first version (Version a) the Option A is more attractive than Option B and that in the second version (Version b) the Option B is more attractive than Option A. The change of attractiveness between the two versions was achieved by changing one or two cue values. With these two pattern versions, it was possible to calculate a qualitative Attraction Search Score that represents the difference of probabilities of behavior consistent with the Attraction Search Effect and behavior inconsistent with the Attraction Search Effect. Behavior was consistent with the Attraction Search Effect when subjects searched for the attractive Option A in Version a and behavior was inconsistent when subjects searched for the unattractive Option A in Version b of the cue-value patterns; $Attraction\ Search\ Score = p(Searching\ for\ Option\ A \mid Version\ a) - p(Searching\ for\ Option\ A \mid Version\ b)$. Thus, the Attraction Search Score is positive if subjects followed iCodes's predictions for information search and zero if subjects did not change their direction of search depending on the attractiveness of the options.

In the first experiment, Jekel et al. (2018) presented the half-open cue-value patterns to subjects and restricted information search to one piece of information. In the second experiment, Jekel et al. (2018) did not restrict information search but manipulated whether information search was costly or free. Both experiments show strong support for the Attraction Search Effect; though, the effect was less pronounced when information search was free. These initial results received further support in a reanalyses of five published experiments that also used a hypothetical stock-market game but were not specifically designed to test for the Attraction Search Effect. In addition, iCodes fit the observed information-search behavior quantitatively well and this fit depended on the influence of options' attractiveness in the model. Thus, there is initial support for iCodes's information-search predictions in probabilistic-inference tasks in the semantic context of an abstract and stylized hypothetical stock-market game.

3 The importance of model generalizability

With the recent extension of PCS-DM to iCodes and the presented empirical support for one of iCodes's core predictions, iCodes can be considered as a general theory for the decision process that incorporates information search, information integration, and decisions. As a general theory of decision making and information search, iCodes's predictions should be applicable to a broad range of different (multi-attribute) decision situations. A strict test of the applicability of a theory can be achieved by conducting a conceptual replication that varies experimental variables of the original studies (Makel et al., 2012). Conceptual replications ensure that the original results are not due to task or situational characteristics of the previous operationalizations but can be attributed with greater confidence to the processes specified by the theory (Bredenkamp, 1980). In our conceptual replications, we want to test whether iCodes's prediction for information-search behavior generalizes to different contexts.

In the previous studies testing iCodes, several aspects of the decision task have been kept constant that should be varied in a conceptual replication. One of these aspects is the semantic setting of the decision task. All experiments conducted and reanalyzed by Jekel et al. (2018) have used a probabilistic-inference task semantically set in a hypothetical stock-market scenario. The hypothetical stock-market game is a commonly used multi-attribute decision task (Bröder, 2003, 2000; Newell et al., 2003) that allows explicit control over different decision parameters, such as validities, and allows observation of information-search and decision behavior relatively unbiased by previous knowledge. Yet, at the same time and somewhat due to the high level of control, the hypothetical stock-market game is a highly artificial setting that lacks ties to the actual daily experiences of subjects. Further, a decision between stocks is only one instance of all possible decisions and such a neglect of stimulus sampling in an experiment is not only problematic with regard to the generalizability of results but also might dilute the validity of the causal inference (Wells & Windschitl, 1999). ICodes's predictions should, therefore, apply to a range of different and possibly more realistic semantic contexts. Testing different semantic contexts is especially relevant as prior work on leader-focused and pseudodiagnostic search has used a wide range of different decision contexts (Evans et al., 2002; Mynatt et al., 1993; Carlson & Guha, 2011). Thus, it is important to show that the Attraction Search Effect generalizes to different content domains as well.

Second, the cue-value patterns used to elicit the Attraction Search Effect have been kept constant between experiments. These patterns were specifically designed to be highly diagnostic for the Attraction Search Effect. However, as a general theory of decision making, iCodes's predictions should not be confined to a specific set of cue-value patterns but should be applicable in other cue-value constellations as well. The cue-value patterns have already been varied to some extent in the reanalyses of previously run studies in Jekel et al. (2018). These reanalyses have, however, all used the same context settings, namely a stock-market game.

A third aspect that was not varied between experiments is the way the information for the current decision task was presented. In all experiments, the cue values were presented in the matrix format of a typical mouselab task. Presenting information this way makes the relevant information highly accessible, facilitates information search itself, and might even influence the subsequent processing of information (Söllner et al., 2013). Yet, in many real-life decision tasks, the necessary information is often presented in a more complex fashion than in a matrix arranged according to cue validity. Thus, in order to claim that iCodes is general theory of decision making, it is important to show that the Attraction Search Effect still emerges when information is structured differently.

The current experiments successively relaxed the restrictions inherent in Jekel et al. (2018) demonstrations of the Attraction Search Effect. First, we extended the semantic contexts to various decision domains beyond the stock-market game in all three experiments, using 13 different decision contexts altogether. Second, we also used cue-value patterns different from the original ones (Experiment 2). Finally, we disposed of the commonly used restrictive matrix format of information presentation that is prevalent in many studies investigating information search in decision making (Experiment 3). By relaxing many of the restrictions inherent in Jekel et al.'s (2018) original experiments, we aim to replicate the Attraction Search Effect in different decision contexts and thus test the limits of its generalizability.

4 Experiment 1: Extension to different decision domains

The first experiment used cue-value patterns from the experiments by Jekel et al. (2018) but in a selection of six different semantic contexts. As we are interested in whether iCodes can predict information search in different contexts, we will concentrate solely on information search as the dependent variable in this and the following experiments. Thus, we will not analyze subjects' choices.

4.1 Method

4.1.1 Materials

Content scenarios. We constructed six different content scenarios for the decision task that represented mainly preferential decisions. These scenarios ranged from choosing a hotel to deciding which weather forecast to trust when planning a trip. One of the scenarios is the task to choose which of two cities is larger, commonly known as *city size task*, and was added to relate to earlier research (e.g., Gigerenzer & Todd, 1999). For every scenario, we chose four cues relevant to this decision. As the validity of these cues is mostly subjective, cues were ordered by our assumed importance for each scenario. To validate our assumptions, subjects were asked after the task for their subjective rating of importance of the cues. The content scenarios and the respective cues are displayed in Table A1 in Appendix 7.2. To make the decision task less abstract, we further changed the format of the cue values from "+" and "−" to different pictoral formats, such as a five- vs. two-star ratings, thumbs-up vs. thumbs-done icons, or "yes" vs. "no" icons for the city size scenario.[3]

Cue patterns. In this experiment, we used a subset of the original cue-value patterns from Jekel et al. (2018). Jekel et al. (2018) designed their cue-value patterns in pairs such that two versions of the same pattern differed in one or two cue values, so that either Option A or Option B was more attractive (see Table 1). For the present experiment, we selected three cue patterns from Jekel et al.'s (2018) studies. Pattern 3 was selected because it illicited the strongest Attraction Search Effect in Jekel et al.'s (2018) studies, with an Cohen's d ranging from 0.81 to 2.66. Patterns 1 and 2 showed the third and fourth strongest Attraction Search Effect, respectively, in the original studies, with Cohen's d ranging from 0.22 to 1.15 and from 0.61 to 0.92, respectively. These cue-value patterns were chosen to increase our chances to find an Attraction Search Effect under more relaxed experimental conditions.

4.1.2 Measures

Subjective importance of cues. To assess the subjective importance of the cues, subjects were asked to rate each cue on how important they thought the cue was for their decision on a scale from 0 to 100, with zero representing *not important at all* and 100 representing *extremely important*. The purpose of this measure was to check whether the assumed validity ordering corresponded to the actual importance ordering by subjects.

Table 1: Version a and Version b of cue patterns used in Experiment 1.

	Pattern 1		Pattern 2		Pattern 3	
	A	B	A	B	A	B
Cue 1	?	−(+)	+(−)	?	+(−)	−(+)
Cue 2	−	?	+(−)	?	?	?
Cue 3	+	−	?	?	+	−
Cue 4	−	+	?	?	−	?

Note. + = positive cue value, − = negative cue value, ? = hidden, searchable cue value; Version a of patterns is displayed, cue values in parentheses are from Version b. Patterns 1, 2, and 3 correspond to Patterns 4, 5, and 7, respectively, in Jekel et al. (2018).

Attraction search score. Just as in the study by Jekel et al. (2018), we computed the individual Attraction Search Scores as the difference of the probability of searching for Option A in Version a vs. in Version b across the three cue-value patterns, $Attraction\ Search\ Score = p(Searching\ Option\ A|Version\ a) - p(Searching\ Option\ A|Version\ b)$.[4] As mentioned above, the first probability represents the probability of behavior consistent with the Attraction Search Effect, whereas the second probability represents the probability of behavior inconsistent with the Attraction Search Effect. Thus, if the Attraction Search Score is larger than zero, subjects show more behavior in line with the Attraction Search Effect.

4.1.3 Design and procedure

Each subject was presented with each of six content scenarios and with each of the six patterns (three patterns in two versions each). To avoid large trial numbers which are suboptimal for online studies, the variable Scenario with six levels and the variable Pattern with six levels (three pattern with two versions each) were balanced using a latin square design which resulted in six experimental groups. Therefore, each experimental group was exposed to every pattern and every content scenario. After opening the online study and agreeing to an informed consent, subjects provided demographic information before working on the actual task. In each of the six trials subjects were familiarized with the decision context and could then search for one piece of additional information. A picture of the task setup can be found in Figure 2. After seeing the additional piece of information, subjects had to choose one of the options. When the decision task was completed, subjects filled out the subjective importance measure for each of the scenario's cues.

[3] All instructions and decision scenarios can be found in the supplementary materials.

[4] As we presented each cue-pattern in both versions once, there are three observations of Version a and three observations of Version b for each

https://doi.org/10.1017/S193029750000615X Published online by Cambridge University Press

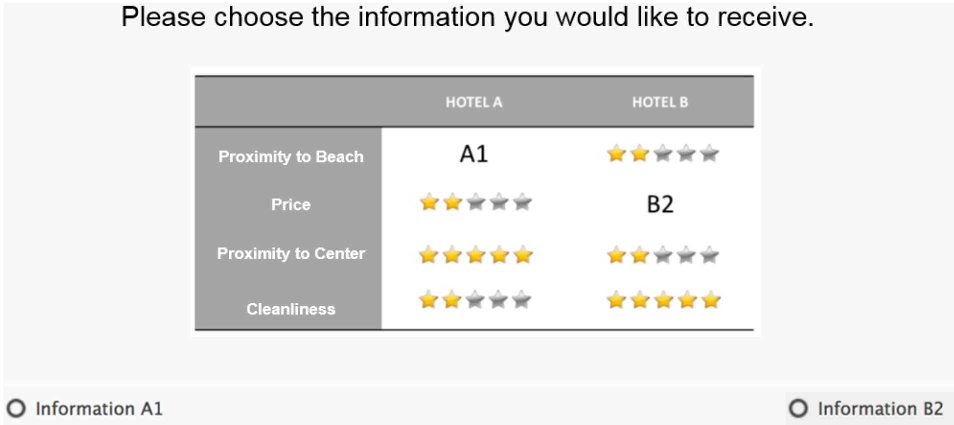

FIGURE 2: A translated (from German) screenshot of the decision task in Experiment 1. The current cue-value pattern is Pattern 1 in Version a. Subjects could search for information by selecting the radio button for the corresponding piece of information in the matrix. On the next screen, the searched-for information appeared in the decision matrix and subjects could choose one of the options.

4.1.4 Subjects

The online experiment was conducted with the program *Unipark* (Questback, 2016). Subjects were recruited online via the registration system of the University of Mannheim and via online platforms such as Facebook research groups. The data collection yielded a sample of 303 subjects (201 female, 47.5 % university students, $M_{age} = 33.7$, $SD_{age} = 15.5$, age range 17–70). Subjects could decide whether they participated for course credit or entered a lottery to win a 15€ online-shop gift certificate.

4.2 Results

All following analyses were conducted with R (R Core Team, 2019). All plots were created by using the *ggplot2* package (Wickham, 2016), mixed model analyses were run with the packages *lme4* (Bates et al., 2015) and *lmerTest* (Kuznetsova et al., 2017).

To test for the Attraction Search Effect, we tested whether the Attraction Search Score was significantly larger than zero. The mean Attraction Search Score of subjects was $M_{ASS} = 0.32$ and was significantly larger than zero, $t(302) = 14.55$, $p < .001$, $d = 0.84$ (see Figure 3 for the distribution of individual Attraction Search Scores in all experiments). We also looked at the Attraction Search Scores per cue-value pattern.[5] The Attraction Search Score was also significantly larger than zero when looking at the three patterns separately, $M_{Pattern1} = 0.25$, $t(302) = 6.06$, $d = 0.35$, $M_{Pattern2} = 0.26$, $t(302) = 8.29$, $d = 0.48$, and $M_{Pattern3} = 0.46$, $t(302) = 13.62$, $d = 0.78$, all $ps < .001$. Note, however, that comparing the Attraction Search Scores of the separate patterns required comparing across different scenarios. To account for this, we also calculated the Attraction Search Scores for each scenario across subjects.[6] As shown in Figure 4, all scenario-wise Attraction Search Scores were above zero; however, there was substantial heterogeneity in the sizes of the scenario-wise Attraction Search Scores.

One explanation for the heterogeneity of the Attraction Search Scores on the scenario level might be that our assumed subjective importance of cues did not match subjects' subjective importance. Looking at the subjective importance ratings, our assumed ordering of cues was mostly matched by the importance ratings of subjects. Subjects' mean subjective importance ratings can be found in Table A1 in the Appendix 7.2. Substantial differences occurred in the *Hotel* scenario, in which subjects considered the last cue as most important. Further, in the *Job* and in the *City Size* scenarios, subjects considered the second cue as more important than the first, more so for the *City Size* scenario.

As the Attraction Search Score aggregated over subjects and content scenarios, we also ran a generalized linear mixed model analysis to investigate the variation across these variables. In this model, the dependent variable was whether subjects searched for Option A in any given trial. The effect-coded predictor in this model was whether Option A was attractive in this trial (Version a; +1) or not (Version b; −1). A significant, positive regression weight for the predictor *version* would indicate an information-search pattern consistent with the Attraction Search Effect. To account for

subject.

[5]As every subject saw each version of every cue-value pattern only once, this analysis rested on only one trial of Version a and one trial of Version b for each pattern and each subject.

[6]As there were no within-subjects repetitions of scenarios, this method resulted in one Attraction Search Score per scenario only and therefore did not allow any statistical inferences about whether the Attraction Search Score for each scenario was larger than zero.

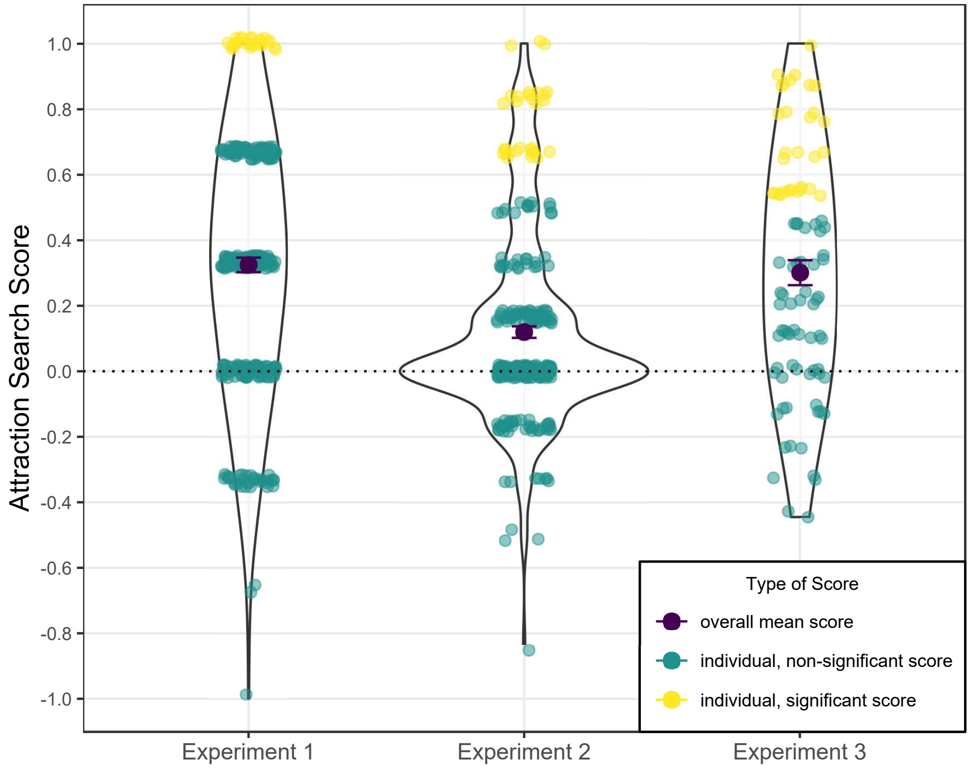

Figure 3: Distribution of individual Attraction Search Scores in all three experiments. The violet points represent the mean Attraction Search Score in each experiment and error bars the standard errors of those means. Attraction Search Scores of zero indicate information search that is independent of the currently available evidence. Thus, every data point above zero indicates that an individual showed a tendency to search for information on the currently attractive option. Yellow points indicate individuals showing a significant ($p < .050$) score at the individual level according to a one-tailed binomial test. The number of trials required for significance is 6 out of 6, 12 out of 14, and 14 out of 18 in Experiments 1–3, respectively.

variation in the data, we implemented a maximum random effects structure with random intercepts for subjects and content scenarios, as well as random slopes for *version*.

The results of this generalized linear mixed model showed that subjects were in general more likely to search for information on Option A given that this option was attractive, $\beta = 0.75$, $SE = 0.11$, $z = 6.77$, $p < .001$ (see Table B1 and Table B2 for all model estimates). More precisely, the probability of searching information for Option A increased from 21.7% in Version b to 55.5% in Version a of the patterns. The effect of pattern version varied across subjects as well as content scenarios (see Figure 6). Specifically, the heterogeneity of the content scenarios matched the one we observed in the aggregated results.

To check whether we could explain some of the heterogeneity when accounting for differences due to cue-value patterns, we added a Helmert-coded *cue pattern* predictor to the mixed model[7] as well as the interaction of *cue pattern* and *version*. The effect of *version* remained positive and significant, $\beta = 0.88$, $SE = 0.13$, $z = 6.84$, $p < .001$. Additionally, there was a significant effect that subjects were less likely to search for Option A when faced with Pattern 2 than when faced with Pattern 1, $\beta = -0.80$, $SE = 0.07$, $z = -10.75$, $p < .001$. Further, the effect of *version* on information search depended on *cue pattern*, such that the *version* effect was the most pronounced for Pattern 3 when comparing it to the other two cue-value patterns, $\beta = 0.15$, $SE = 0.04$, $z = 3.72$, $p < .001$. There also was a larger effect for Pattern 1 compared to Pattern 2, $\beta = 0.16$, $SE = 0.07$, $z = 2.14$, $p = .032$.

4.3 Discussion

The first experiment shows strong support for the Attraction Search Effect in semantic contexts different from the hypothetical stock-market game originally used by Jekel et al. (2018). Subjects tended to search for information about the more attractive option in all of the three cue-value patterns as

[7]With the Helmert-coding, two predictors were added to the model: one, comparing Pattern 3 (+2) against Pattern 1 (−1) and 2 (−1), and therefore comparing the cue-value pattern with the strongest effect against the other two cue-value patterns. The other predictor compared Pattern 2 (+1) against Pattern 1 (−1).

https://doi.org/10.1017/S193029750000615X Published online by Cambridge University Press

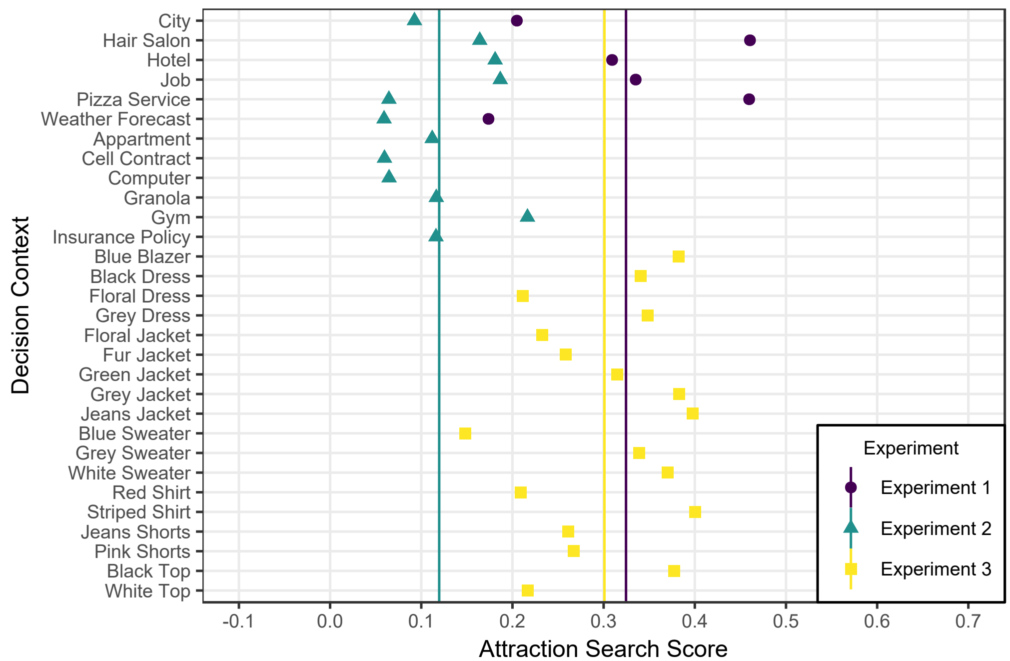

Figure 4: Distribution of Attraction Search Scores for each decision context in all three experiments. The lines represent the mean Attraction Search Scores across subjects and scenarios in the respective experiments.

well as in every content scenario. The effect sizes as well as the absolute Attraction Search Scores overall and for the separate cue-value patterns mirror those from Jekel et al. (2018) in their study without information search costs (for the Attraction Search Scores in Jekel et al. (2018) experiments see Figure 5).

Our mixed model analyses reveals that the strength of the Attraction Search Effect differs between individuals as well as semantic contexts. The differences in effect size for the semantic contexts might be due to the fact that our assumed subjective importance ordering did not always match those of subjects. This assumption is supported by the fact that among the weakest predicted effects for decision context are the City and the Hotel Scenario.[8] Both semantic contexts showed on average a different ordering in subjects' importance ratings. In sum, we replicated the results from Jekel et al. (2018) in a more diverse setting, however, while still using the cue-value patterns that were specifically designed to elicit the Attraction Search Effect. Therefore, it is an important next step to show that the Attraction Search Effect can be found with different cue-value patterns.

[8]A mixed logistic regression directly investigating the effect of subjective importance orderings on the Attraction Search Effect is reported in Appendix 7.2. It includes the individual rank correlations of the intended and the individually rated cue order per scenario and hints at a moderating effect of the ordering of importance ratings on the Attraction Search Effect. However, see also Appendix 7.2 for a caveat of this analysis.

5 Experiment 2: Extension to different cue patterns

In the second experiment, we extended the results from the first experiment by testing whether the Attraction Search Effect can be found in more diverse semantic contexts and even without using specifically designed, highly diagnostic cue patterns. Therefore, we did not present any information before search and manipulated only the valence of the first cue value subjects searched for while randomizing the valence of the remaining cue values. This experiment and the respective hypothesis were preregistered (Open Science Framework; Scharf et al., 2017, osf.io/j7vg4).

5.1 Method

5.1.1 Materials

In addition to the six decision scenarios used in the first experiment, we developed six further decision contents, ranging from renting a new apartment to deciding on a new gym or to buying a new computer (all scenarios and cues can be found in Table 2).

We presented a completely closed mouselab matrix to our subjects. In this matrix, the valences for all but the first opened cue values were randomly assigned. The valence of the first searched-for cue value was counterbalanced, to achieve an experimental manipulation of the attractiveness of options. This manipulation thus ensures that in six of the

https://doi.org/10.1017/S193029750000615X Published online by Cambridge University Press

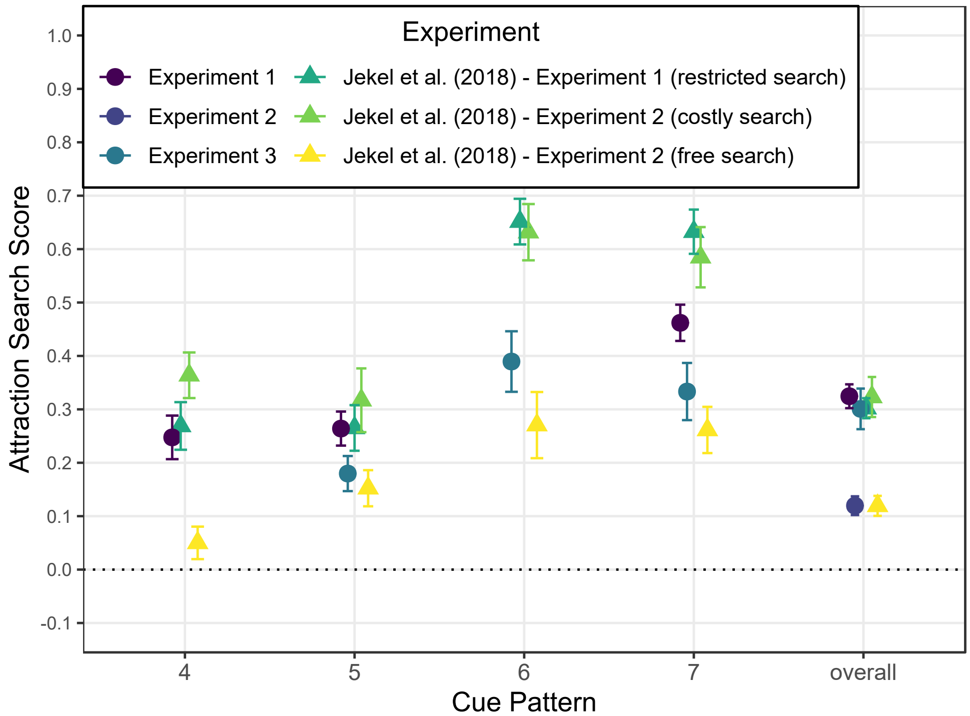

FIGURE 5: Mean Attraction Search Scores for each cue-value pattern and overall from all three experiments in comparison with the Attraction Search Scores from Jekel et al. (2018). The triangles represent the mean Attraction Search Scores from the first two studies by Jekel et al. (2018) for each pattern and overall. Cue-pattern names on the x axis are the original names from Jekel et al. (2018): Patterns 4, 5, and 7 correspond to Patterns 1, 2, and 3 in Experiment 1, respectively; Patterns 5, 6, and 7 correspond to Patterns 1, 2, and 3 in Experiment 3, respectively.

twelve trials the first searched-for cue value yielded positive information (and thus made the first searched-for option attractive) whereas in the other six trials the first searched-for cue value yielded negative information (and thus made the first searched-for option unattractive). It is important to note that it did not matter which specific piece of information subjects searched for first for this manipulation to take effect.

To control whether subjects complied with instructions and read the decision scenarios, we included a decision scenario recognition test. After subjects completed the decision trials, they were asked to identify on which topics they had just decided. For this purpose, they were shown six out of the twelve original decision scenarios and six distractor scenarios. If they answered more than two scenarios incorrectly, subjects were excluded from analysis.

5.1.2 Measures

As we did not use the cue-value patterns from the original study by Jekel et al. (2018), we computed the individual Attraction Search Scores as the difference of the probability of switching options between the first and the second information search across subjects and scenarios when the initial evidence was negative vs. positive; $\textit{Attraction Search Score} = p(\textit{switching options}|\textit{initial negative information}) - p(\textit{switching options}|\textit{initial positive information})$.[9] Switching options when the initially found evidence is negative is consistent with the Attraction Search Effect, while switching options when the initially found evidence is positive is inconsistent search behavior. Therefore, as in the first experiment, if the Attraction Search Score is larger than zero, subjects show more behavior in line with the Attraction Search Effect.

5.1.3 Design and procedure

We manipulated the valence of the first clicked-on cue value (positive vs. negative) within-subjects. As Jekel et al. (2018) showed that the Attraction Search Effect is stronger when information search is costly, we additionally tried to induce a sense of search costs by restricting the number of possible searches per trial (either three, five, or seven searches). We opted for restricting information search instead of implementing explicit search costs, as implementing monetary search costs is difficult in preferential decision tasks, especially with hypothetical tasks conducted online. Since the Attraction Search Effect requires available information to

[9]The probabilities were calculated based on six trials with initial positive information and six trials with initial negative information for each subject.

https://doi.org/10.1017/S193029750000615X Published online by Cambridge University Press

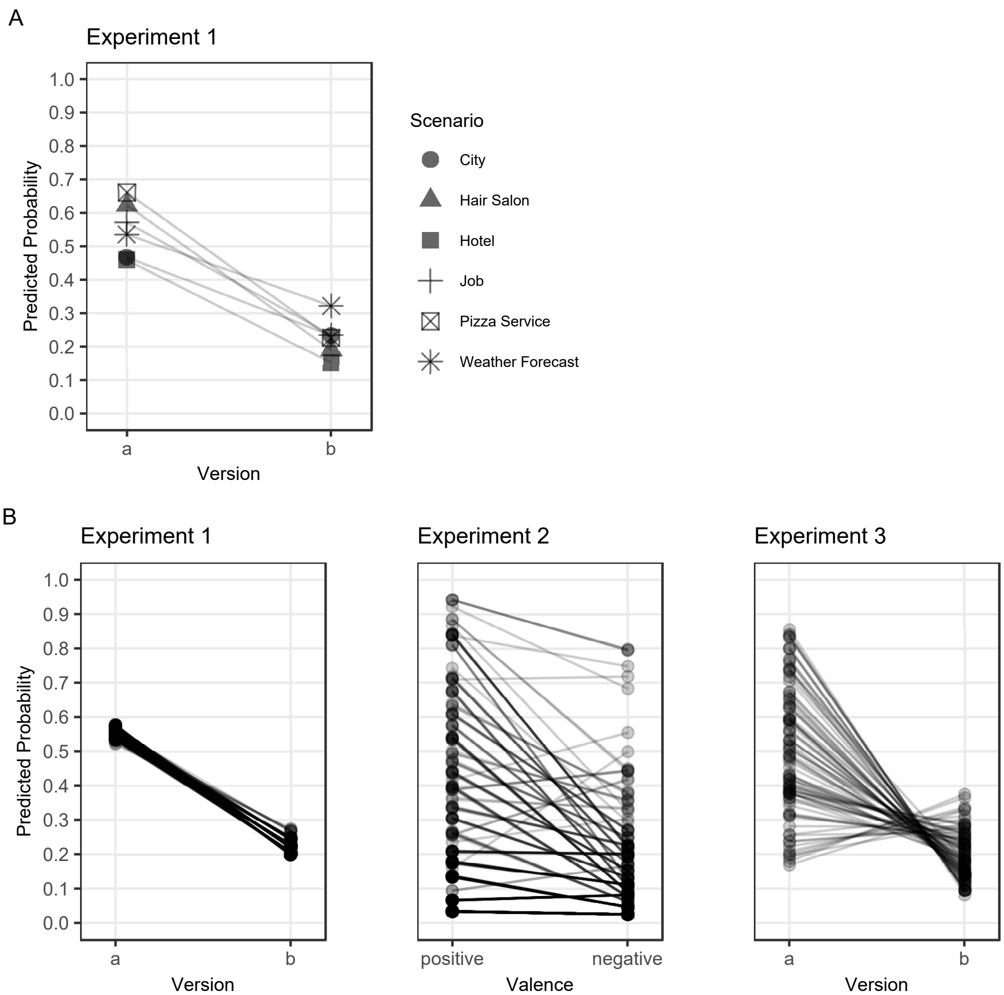

FIGURE 6: Predicted probabilities of searching for Option A (Experiment 1 and 3) or of searching for the same option (Experiment 2) based on random slopes of mixed logistic regression analyses. The plot under A represents the random slope for the different decision scenarios in Experiment 1, the plots under B represent the random slopes for subjects in all three experiments. These plots can be read as follows: the more negative the slope between Version a and b (or positive and negative initial valence in Experiment 2, respectively), the stronger the predicted Attraction Search Effect for this scenario or subject.

take effect, restricting search to one piece of information as in the original experiments by Jekel et al. (2018) is not possible in a completely closed matrix. In order to restrict information search and at the same time to avoid subjects immediately opening the fixed amount of information granted to them, we opted for restricting information search variably from trial to trial without subjects knowing beforehand how much information they could open in this specific trial. This way, every piece of information subjects chose to open during a trial should rationally be the most informative piece of information they could choose, as it could be their last piece of information. Therefore, subjects were not informed about the restriction of search before starting a trial but were only informed whenever they opened the maximal number of possible information for the trial. It is important to note that information search was restricted only in the sense that subjects could not open more information — they were free to search for less information than the allowed amount per trial given they opened at least one cue value.

The order of trials and thus the valence of the first cue value and the amount of search was randomized for each subject. After following the link to the online study, subjects first gave their consent for participating in the study. Following a practice task, subjects started working on the actual decision trials. Before each trial, subjects were presented with a brief introduction into the ensuing content scenario. Subjects had to open one piece of information in every trial. They could then search for either two, four, or six additional pieces of information; however, they did not know how many pieces of information they could search for in a specific trial.

TABLE 2: Additional content scenarios and cues in Experiment 2.

Granola	**Gym**
Amount of Dietary Fiber	Monthly Pay
Number of Calories	Offered Courses
Proportion Organic Ingredients	Equipment
Proportion Fairtrade Ingredients	Opening Hours
Computer	**Apartment**
Price	Proximity to City Center
Speed	Sufficient Lighting
Design	Square Footage
Loudness	Friendliness of Neighbors
Insurance Company	**Cell Contract**
Coverage	Monthly Pay
Monthly Pay	Network Reception
Accessibility in Case of Damage	Number of Free Minutes
Customer Friendliness	Data Volume

Note. Scenario names are printed in bold font, the four cue names are printed underneath the respective scenario name.

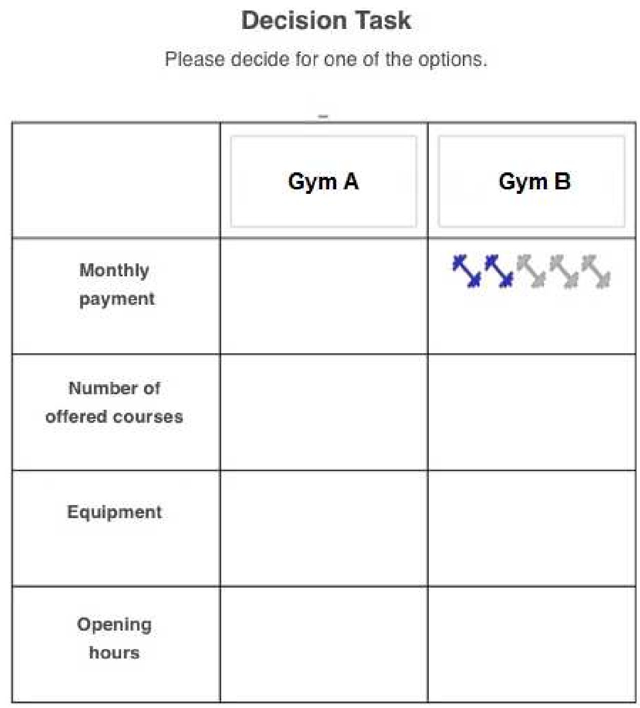

FIGURE 7: A translated screenshot of the decision task in Experiment 2. In the current trial, the valence of the first opened information was negative (2 of 5 dumbbells). Subjects could search for information by clicking on the empty boxes in the matrix. Then the respective cue value would appear. Afterwards, they chose one of the options by clicking on the button around the options.

When subjects reached the limit of searchable information in a trial, they were informed that they could no longer search for additional information and that they had to decide now (for an example trial of the decision task see Figure 7). After completing all 12 trials, subjects had to work on the recognition task, in which they had to identify six of the original content scenarios among a list with additional six distractor scenarios.[10] After finishing this task, subjects went on to provide some demographic details about themselves and then could decide whether they wanted to receive course credit; participate in the lottery, in which they could win one of ten 10€-online shop gift certificates; or neither of these two options. Finally, subjects were debriefed and thanked for their participation.

5.1.4 Subjects

An a-priori power analysis assuming $\alpha = \beta = .05$ for a one-tailed one sample t test and a small Attraction Search Effect with a Cohen's $d = 0.20$ yielded a sample size of 272 subjects (Faul et al., 2007). Due to expected dropout, a sample of 300 subjects was aspired to collect. The stopping rule was to either stop data collection after two months or when 300 subjects were collected. The study was programmed with *lab.js* (Henninger et al., in press) in conjunction with the *Multi-Attribute Decision Builder* (Shevchenko, 2019). The original sample included 305 completed data sets. From these 305 subjects, eight subjects were excluded because data were not saved for all of the twelve decision trials. Thus, the complete sample included a sample of 297 subjects (230 female, 1 other, $M_{age} = 22.9$, $SD_{age} = 5.6$). Seventeen subjects were excluded because they answered more than two questions incorrectly in the recognition test. After exclusion, a total of 280 subjects remained in the final sample (217 female, 1 other, 84.6% university students). The mean age of the sample was $M_{age} = 22.8$ ($SD_{age} = 5.6$, range 18–63).

5.2 Results

5.2.1 Preregistered analyses

To test whether the Attraction Search Effect emerged in a preferential decision task without specifically designed patterns, we calculated the Attraction Search Score for each subject over all trials. As predicted, the Attraction Search Score was significantly larger than zero $M_{ASS} = 0.12$, $t(279) = 6.82$, $p < .001$, Cohen's $d = 0.41$. Thus, we

[10]Due to an error in the programming of the experimental software, some subjects were presented with only five distractors and seven targets instead of six of each. As there is no difference in performance in the recognition task between subjects who saw seven targets and subjects who saw six targets, we still used the recognition test data for exclusion, $M_{correct,6targets} = 0.96$, $M_{correct,7targets} = 0.95$, $t(284.41) = 0.73$, $p = .464$

https://doi.org/10.1017/S193029750000615X Published online by Cambridge University Press

found evidence for the Attraction Search Effect in different semantic contexts and closed cue-value patterns.

5.2.2 Additional exploratory analyses

To compare the heterogeneity between decision scenarios to the first experiment, we also calculated the Attraction Search Scores for each scenario across subjects. As shown in Figure 4, all scenario-wise Attraction Search Scores were above zero and there was less heterogeneity between scenarios compared to Experiment 1.

To account for the multi-level structure of the data and to explore the heterogeneity between scenarios further, we also ran a generalized linear mixed model analysis comparable to that in Experiment 1. In this model, the dependent variable was whether subjects continued to search for the same option as in their first search in any given trial. The predictor was whether the valence of the first opened cue value was positive or negative. Again, a significant, positive regression weight for the predictor *valence* would indicate an information-search pattern consistent with the Attraction Search Effect. To account for variation in the data, we implemented a model with random intercepts for subjects and content scenarios as well as a random slope for *valence* for subjects.[11]

The results of this generalized linear mixed model showed that subjects were in general more likely to stay with the searched-for option when the first opened cue value was positive, $\beta = 0.38$, $SE = 0.11$, $z = 3.58$, $p < .001$ (see Table B1 and Table B2 for all model estimates). Specifically, the probability of staying with the searched-for option increased on average from 6.5%, when the first opened cue value was negative, to 12.9%, when the first cue value was positive. The results for the random effects showed considerable variance of the effect of *valence* between subjects (see Figure 6).

Looking at the distribution of the Attraction Search Score values in Figure 3 and the heterogeneity of the individual effects in the mixed model, it was apparent that there is a large proportion of subjects that did not show the Attraction Search effect. In fact, the median of the overall Attraction Search Score distribution was $Md_{ASS} = 0$. One difference between subjects with an Attraction Search Score of zero and subjects with a non-zero Attraction Search Score was the amount of searched cue values. Subjects with an Attraction Search Score of zero tended to search for more cue values, $M_{ASS=0} = 4.72$, than subjects with a non-zero Attraction Search Score, $M_{ASS\neq 0} = 4.57$, $t(277.09) = -2.61$, $p = .010$, Hedge's $g = -0.31$. Additionally, we found that subjects with higher individual Attraction Search Scores tended to take longer to open the first cue value, $r(278) = .341$, $p < .001$.

To further investigate subjects who had an Attraction Search Score of zero, we hypothesized that some subjects used predetermined, fixed search strategies. To test this assumption, we formulated three different search strategies: strictly cue-wise, lenient cue-wise, and strictly option-wise information search.[12] The strictly cue-wise search was defined as subjects starting to search for information on one option's side, continuing their search on the same cue on the other option's side, and then returning to the first option's side for the ensuing search and so on. The lenient cue-wise search also was defined as always searching for two pieces of information from the same cue consecutively but did not require to always start the search on the same option. The strictly option-wise search was defined as searching information on one option until all information for this option was acquired and then switching to the other option. On average, subjects used a strictly cue-wise search strategy in 39.1% ($SD = 25.0$), a lenient cue-wise search strategy in 23.7% ($SD = 17.9$), and an option-wise search strategy in 7.1% ($SD = 14.2$) of trials. In 30.1% ($SD = 23.4$) of trials, subjects' information-search pattern could not be classified as belonging to one of the aforementioned strategies. Thus, in over half of all trials some kind of fixed cue-wise search strategy was used.

In order to test whether the occurrence of Attraction Search Scores of zero could be explained by subjects using predetermined search strategies, we correlated the individual Attraction Search Scores with the number of trials of each subject belonging to one of formulated search strategies. Indeed, the correlation of individual Attraction Search Scores and the number of trials in which subjects searched strictly cue-wise was negative, $r = -.31$, $n = 280$, $p < .001$; indicating that subjects who searched for information strictly cue-wise in more trials had lower Attraction Search Scores. The results were similar for the lenient cue-wise strategy for which the correlation was negative as well, $r = -.16$, $n = 280$, $p = .008$. For the number of trials searched following an option-wise strategy, we found a positive correlation, $r = .28$, $n = 280$, $p < .001$. The correlation between the number of unclassified trials per subject and the individual Attraction Search Scores was also positive, $r = .28$, $n = 280$, $p < .001$. Therefore, subjects with a low Attraction Search Score had a stronger tendency to search for information consistent with a pre-determined, cue-wise search strategy.

To analyze the influence of strategies on the trial level, we ran the same mixed logistic regression as described above and added the count of trials following any of the above-

[11]The maximum random model structure did not converge. This random effects structure was achieved by starting with the maximum random structure, then to first exclude correlations between random effects and then to remove the random slope(s) with the smallest variance until the model converged.

[12]We did not calculate the often used Payne Index (Payne, 1976), as this index is biased if the number of options is not equal to the number of cues (Böckenholt & Hynan, 2006).

mentioned strategies as a predictor.[13] In this model, the probability of searching for the same option was 12.6% when finding initial positive evidence compared to 6.2% when finding initial negative evidence, $\beta = 0.38$, $SE = 0.11$, $z = 3.63$, $p < .001$ (see Table B1 and Table B2 for all model estimates). Additionally, the more trials in which a subject showed information-search behavior that followed a specific strategy the less likely she was to continue to search for the same option, $\beta = -0.41$, $SE = 0.04$, $z = -9.99$, $p < .001$. The number of trials following a search strategy also influenced the strength of the effect of the first opened cue value, $\beta = -0.09$, $SE = 0.03$, $z = -2.71$, $p = .007$. This interaction took the effect that if no strategy was used in any trial, the predicted probability of searching for the same option when the initial information was positive was 90.4% compared to 51.0% when the initial information was negative. On the other hand, when an information search strategy was used in every trial, the predicted probability of searching for the same option was 2.3% when the initial information was positive and 2.0% when the initial information was negative. Note that the overall effect of searching with a strategy was negative because cue-wise search strategies, which had a negative effect on the Attraction Search Score, were much more common (in total 62.8% of trials) than option-wise search strategies (7.1% of trials), which had a positive effect on the Attraction Search Score.

5.3 Discussion

In the second experiment, we took a step further away from the original setup of Jekel et al. (2018) by extending the range of semantic contexts and using closed cue-value patterns with randomized cue values. The results show that the Attraction Search Effect emerges under these conditions as well and, thus, does not appear only when using highly diagnostic cue-value patterns. Further, in contrast to the first experiment, the effect of the valence manipulation did not differ between decision contexts and there were systematic differences only in how likely subjects were to continue to search for the same option in different contexts. The systematic differences in the valence effect between different scenarios might be absent because in this experiment the prediction of the Attraction Search Effect did not require the subjects to have the correct subjective importance ordering. Rather, we assumed that the first opened cue is likely to be the most valid cue.

We did observe a considerable drop in effect size in the second experiment compared to the first. This drop is due to a large number of subjects who had an Attraction Search Score of zero. This finding is also supported by the large variability due to subjects in the mixed model analysis. The heterogeneity can partly be explained by looking at subjects' search behavior: Subjects with Attraction Search Scores of zero tended to search for more information. Additionally, subjects with lower Attraction Search Scores tended to open the first cue value faster and searched for information in a cue-wise fashion in more trials. The results of the mixed logistic regression corroborate these findings by showing that the Attraction Search Effect is weakened the more subjects followed specific information search strategies on the trial level. Taken together, these exploratory results show similarities to Jekel et al.'s (2018) results in the condition without search costs. Jekel et al. (2018) showed that subjects searched for more information faster and that individual Attraction Search Scores were considerably reduced when no information search costs were implemented. Thus, the results of Experiment 2 indicate that the restriction of search might not have been strong enough to induce a sense of search costs.

Besides the aforementioned limitations, we still found a medium-sized Attraction Search Effect in an experiment that did not rely on a specific semantic context or specifically designed cue-value patterns. Thus, the results of this experiment emphasize the overall robustness of the effect and the range of applicability of iCodes.

[13] The individual count was mean-centered across subjects for this analysis.

Table 3: Version a and Version b of cue patterns used in Experiment 3.

	Pattern 1		Pattern 2		Pattern 3	
	A	B	A	B	A	B
Cue 1	+(−)	?	+(−)	−(+)	+(−)	−(+)
Cue 2	+(−)	?	?	?	?	?
Cue 3	?	?	+	−	+	−
Cue 4	?	?	−	+	−	?

Note. + = positive cue value, − = negative cue value, ? = hidden, searchable cue value; Version a of patterns is displayed, cue values in parentheses are from Version b. Patterns 1, 2, and 3 correspond to Patterns 5, 6, and 7, respectively, in Jekel et al. (2018).

6 Experiment 3

Experiment 3 varied another aspect of the decision task that has been kept constant in Jekel et al.'s (2018) studies and in our studies so far: the way in which information is presented. Until now, every experiment testing the predictions of iCodes has used the matrix presentation of the classic mouselab task. It has been shown that the way information is presented influences information-search behavior (Bettman & Kakkar, 1977; Ettlin et al., 2015). Presenting information in a matrix organizes the information for the decision

https://doi.org/10.1017/S193029750000615X Published online by Cambridge University Press

maker and this organization in turn influences search behavior (Schkade & Kleinmuntz, 1994). Thus, in this experiment we test whether the Attraction Search Effect still emerges in a quasi-realistic online shop setting. The subjects' task in this experiment was to imagine being a buyer for an online clothing shop and to buy clothes online. In addition, as the two previous experiments were both run in German and with German samples, we decided to collect data from a different, non-German subject pool via the platform Prolific (Palan & Schitter, 2018). This experiment and our hypothesis were preregistered (Open Science Framework; Scharf et al., 2018, osf.io/nfruq).

6.1 Method

6.1.1 Materials

Cue patterns. As in Experiment 1, we again used a subset of the original cue-value patterns from Jekel et al. (2018). As described above, each pattern has two versions that differ in which option is currently more attractive. For this experiment, we selected three from the original eight patterns, displayed Table 3. Pattern 2 and Pattern 3 were chosen because they elicited the strongest and the second strongest Attraction Search Effect in the original studies. Pattern 1, which elicited the fourth strongest Attraction Search Effect in the original studies, was chosen to include a pattern that showed a strong effect but at the same time has more than three searchable cue values. Thus, the addition of Pattern 1 was supposed to increase the variability between patterns. Each pattern in both versions was presented three times, leading to a total number of 18 trials per subject.

Shop items. We used images of 18 different items of clothing for this experiment. These articles of clothing were each described by customer ratings on four attributes. Subjects were told that these attributes differed in their relative importance for the online shop they are shopping for. The attributes in the order of their importance were the fit of the clothes, the comfort of the fabric, the availability of sizes, and the ease of care. The customer ratings were dichotomized, such that a negative overall rating of one of the attributes was described by two stars and a positive overall rating was described by five stars. To increase the realism of the online shop, each item was assigned a fictional brand name (four-letter pseudowords adapted from Stark & McClelland, 2000) and a fictional brand logo. In each trial, subjects had to decide between the same article of clothing that differed in their brands and the customer ratings of their attributes only. An example trial is displayed in Figure 8.

6.1.2 Measures

Just as in Experiment 1, we computed the individual Attraction Search Scores as the difference of the probability of searching for Option A in the nine trials of Version a vs. of Version b across articles of clothing, $Attraction\ Search\ Score = p(Searching\ Option\ A \mid Version\ a) - p(Searching\ Option\ A \mid Version\ b)$.[14]

Figure 8: A screenshot of the decision task in Experiment 3. The current cue-value pattern is Pattern 3 in Version b. Subjects could search for information by clicking on the number under the cue name. The number indicated the importance of the cue for the decision, with "1" representing the most important attribute and "4" representing the least important attribute. Then the respective cue value would appear. Afterwards, they chose one of the options by clicking on its "Add to cart" button.

6.1.3 Design and procedure

All subjects were presented with all cue-value patterns in both versions and all shop items in a total of 18 trials (3 cue-value patterns x 2 pattern versions x 3 repetitions). Note that the cue patterns were repeated but not the items of clothing. The order of trials as well as the combination of cue-value patterns, shop items, logos, and brand names were randomized for each subject. We further balanced presentation of the cue-value patterns for the repetitions, such that Option A of each pattern was once on the left side, once on the right side, and assigned to a side randomly for the third repetition. The online experiment was programmed in *lab.js* (Henninger et al., in press) and run via the platform Prolific (Palan & Schitter, 2018). Subjects received £1.10 for their participation. Before working on the actual task, subjects agreed to an informed consent form and read the instructions for the task.

Subjects were asked to imagine that they work as a buyer for an online clothing shop and that their task was to choose

[14] Due to the three repetitions of each cue pattern, Version a and Version b were each presented nine times.

18 different articles of clothing in order to restock their employer's warehouse. We included three questions about the instructions that had to be answered correctly before the subjects could continue with the actual task. The number of repetitions it took to answer these questions correctly were used as an exclusion criterion, such that when subjects had to repeat these questions more then once they were excluded from analysis. During the task, subjects were allowed to search one additional piece of information, after which they had to decide which article of clothing they wanted to buy. Before finishing the study, subjects were asked to provide some demographic information and were then thanked for their participation.

6.1.4 Subjects

In a student project conducted to pretest the materials, we found an Attraction Search Effect with an effect size of Cohen's $d = 1.34$ with $N = 312$. As the current experiment was run in a non-German and likely more diverse sample, we decided to be rather conservative for our sample-size rationale. A sensitivity analysis revealed that we could find an effect of Cohen's $d = 0.33$ for a one-sided one-sample t-test with an $\alpha = \beta = .05$ and a sample of $N = 100$ subjects. As we expected some experimental mortality due to the fact that this experiment was run online, we aimed to collect 10% more than the needed sample, which resulted in a total sample size of 110 subjects. We collected data of $N = 110$ subjects, from which $N = 99$ were complete data sets (48 female, 1 other, $M_{age} = 31.3$, $SD_{age} = 10.0$). Ten subjects were excluded because they had to repeat the instruction check two or more times which resulted in a final sample of $N = 89$ (44 female, 1 other, 16.9% university students). The mean age of the sample was $M_{age} = 31.3$ ($SD_{age} = 10.0$, Range 18–60). All but one subject indicated that they were native English speakers.

6.2 Results

6.2.1 Preregistered analyses

Just as in the first and the second experiment, we hypothesized that the average Attraction Search Score is significantly larger than zero. In order to test this hypothesis, we calculated the individual Attraction Search Scores for all subjects. The mean Attraction Search Score was $M_{ASS} = 0.30$, $t(88) = 7.92$, $p < .001$, Cohen's $d = 0.84$. Therefore, we found evidence for subjects' search behavior being consistent with iCodes's predictions even when the cue-value information was not presented in a matrix.

6.2.2 Exploratory analyses

As a first exploratory analysis, we tested whether we could find an Attraction Search Score larger than zero when looking at the three patterns separately.[15] Each pattern yielded a significantly positive Attraction Search Score, $M_{Pattern1} = 0.18$, $t(88) = 5.47$, $d = 0.58$, $M_{Pattern2} = 0.39$, $t(88) = 6.87$, $d = 0.73$, and $M_{Pattern3} = 0.33$, $t(88) = 6.23$, $d = 0.66$, all $p < .001$. We also calculated the Attraction Search Scores for each article of clothing, which can be found in Figure 4. The heterogeneity between items of clothing seemed to be more pronounced than in Experiment 2 but somewhat less pronounced than in Experiment 1.

We also ran a generalized linear mixed model for Experiment 3. Just as in Experiment 1, the dependent variable was whether subjects searched for Option A in any given trial and the effect-coded predictor was whether Option A was attractive in that trial (Version a; +1) or not (Version b; −1). To account for variation in the data, we added random intercepts for subjects and content scenarios as well as a random slope for *version* for subjects.[16]

The results showed that subjects were on average more likely to search for information on Option A given that this option was attractive, $\beta = 0.76$, $SE = 0.10$, $z = 7.18$, $p < .001$ (see Table B1 and Table B2 for all model estimates). Specifically, the probability of searching information for Option A increased from 18.5% in Version b of the pattern to 51.0% in Version a of the pattern. At the same time, the effect of pattern version varied across subjects systematically, as shown in Figure 6.

To try to explain some of the inter-individual variance in the effect, we added the Helmert-coded *cue pattern* predictor[17] to the model. The effect of *version* was still significantly positive in this model, $\beta = 0.91$, $SE = 0.14$, $z = 6.60$, $p < .001$, indicating that the probability of searching for Option A increased from 14.3% in Version b to 50.8% in Version a. There were also significant effects for both pattern predictors, indicating that subjects were more likely to search for Option A in Pattern 2 compared to Pattern 1, $\beta = 1.36$, $SE = 0.11$, $z = 12.96$, $p < .001$, as well as in Pattern 3 compared to Pattern 1 and 2, $\beta = 0.18$, $SE = 0.05$, $z = 3.81$, $p < .001$. However, there was no significant interaction between the *cue pattern* and the *version* predictors, $ps > .100$.

[15] This analyses included three observations of Version a and three observations of Version b for each subject and each cue-value pattern.

[16] The maximum random model structure did not converge with a random slope for *version* for decision scenarios. Just as in Experiment 2, this random effects structure was achieved by starting with the maximum random structure and then excluding correlations between random effects and random slopes with the least variance successively until the model converged.

[17] Due to the Helmert coding, two predictors were added to the model: the first compared Pattern 3 (+2) against Pattern 1 (−1) and 2 (−1); the second compared Pattern 2 (+1) against Pattern 1 (−1).

https://doi.org/10.1017/S193029750000615X Published online by Cambridge University Press

6.3 Discussion

The results of Experiment 3 show that the Attraction Search Effect is not restricted to a matrix presentation format but can also be found in a more realistic, less restrictive setting. The effect sizes of the separate cue patterns as well as the absolute Attraction Search Scores are comparable to those of Jekel et al. (2018) in the condition without search costs (see Figure 5), as all three patterns show a medium to large effect. The results plotted in Figure 3 further show that, albeit not restricted to the original cue-value patterns, the effect is more pronounced with the original cue-value patterns, when comparing the results of Experiment 2 with Experiment 3. We do not find the same level of heterogeneity between decision contexts in Experiment 3 compared to the first experiment (see Figure 4). This might be explained by the fact that the decision content is more homogeneous in Experiment 3 compared to Experiment 1 because all decisions were made between articles of clothing. There is also no evidence in the results of Experiment 3 for the same interaction of the cue patterns and the cue pattern version that was found in Experiment 1. The absent interaction is probably due to two reasons: first, the original effect sizes in Jekel et al. (2018) of the cue patterns used in Experiment 3 were more homogenous from the start when compared to the cue patterns from Experiment 1. Second, the interaction between subjective importance of cues and option attractiveness was reduced in Experiment 3 as the ordering of the cues' importance was given at the start of the experiment.

7 General discussion

The Attraction Search Effect is the core prediction by iCodes that states that information search is influenced not only by the validity of the information but also by the attractiveness of the options. Jekel et al. (2018) provided first evidence for this prediction in three experiments that all shared the same task characteristics and the same semantic content. The goal of the current project was to test the range of applicability of iCodes's search predictions. For this purpose, we ran three conceptual replications of the original studies that varied aspects that were kept constant in the original experiments. In the first experiment, we showed that the Attraction Search Effect is not restricted to the probabilistic-inference tasks in Jekel et al.'s (2018) experiments but also emerges in preferential decision tasks in six every-day content domains. The results of the second experiment, which was preregistered, illustrate that the Attraction Search Effect generalizes to a wider range of different semantic contexts and further show that the Attraction Search Effect also emerges without specifically designed and diagnostic cue-value patterns, albeit with a somewhat reduced effect size. In the last experiment, also preregistered, we found evidence that the Attraction Search Effect is also present when one moves away from the classic matrix format of information presentation to a more realistic simulated online-shop setting. Thus, we found evidence for iCodes's information-search prediction in three experiments with in total 627 subjects. These results show that the influence of the already available information on information-search direction is a robust phenomenon that can be found in different variants of the classic multi-attribute decision task. They further strengthen iCodes as a general theory of decision making and information search.

7.1 Limitations and future directions

The results of Experiment 2 show that there are boundary conditions for the generalizability of the Attraction Search Effect. As the second experiment was the only experiment that did not use the cue-value patterns from Jekel et al. (2018) and did not restrict information search to one piece of information, it is likely that the reduced effect size in Experiment 2 was at least partially caused by the change in the experimental setup. The change from specifically designed, diagnostic cue-value patterns to randomized cue-value patterns naturally weakens the effect of the experimental manipulation, as the reduced experimental control due to the randomization of cue values may have increased the noise in the data. The second aspect that was different in Experiment 2 compared to the two other experiments was that search was less restrictive. The original results by Jekel et al. (2018) showed that costly or restricted search is relevant for the strength of the Attraction Search Effect. It is possible that the restriction of search, that varies from trial to trial, we used to implement search costs was not strong enough to elicit a reliable Attraction Search Effect for many subjects who instead opted for a heuristic search strategy. This assumption is supported by the fact that subjects that showed no Attraction Search Effect tended to search for more information and did so faster than subjects that did show the Attraction Search Effect in this experiment, just like subjects in the condition without search costs in Jekel et al. (2018). In fact, individual Attraction Search Scores tended to be lower for subjects that used cue-wise search strategies more often and higher for subjects whose search behavior could not be classified as belonging to one search strategy.

The results of Experiment 2 show that we observed larger interindividual heterogeneity in the Attraction Search Effect than in Experiments 1 and 3 in this paper (see Figure 3). This larger heterogeneity in Experiment 2 was also revealed by the mixed model analyses of all three experiments. The fact that the most variance in individual Attraction Search Effects was found in Experiment 2 hints that the diagnostic cue-value patterns as well as the restricted information search are relevant for the homogeneity and strength of the effect. Future research should tease apart the effects underlying the heterogeneity of the Attraction Search Effect.

The variability of individual Attraction Search Effects in Experiment 2 also points to hidden moderators determining the individual strength of the effect. Jekel et al. (2018) already identified search costs as a moderator of the Attraction Search Effect and the results of Experiment 2 corroborate this finding. A still unanswered question is what happens to the information-search process when information-search costs are introduced. One explanation for the effect of search costs might be that costs increase the deliberation about the search decision (Jekel et al., 2018). This assumption is corroborated by the fact that subjects with a higher Attraction Search Score tend to take slightly longer to search for the first piece of information. A promising avenue for future research is to investigate the role of deliberation in the Attraction Search Effect more closely, for example by employing dual-task (Schulze & Newell, 2016) or time-pressure manipulations (Rieskamp & Hoffrage, 2008; Payne et al., 1988). Further, the emergence of the Attraction Search Effect might be moderated by different individual characteristics. One may assume, for example, that subjects differ in their tendency to focus on the more attractive option (Mather & Carstensen, 2005; Noguchi et al., 2006). When investigating potential moderators of the effect, one should keep in mind that using the original cue-value patterns decreases heterogeneity of the Attraction Search Effect and thus might mask interinidvidual differences.

While finding substantial interindividual differences in the Attraction Search Effect, we find only a little evidence for differences in Attraction Search Effect between content scenarios. Only in Experiment 1 do we find support for differences between decision contexts from the mixed model analyses. This might be due to the fact that in that experiment only the order of subjective importance for the cues was implied rather than explicitly stated (Experiment 3) or inferred from subjects' behavior (Experiment 2). This explanation is further supported by the fact that the same decision scenarios that differed in effect size in Experiment 1 were also included in Experiment 2 and did not show the same variability in that experiment. The findings with regard to decision contexts emphasize the role of cues' importance in the information-search process and, thus, reveals an important variable to control in future investigations of the Attraction Search Effect.

When comparing our results to those from Jekel et al. (2018), we find that the overall Attraction Search Score results from Experiments 1 and 3 are similar to those of the experiments with restricted and costly information search by Jekel et al. (2018), whereas the results from Experiment 2 are comparable to Jekel et al.'s experiment without information search costs (see Figure 5). The effect sizes in our three experiments are considerably reduced compared to the original results, but they are still medium (Experiment 2) to large (Experiment 1 and 3). Next to reducing the level of experimental control in our replications, this decrease is probably also due to the reduced number of trials in our studies, which reduces the reliability of the estimation per individual. Nonetheless, the fact that we are still able to find the Attraction Search Effect with fewer trials opens up the possibility to investigate even more diverse contexts.

One of iCodes' advantages is that it is a fully formalized model that gives process descriptions of a well-documented phenomenon of information search (Doherty et al., 1979; Mynatt et al., 1993; Hart et al., 2009). The formalization of iCodes allows researchers to determine the fit of the observed behavior with model predictions and to compare this fit with the search predictions of other models for information search (Jekel et al., 2018). One prerequisite for fitting iCodes, however, is knowing the exact cue validities, as they heavily influence iCodes predictions. In case of preferential tasks, the importance of cues is difficult to determine due to the subjective nature of the relative importance of the cues. Further, we do not know the relationship between ratings of importance and perceptions of cue validities. In the current experiments, we opted to test iCodes's qualitative predictions for information search only. In order to fit iCodes to search behavior in preferential tasks, one might utilize methods such as conjoint analysis (as, for example, done in Meißner et al., 2015) in order to deduce the individual importance weights.

In this project, we varied the semantic content, the cue-value patterns, and the way of information was presented to test whether the Attraction Search Effect generalizes to various decision settings. However, there are still multiple aspects of the decision situation that have been kept constant between the experiments in this project and the experiments by Jekel et al. (2018). A next step might be to change the way information is presented more radically, for example by randomizing the position of the information on the screen between trials, as has been done for instance in Söllner et al. (2013), so that subjects can not memorize the positions on screen. In addition, it might be interesting to refrain from using variants of the classic decision board altogether by utilizing a procedure in which subjects can naturally search for information by asking questions (Huber et al., 2011). Another characteristic all studies shared was that information search was tracked in a mouselab-type setting via recording mouse clicks on a computer screen. As using the mouselab setup for process tracing might influence information search (Glöckner & Betsch, 2008; Lohse & Johnson, 1996), a fruitful avenue for future research might be to investigate information search with other process-tracing measures such as eye-tracking. Utilizing eye-tracking as a process-tracing method for information search would further allow one to observe information-search behavior in naturalistic settings, such as an actual online shop.

With showing that the Attraction Search Effect appears in diverse settings, we take a step closer to connecting iCodes's predictions to the already existing literature on biased information search. Selective exposure, pseudo-diagnostic search, and leader-focused search have all been investigated in various semantic settings and paradigms (Mynatt et al., 1993; Fraser-Mackenzie & Dror, 2009; Carlson & Guha, 2011). In this project, we could show that the Attraction Search Effect also generalizes to diverse contextual settings. In future research, the iCodes model could be extended in such a way that it can be applied to data from different research paradigms for biased information search. Doing so would allow a bridge to prior research and extend the applicability of iCodes. It would also allow researchers to test which parameters in the iCodes model are affected by manipulations that have been known to influence biased information search (see Hart et al., 2009, for an overview of potential moderators of selective exposure).

7.2 Conclusion

We showed that the Attraction Search Effect, an important prediction of the new iCodes model, is a robust finding that is not restricted to specific decision task settings. The results of the three experiments further highlight that the already available information about choice options is highly relevant for information search and that the direction of information search is not necessarily subject to strict rules but rather is influenced by coherence as well.

References

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1), 1–48, https://doi.org/10.18637/jss.v067.i01.

Bettman, J. R. & Kakkar, P. (1977). Effects of information presentation format on consumer information acquisition strategies. *Journal of Consumer Research*, *3*(4), 233–240, https://doi.org/10.1086/208672.

Bredenkamp, J. (1980). *Theorie und Planung Psychologischer Experimente*. Heidelberg: Steinkopff-Verlag.

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

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

Böckenholt, U. & Hynan, L. S. (2006). Caveats on a process-tracing measure and a remedy. *Journal of Behavioral Decision Making*, *7*(2), 103–117, https://doi.org/10.1002/bdm.3960070203.

Carlson, K. A. & Guha, A. (2011). Leader-focused search: The impact of an emerging preference on information search. *Organizational Behavior and Human Decision Processes*, *115*(1), 133–141, https://doi.org/10.1016/j.obhdp.2010.12.002.

Doherty, M. E., Mynatt, C. R., Tweney, R. D., & Schiavo, M. D. (1979). Pseudodiagnosticity. *Acta Psychologica*, *43*(2), 111–121, https://doi.org/10.1016/0001-6918(79)90017-9.

Ettlin, F., Bröder, A., & Henninger, M. (2015). A new task format for investigating information search and organization in multiattribute decisions. *Behavior Research Methods*, *47*(2), 506–518, https://doi.org/10.3758/s13428-014-0482-y.

Evans, J. S. B. T., Venn, S., & Feeney, A. (2002). Implicit and explicit processes in a hypothesis testing task. *British Journal of Psychology*, *93*(1), 31–46, https://doi.org/10.1348/000712602162436.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191, https://doi.org/10.3758/BF03193146.

Fischer, P. & Greitemeyer, T. (2010). A New Look at Selective-Exposure Effects: An Integrative Model. *Current Directions in Psychological Science*, *19*(6), 384–389, https://doi.org/10.1177/0963721410391246.

Fischer, P., Lea, S., Kastenmüller, A., Greitemeyer, T., Fischer, J., & Frey, D. (2011). The process of selective exposure: Why confirmatory information search weakens over time. *Organizational Behavior and Human Decision Processes*, *114*(1), 37–48, https://doi.org/10.1016/j.obhdp.2010.09.001.

Fraser-Mackenzie, P. A. F. & Dror, I. E. (2009). Selective information sampling: Cognitive coherence in evaluation of a novel item. *Judgment and Decision Making*, *4*(4), 307–316.

Frey, D. (1986). Recent Research on Selective Exposure to Information. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology*, volume 19 (pp. 41–80). Academic Press.

Gigerenzer, G., Dieckmann, A., & Gaissmaier, W. (2014). Efficient cognition through limited search. In P. M. Todd, G. Gigerenzer, & T. A. R. Group (Eds.), *Ecological Rationality: Intelligence in the World*. Cary: Oxford University Press.

Gigerenzer, G. & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669, https://doi.org/10.1037/0033-295X.103.4.650.

Gigerenzer, G. & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. In *Simple heuristics that make us smart*, Evolution and cognition. (pp. 3–34). New York: Oxford University Press.

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

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

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

Glöckner, A., Heinen, T., Johnson, J. G., & Raab, M. (2012). Network approaches for expert decisions in sports. *Human Movement Science*, *31*(2), 318–333, https://doi.org/10.1016/j.humov.2010.11.002.

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666, https://doi.org/10.1016/j.cognition.2014.08.017.

Glöckner, A. & Hodges, S. D. (2010). Parallel constraint satisfaction in memory-based decisions. *Experimental Psychology*, *58*(3), 180–195, https://doi.org/10.1027/1618-3169/a000084.

Hart, W., Albarracín, D., Eagly, A. H., Brechan, I., Lindberg, M. J., & Merrill, L. (2009). Feeling validated versus being correct: A meta-analysis of selective exposure to information. *Psychological Bulletin*, *135*(4), 555–588, https://doi.org/10.1037/a0015701.

Harte, J. M. & Koele, P. (2001). Modelling and describing human judgement processes: The multiattribute evaluation case. *Thinking & Reasoning*, *7*(1), 29–49, https://doi.org/10.1080/13546780042000028.

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

Henninger, F., Shevchenko, Y., Mertens, U. K., & Hilbig, B. E. (in press). lab.js: A free, open, online study builder. *Behavior Research Methods*, https://doi.org/10.5281/zenodo.597045.

Huber, O., Huber, O. W., & Schulte-Mecklenbeck, M. (2011). Determining the information that participants need: Methods of active information search. In M. Schulte-Mecklenbeck, A. Kühberger, & R. Ranyard (Eds.), *A Handbook of Process Tracing Methods for Decision Research: A Critical Review and User's Guide* (pp. 65–85). New York: Psychology Press.

Jekel, M., Glöckner, A., & Bröder, A. (2018). A new and unique prediction for cue-search in a parallel-constraint satisfaction network model: The attraction search effect. *Psychological Review*, *125*(5), 744–768, https://doi.org/10.1037/rev0000107.

Johnson, E. J., Payne, J. W., Bettman, J. R., & Schkade, D. A. (1989). *Monitoring information processing and decisions: The mouselab system*. Technical report, Duke University, Durham, NC, Center For Decision Studies.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*(13), 1–26, https://doi.org/10.18637/jss.v082.i13.

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

Lohse, G. L. & Johnson, E. J. (1996). A comparison of two process tracing methods for choice tasks. *Organizational Behavior and Human Decision Processes*, *68*(1), 28–43, https://doi.org/10.1006/obhd.1996.0087.

Makel, M. C., Plucker, J. A., & Hegarty, B. (2012). Replications in psychology research: How often do they really occur? *Perspectives on Psychological Science*, *7*(6), 537–542, https://doi.org/10.1177/1745691612460688.

Marewski, J. N. (2010). On the theoretical precision and strategy selection problem of a single-strategy approach: A comment on Glöckner, Betsch, and Schindler (2010). *Journal of Behavioral Decision Making*, *23*(5), 463–467, https://doi.org/10.1002/bdm.680.

Mather, M. & Carstensen, L. L. (2005). Aging and motivated cognition: the positivity effect in attention and memory. *Trends in Cognitive Sciences*, *9*(10), 496–502, https://doi.org/10.1016/j.tics.2005.08.005.

Meißner, M., Musalem, A., & Huber, J. (2015). Eye tracking reveals processes that enable conjoint choices to become increasingly efficient with practice. *Journal of Marketing Research*, *53*(1), 1–17, https://doi.org/10.1509/jmr.13.0467.

Mynatt, C. R., Doherty, M. E., & Dragan, W. (1993). Information relevance, working memory, and the consideration of alternatives. *The Quarterly Journal of Experimental Psychology Section A*, *46*(4), 759–778, https://doi.org/10.1080/14640749308401038.

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

Noguchi, K., Gohm, C. L., & Dalsky, D. J. (2006). Cognitive tendencies of focusing on positive and negative information. *Journal of Research in Personality*, *40*(6), 891–910, https://doi.org/10.1016/j.jrp.2005.09.008.

Palan, S. & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22–27, https://doi.org/10.1016/j.jbef.2017.12.004.

Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance*, *16*(2), 366–387, https://doi.org/10.1016/0030-5073(76)90022-2.

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

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge: University Press.

Questback (2016). Unipark EFS Survey (Version 10.9).

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.

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

Scharf, S., Wiegelmann, M., & Bröder, A. (2017). Generalizability of the attraction search effect. (Preregistration.) https://osf.io/j7vg4/.

Scharf, S., Wiegelmann, M., & Bröder, A. (2018). Generalizability of the attraction search effect. (Preregistration). https://osf.io/nfruq/.

Schkade, D. A. & Kleinmuntz, D. N. (1994). Information displays and choice processes: Differential effects of organization, form, and sequence. *Organizational Behavior and Human Decision Processes*, *57*(3), 319–337, https://doi.org/10.1006/obhd.1994.1018.

Schulze, C. & Newell, B. R. (2016). Taking the easy way out? Increasing implementation effort reduces probability maximizing under cognitive load. *Memory & Cognition*, *44*(5), 806–818, https://doi.org/10.3758/s13421-016-0595-x.

Shevchenko, Y. (2019). Multi-attribute task builder. *Journal of Open Source Software*, *38*(4), 1409, https://doi.org/10.21105/joss.01409.

Stark, C. E. L. & McClelland, J. L. (2000). Repetition priming of words, pseudowords, and nonwords. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(4), 945–972, https://doi.org/10.1037/0278-7393.26.4.945.

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

Wells, G. L. & Windschitl, P. D. (1999). Stimulus Sampling and Social Psychological Experimentation. *Personality and Social Psychology Bulletin*, *25*(9), 1115–1125, https://doi.org/10.1177/01461672992512005.

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. New York: Springer-Verlag.

Wilson, T. D., Wheatley, T., Meyers, J. M., Gilbert, D. T., & Axsom, D. (2000). Focalism: A source of durability bias in affective forecasting. *Journal of Personality and Social Psychology*, *78*(5), 821–836, https://doi.org/10.1037/0022-3514.78.5.821.

Appendix A: Results for importance ratings in Experiment 1

These are the results of the cue ratings made by subjects in Experiment 1. Subjects had to answer the question "How important were these dimensions for you when deciding between (decision scenario)?".

Table A1: Mean importance ratings and respective standard deviations of scenarios' cues in Experiment 1.

City Size Scenario		Hair Salon Scenario	
Cue	M_{Rating} (SD)	Cue	M_{Rating} (SD)
State Capital	57.47 (32.66)	Competency	85.16 (22.04)
International Airport	68.05 (29.81)	Price	58.02 (26.02)
University	47.36 (28.24)	Proximity to Home	37.59 (26.62)
Opera	36.99 (29.95)	Scheduling Appointments	36.31 (26.68)
Hotel Scenario		Job Scenario	
Cue	M_{Rating} (SD)	Cue	M_{Rating} (SD)
Proximity to Beach	59.07 (29.51)	Pay	72.41 (23.32)
Price	64.70 (24.84)	Working Conditions	73.52 (27.33)
Proximity to City Center	37.67 (26.01)	Colleagues	64.64 (28.43)
Cleanliness	76.33 (27.15)	Proximity to Home	44.95 (27.35)
Pizza Service Scenario		Weather Forecast Scenario	
Cue	M_{Rating} (SD)	Cue	M_{Rating} (SD)
Quality	89.16 (18.21)	German Weather Service	82.68 (24.89)
Price	55.12 (26.32)	"ZDF" Weather Forecast	63.22 (30.12)
Timeliness	47.25 (28.04)	"BILD" Weather Forecast	23.69 (24.09)
Friendliness	33.33 (27.04)	Horoscope	5.17 (12.54)

Note. Ratings were made on a scale from 0 to 100; the displayed order of the cues in the tables represents the displayed order, and therefore the assumed ranking, of the cues in the experiment.

Appendix B: Results of mixed logistic regressions of all three experiments

Table B1. Variances and correlations of random effects in mixed logistic regressions for Experiment 1–3.

	Model 1		Model 2	
Random Effects	Variance	Correlation	Variance	Correlation
Experiment 1				
Subject				
Intercept	0.04		0.16	
Pattern Version	0.06		0.18	
Intercept, Pattern Version		−.42		−.35
Decision Scenarios				
Intercept	0.07		0.08	
Pattern Version	0.05		0.07	
Intercept, Pattern Version		.00		−.02
Experiment 2				
Subjects				
Intercept	3.12		1.96	
Valence of First Search	0.60		0.59	
Intercept, Valence of First Search		0.40		0.26
Decision Scenarios				
Intercept	0.01		0.01	
Experiment 3				
Subjects				
Intercept	0.11		0.31	
Pattern Version	0.63		1.11	
Intercept, Pattern Version		0.67		0.71
Shop Item				
Intercept	0.05		0.07	

Note. Model 1 represents the mixed logistic regression with only one predictor: *pattern version* in Experiment 1 and 3 and the valence of the first searched-for cue value in Experiment 2. Model 2 includes the *cue pattern* predictor for Experiment 1 and 3 and the *strategy count* predictor for Experiment 2.

Table B2. Fixed effects estimates of mixed logistic regressions for Experiment 1–3.

	Model 1				Model 2			
Fixed Effects	*B*	SE	*z*	*p*	*B*	SE	*z*	*p*
Experiment 1								
Intercept	−0.53	0.12	−4.40	<.001	−0.64	0.14	−4.67	<.001
Version a	0.75	0.11	6.77	<.001	0.88	0.13	6.84	<.001
Pattern 1 vs. Pattern 2					−0.80	0.07	−10.75	<.001
Patterns 1 & 2 vs. Pattern 3					0.02	0.04	0.58	.563
Version a * Pattern 1 vs. Pattern 2					0.16	0.07	2.14	.032
Version a * Patterns 1 & 2 vs. Pattern 3					0.15	0.04	3.73	<.001
Experiment 2								
Intercept	−2.29	0.15	−15.42	<.001	−2.32	0.13	−17.52	<.001
Valence positive	0.38	0.11	3.58	<.001	0.38	0.11	3.63	<.001
Strategy Count					−0.41	0.04	−9.99	<.001
Valence positive * Strategy Count					−0.09	0.03	−2.71	.007
Experiment 3								
Intercept	−0.72	0.09	−8.09	<.001	−0.88	0.12	−7.38	<.001
Version a	0.76	0.11	7.18	<.001	0.91	0.14	6.60	<.001
Pattern 1 vs. Pattern 2					1.36	0.11	12.96	<.001
Patterns 1 & 2 vs. Pattern 3					0.18	0.05	3.81	<.001
Version a * Pattern 1 vs. Pattern 2					0.17	0.10	1.64	.100
Version a * Patterns 1 & 2 vs. Pattern 3					−0.01	0.05	−0.22	.828

Note. Predictors *valence* and *version* were both effect coded in all analyses, such that Version a/positive valence was coded with +1 and Version b/negative valence with −1. The predictor *pattern* in Experiment 1 and 3 was Helmert-coded, always comparing the cue pattern with the strongest effect in Jekel et al. (2018) with the remaining cue patterns. Thus, Pattern 3 (+2) was compared to Patterns 1 and 2 (both −1) and Pattern 2 (+1) was compared with Pattern 1 (−1) in both experiments. The predictor *strategy count* was mean centered across subjects.

Appendix C: The effect of (mis-)match in importance ratings on the attraction search effect

We ran a generalized linear mixed model with the data from Experiment 1, including the individual (rank) correlations of the intended ordering of the cues and the ordering of the cues following subjects' ratings for each scenario. Thus, a high, positive correlation represents very similar orderings, whereas a zero correlation represents no association of the intended and the rated cue ordering. Just as with the other mixed logistic regressions, the dependent variable was whether subjects searched for Option A in any given trial and the effect-coded predictor whether Option A was attractive in this trial (Version a; +1) or not (Version b; −1). To account for systematic variation in the data, we added random intercepts for subjects and content scenarios as well as a random slopes for *version* for both subjects and content scenarios. We additionally included the (as described above) Helmert-coded *cue pattern* predictor as well as the individual rank correlations in the model.

The effect of interest here is the interaction of *version* and *rank correlation*, $\beta = 0.26$, $SE = 0.14$, $z = 1.91$, $p = .056$. Although the interaction is not significant, the predicted probabilities for searching for Option A depict the expected pattern: The probability to search for Option A increases from 21.0% in trials with Version b to 42.3% in trials with Version a, when the correlation of subjective cue order and intended cue order is −1. When the subjective cue order and intended cue order are not correlated at all, the probability to search for Option A increases from 18.8% in trials with Version b to 52.1% in trials with Version a. Finally, when the cue orderings are perfectly (positively) correlated, the probability of searching for Option A in Version b is 16.9% and in Version a 61.8%. Thus, the effect of version on search behavior increases with an increasing correlation between the intended and the rated cue ordering. The remaining results from this analyses can be found in Tables C1 and C2. One thing to note is that compared to the analyses of Model 2 from Experiment 1 (see Tables C1 and C2), the variance of the Decision Scenarios random slope slightly increased when including the rank correlation predictor (from 0.07 in Model 2 of Experiment 1 to 0.08 in the Model with rank correlations as predictor). Thus, it is not entirely clear whether including the rank correlations actually explained variation in the effect of pattern version between Decision Scenarios.

Table C1. Variances and correlations of random effects in mixed logistic regressions for Experiment 1 including rank correlations.

Random Effects	Variance	Correlation
Subjects		
Intercept	0.16	
Pattern Version	0.15	−.23
Scenarios		
Intercept	0.04	
Pattern Version	0.08	−.10

Table C2. Fixed effects estimates of mixed logistic regressions for Experiment 1 including rank correlations.

Fixed Effects	Estimate	SE	z	p
Intercept	−0.69	0.13	−5.21	<.001
Version a	0.77	0.15	5.05	<.001
Pattern 1 vs. Pattern 2	−0.07	0.10	−0.73	.465
Patterns 1 & 2 vs. Pattern 3	0.01	0.06	0.16	.870
Rank Correlations	0.13	0.14	0.92	.359
Version a * Pattern 1 vs. Pattern 2	0.26	0.10	2.58	.010
Version a * Patterns 1 & 2 vs. Pattern 3	0.12	0.06	2.09	.037
Version a * Rank Correlation	0.26	0.14	1.91	.056
Pattern 1 vs. Pattern 2 * Rank Correlation	−1.42	0.15	−9.76	<.001
Patterns 1 & 2 vs. Pattern 3 * Rank Correlation	0.02	0.08	0.28	.783
Version a * Pattern 1 vs. Pattern 2 * Rank Correlation	−0.20	0.15	−1.40	.162
Version a * Patterns 1 & 2 vs. Pattern 3 * Rank Correlation	0.01	0.08	0.18	.860

Note. Predictor *version* was effect coded, such that Version a was coded with +1 and Version b with −1. The predictor *pattern* was Helmert-coded, comparing the cue pattern with the strongest effect in Jekel et al. (2018) with the remaining cue patterns. Thus, Pattern 3 (+2) was compared to Patterns 1 and 2 (both −1) and Pattern 2 (+1) was compared with Pattern 1 (−1) in both experiments.