A new way to guide consumer's choice: Retro-cueing alters the availability of product information in memory

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Abstract

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Keywords: consumer behavior; process tracing, eye movements, eye tracking, multiattribute decisions; adaptive decision making

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1. Introduction

Imagine you are planning to buy a new car. After reading several prospectuses, you come up with a final selection of two cars from different dealers. You tell your friend about the options and she asks you for the gas consumption of the cars. Indeed, one of the cars has lower gas consumption than the other. In this case, you would probably select the car with the lower gas consumption. Now imagine a different scenario: Instead of your friend, one of the car dealers recommends you consider gas consumption. Unsurprisingly, the car offered by this dealer has the lowest gas consumption. In this case, you might become suspicious and reconsider the alternatives in more detail before deciding.

In both scenarios, the availability of an attribute was increased because your attention was drawn to this attribute. In the first scenario, you would probably decide on the basis of your friend's recommendation, but in the second scenario you might carefully reconsider all the attributes and eventually come up with a different decision, since a consideration of all information can favor another option. Recent research has indeed shown that increasing the availability of attribute information in decision making—for instance, via increasing visual attention to attribute information with visually salient cues—can guide purchase decisions to be in line with this attribute (Bordalo, Gennaioli, & Shleifer, 2013; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Mandel & Johnson, 2002).

Recent research also showed that the availability of attribute information in memory influences information search, which can also alter subsequent choice behavior (Lawrence, Thomas, & Dougherty, 2018; Platzer, Bröder, & Heck, 2014). Consequently, despite the car dealer's intention to increase the weight of only one specific attribute in the opening scenario, changing the availability of one attribute can change the weight of the remaining attributes as well. This can have unintended consequences for consumers' preferences if, for instance, the remaining attributes favor a competing option. Therefore, a better understanding of how the availability of attributes influences consumers' decision making is necessary to predict choices and to avoid unintended consequences (Wright, 1975). On that account, in three experiments we studied how the availability of attribute information in memory influences consumer choice, by changing the attribute weights (Bordalo et al., 2013) and influencing strategy selection.

1.1. Adaptive Decision Making in Multiattribute Choices

Purchase decisions are often described as choices between two or more alternatives that differ on a couple of attributes (Bettman, Luce, & Payne, 1998). For instance, in the introductory scenario the different cars are the decision alternatives and each car can be described on several attributes, such as gas consumption, engine type, or kilometers driven. Those attributes can also differ according to their importance for the criterion. For example, although gas consumption may be an important attribute for judging the car's energy efficiency, the color of the car is not, yet that may be an important attribute for judging the car's design.

Decision making in multiattribute choice tasks is adapted to the task structure and varies between individuals. The adaptivity of human choice behavior becomes visible, for instance, in the flexible way in which people choose between different decision strategies to optimize their behavior (Gigerenzer & Todd, 1999; Payne, Bettman, & Johnson, 1988; Bröder & Newell, 2008; Krefeld-Schwalb, Donkin, Newell, & Scheibehenne, 2019; Scheibehenne, Rieskamp, &

Wagenmakers, 2013; for alternative approaches see Busemeyer & Townsend, 1993; Glöckner, Hilbig, & Jekel, 2014; Newell, 2005). Herein, a key difference exists between compensatory and noncompensatory decision strategies. Compensatory in this context means that less important attributes can overshadow attributes with a higher importance. In contrast, noncompensatory means that more important attributes cannot be overshadowed by less important attributes. Consequently, behavioral decision theorists have associated compensatory and noncompensatory strategies with different information search behavior (Payne, Bettman, & Johnson, 1988). In the latter, only particular pieces of information—for instance, only the most discriminating attribute, as in the Take-the-Best (TTB) decision strategy—are searched for and compared between the options. In contrast, individuals search for more information if they apply a compensatory strategy, for instance, searching through all presented information for each option when using the weighted additive (WADD) strategy. Likewise, information search patterns differ between these strategies. Noncompensatory decision strategies are associated with more search *between the options* whereas compensatory decision strategies are associated with more search *between attributes within* the options (Payne, 1976).

The extent to which a decision maker applies either a compensatory or a noncompensatory decision strategy depends on several factors, such as emotions (Suter, Pachur, & Hertwig, 2016; Scheibehenne & von Helversen, 2014), the pay-off structure in the environment (Rieskamp & Otto, 2006), and search costs (Bröder & Schiffer, 2003; Gigerenzer & Todd, 1999). Maity, Dass, and Kumar (2018) illustrated, for instance, how perceived search costs influenced consumers' use of decision strategies.

The distribution of attribute information (i.e., the decision environment) is another important factor influencing strategy selection. More noncompensatory strategy use has been observed in decision-making environments in which one attribute is much more informative than the other attributes. In contrast, uniformly distributed information led to more compensatory strategy use (Krefeld-Schwalb et al., 2019; Mata, Schooler, & Rieskamp, 2011).

Although previous research has led to a greater understanding of the environmental factors driving adaptive decision-making behavior, it remains an open question what cognitive processes may contribute to the adaptation. Recent research points toward an influential role of the availability of information in memory (Lawrence et al., 2018, Platzer et al., 2014). In a study by Platzer et al. (2014), the authors showed that spatially cueing the position of previously presented information increased the influence of this information on the choice. This procedure, also referred to as retro-cueing, has been extensively explored in the memory literature (for an overview see Souza & Oberauer, 2016). It has been established that cueing the spatial location of previously presented information with the help of a visually salient cue can increase the availability of this information in memory. Beyond establishing the effects on memory performance, Platzer et al. (2014) were the first to show that retro-cueing attribute information also affects the decision strategies people use in multiattribute inferences from memory. The authors found that cueing the position of less important pieces of information led to the selection of more compensatory decision strategies, whereas cueing more important pieces of information led to selecting more noncompensatory decision strategies.

Understanding how the availability of information in memory influences decision making opens new ways to guide consumer choice. However, to evaluate the potential use of a retro-cueing procedure for this task, it is necessary to go beyond measuring the observable outcomes of the decision-making process. Choice behavior is always just a proxy for strategy use and the weighting of information; in contrast, process-tracing methods make it possible to assess the decision-making process more directly (Schulte-Mecklenbeck, Kühberger, Gagl, & Hutzler, 2017).

1.2. Eye Tracking as a Process-Tracing Method

Tracking eye movements is a process measure that allows deep insights on information processing during decision making (for overviews see Orquin & Mueller Loose, 2013; Russo, 2010). For one, the position people look at can be informative about the information they attended to during decision making. For instance, recent research has suggested a link between the amount of time people look at information presented on a computer screen and the importance of these information for the decision-making process (e.g., Glaholt & Reingold, 2011; Glaholt, Wu, & Reingold, 2009; Glöckner & Herbold, 2011).

Moreover, the amount of looking back and forth between choice options and attributes, so-called eye-movement transitions, were linked to compensatory and noncompensatory information search strategies (e.g., Russo & Dosher, 1983). Using a compensatory decision strategy goes along with more transitions to attribute information *within* one option (option-wise information search). Using a noncompensatory TTB strategy shows more transitions *between* choice options (attribute-wise information search; e.g., Payne, 1976; Perkovic, Bown, & Kaptan, 2018; Reisen, Hoffrage, & Mast, 2008; Renkewitz & Jahn, 2012).

Research has shown that eye movements can be used as a proxy for the allocation of attention not only when information is visible, but also when the visual environment is almost devoid of any useful information and it has to be retrieved from memory (e.g., Altmann, 2004;

Ferreira, Apel, & Henderson, 2008; Hoover & Richardson, 2008; Martarelli & Mast, 2013; Richardson, Altmann, Spivey, & Hoover, 2009; Richardson & Kirkham, 2004; Richardson & Spivey, 2000; Johansson, Holsanova, & Holmqvist, 2006; Scholz, Klichowicz, & Krems, 2018; Scholz, Mehlhorn, & Krems, 2016; Wantz, Martarelli, & Mast, 2016). This so-called looking-at-nothing behavior has recently been proposed to reflect information search in memory during decision making (Pärnamets, Johansson, Gidlöf, & Wallin, 2016; Platzer et al., 2014; Renkewitz & Jahn, 2012; Scholz, von Helversen, & Rieskamp, 2015). For instance, in a binary choice task, Renkewitz and Jahn (2012) observed that prior to making a choice, participants looked at spatial locations on a blank screen that were associated with previously presented—and for the choice task—relevant information.

Besides its merits, it must be noted that eye movements can be biased toward spatial positions on a screen (for instance the upper half) independently of experimental manipulations (Glaholt, Wu, & Reingold, 2010). Furthermore, it is not yet clear if eye movements are the consequence of decision making or if they play an active role in constructing the decision (e.g., Shimojo, Simion, Schimojo, & Schreier, 2003). Still, in addition to analyzing choice data alone, eye tracking can provide useful information on what pieces of information people attend to during decision making which strongly contributes to a better understanding of how people decide (Orquin & Mueller Loose, 2013).

1.3. This Study

In this study we used eye tracking in an attempt to gain a better understanding of the influence of the availability of information on consumer choice. To manipulate the availability of information in memory, we combined a binary multiattribute choice task with the retro-cueing paradigm (Souza & Oberauer, 2016).

Experiment 1 aimed at establishing the retro-cue effect on consumers' choices and explored if the assumed retro-cueing effect differs between decision environments. In the main Experiment 2, we used eye tracking to measure attentional allocation during the decision-making process. Experiment 3 tested the retro-cue effect in an applied setting and with verbal instead of visual cues, to generalize the effect for application in marketing.

2. Experiment 1

Experiment 1 consisted of two independent experiments. Experiment 1a tested the retro-cue effect in an inferential, multiattribute choice task, in a decision environment in which the attributes were almost equally informative for the choice in a managerial context. As we were particularly interested in consumer choices, Experiment 1b further established the retro-cue effect on choice probabilities and strategies in a preferential choice task in a consumer context. Additionally, Experiment 1b further tested how the retro-cue effect interacted with different decision environments.

2.1. Method

2.1.1. Participants

We tested 58 students from the University of Geneva (48% female, 52% male, M_{age} = 21.7 years) in Experiment 1a and 28 students in Experiment 1b (54% female, 46% male, M_{age} = 22.8 years) who received course credits for participating in the experiment.[1]

2.1.2. Apparatus

Experiments were programmed in Python using functions from the PsychoPy library

[1] We did not run a power analysis for the experiment, but the sample size was determined by the number of voluntary participants in two lectures at the University of Geneva.

(Peirce, 2007). The tasks were presented on 24" screens with a 1920 × 1080 pixel resolution.

2.1.3. Materials and Procedure

Participants were repeatedly asked to choose from two hypothetical movies the one they thought would be more successful at the box office (see Scheibehenne & von Helversen, 2014) in Experiment 1a, and to make a preferential choice between two books for themselves in Experiment 1b. To inform their choices, participants received recommendations from six hypothetical movie critics (Experiment 1a) or six reviewers (Experiment 1b). The critics and reviewers represent the attributes in the multi-attribute choice task, and the recommendations represent the attribute values (recommendation vs. no recommendation). In Experiment 1a the critics differed in their probability of recommending the more successful movie, representing attribute validities. In Experiment 1b the attribute validities were framed as ratios indicating how the reviewers' recommendations helped other clients in the past. Online platforms, such as amazon.com, provide this information about reviewers. We refer to these values as validities in the following.

In Experiment 1a the validities were uniformly distributed across the critics [65%, 63%, 63%, 62%, 60%, 58%] so that all information was almost equally important for the choices, but still not identical, thereby increasing the external validity of the task. In Experiment 1b we varied the validity distributions in blocks of decision trials between (a) the same uniform distribution as in Experiment 1a, (b) a J-shaped distribution [90%, 69%, 68%, 66%, 63%, 60%], and (c) a linear distribution [90%, 83%, 76%, 69%, 62%, 55%].

All information was presented on an information board in the center of the screen. Asterisks represented a recommendation and hyphens represented no recommendation. In addition, in Experiment 1a, the critics were visualized with cartoon animal icons on the left side of the information board. The validities were expressed as percentages next to the board. The information was ordered such that the attribute with the highest validity always appeared at the top of the information board and the one with the lowest validity at the bottom.

Figure 1 illustrates the procedures in Experiment 1a and b. All information was presented at the beginning of each trial (Figure 1A). Thereafter, the information was deleted from the board and only the grid remained on the screen (Figure 1B). After a blank screen, in 50% of the trials the retro-cue was shown. One row of the empty grid was emphasized with a black frame, to visually cue the information of the attribute (the recommendations of one critic or reviewer) that was previously presented at this position (see Figure 1C). To justify the appearance of the cue to participants, they were instructed that the cue might help them memorize the previously seen information. The cued row was randomly chosen from the attributes that distinguished between the options. But the predictions of the cue and the strategies were balanced, such that in 25% of trials each, either the TTB choice, the WADD choice, the choice that both TTB and WADD predict, or a choice that neither TTB nor WADD predict was cued. While applying the same rule for each of the cued trials, we also selected one row in the trials without a cue. This procedure allowed us to quantify the cueing effect while simultaneously controlling for the validity of the cued attribute and the correspondence of the attribute's prediction with either of the decision strategies.

After the cue disappeared, the empty grid remained on the screen until the choice task started (Figure 1D). During the choice phase, the participants could subsequently choose either of the two movies or books with a mouse click (Figure 1E). Cued trials are henceforth called

CUE trials and those without cueing NoCUE trials.

In Experiment 1a, all participants made 63 choices in two blocks, in total, preceded by eight practice trials.[2] In Experiment 1b, 64 trials were conducted in every validity condition, after eight practice trials, resulting in 192 experimental trials per participant in total.

2.2. Results

2.2.1. Retro-Cue Effect on Choices

The average choice proportions are illustrated in Figure 2.[3] To test whether the cue altered choices (see Platzer et al., 2014), we fitted a generalized mixed model[4] that included fixed effects for the cue, and the rank of the cued attribute. The factor cue consisted of two levels representing the two cueing conditions, CUE and NoCUE. Additionally, we added random intercepts for participants[5] to account for individual differences. In the analysis of Experiment 1b, the environment (linear, J-shaped, or uniform distribution of validities) was added as an additional fixed effect.

Figure 2A and C shows that cueing an attribute increased the likelihood of choosing the option in line with the cued attribute by about 15%, in comparison to the NoCUE condition. The observed difference reached significance, as indicated by the main effect of the cue in Experiment 1a, $\chi^2(1) = 91.68$, $p < .001$. The same was true in Experiment 1b with an average increase in the choice likelihood of 12%, $\chi^2(1) = 80.10$, $p < .001$. Additionally, there was a main

[2] Due to experimenter error, the blocks in Experiment 1a were not equally sized; the first block consisted of 32 trials and the second block consisted of 31 trials. Furthermore, the CUE trials were not perfectly balanced between the participants; half of the participants conducted 32 retro-cue trials and the other half conducted only 31 trials.
[3]The data and code for running the following analyses can be found at https://osf.io/ke7az/.
[4] The mixed models were fitted using the R packages lme4 (Bates, Mächler, Bolker, & Walker, 2015) and afex (Singmann, Bolker, Westfall, & Aust, 2018). The *p* values for the effect-coded predictors were calculated with the likelihood ratio test.
[5] Adding random slopes for the factor CUE and validity yielded the same results patterns. We did not include random effects for items as the design was not fully balanced.

effect of the rank of the cued attribute in both experiments, Experiment 1a: $\chi^2(5) = 20.31$, $p < .001$; Experiment 1b: $\chi^2(5) = 71.80$, $p < .001$, indicating that the probability of choosing the recommended option differed with regard to the rank of the attribute. In Experiment 1b, we further observed an interaction between the rank and the environment, $\chi^2(10) = 28.53$, $p < .001$. Participants' choices were indeed sensitive to the decision environments (see Figure 3). We did not observe an interaction of the cue and the environment, $\chi^2(2) = 0.39$, $p = .82$, nor a three-way interaction of Cueing condition × Rank × Environment, $\chi^2(10) = 3.85$, $p = .95$. This result indicates that the presence of the retro-cue affected choice probabilities similarly over all attributes and environments.

2.2.2. Retro-Cue Effect on Strategy Selection

To investigate strategy selection, we analyzed the proportion of choices in accordance with the noncompensatory TTB strategy (henceforth called TTB choices). As in the first set of analyses, we included the cue and the rank of the cued attribute as fixed effects. Additionally, we added two control variables. First, we coded if the cue favored the noncompensatory TTB choice. If the cue and TTB make the same prediction, choices in accordance with the cue are not distinguishable from choices in accordance with TTB. Second, we added a factor coding if a noncompensatory and compensatory strategy made the same choice prediction. This is relevant because in those trials in which TTB and WADD made the same prediction, TTB choices are equivalent to WADD choices and were thus more likely to occur than in trials where the two strategies made different predictions. We again added by-subject random intercepts. In Experiment 1b, we additionally added a fixed effect for the environment.

In the NoCUE condition, participants made on average 58% TTB choices in Experiment

1a and 68% in Experiment 1b. In the presence of the cue, noncompensatory TTB choices were reduced by on average 3% and 5% in the two experiments. The main effect of the cue was significant in both experiments, in Experiment 1a: $\chi^2(1) = 7.15$, $p = .007$, and in Experiment 1b across all environments, $\chi^2(1) = 24.44$, $p < .001$. Figures 2B and D illustrate the corresponding difference in the proportions of TTB choices, relative to the NoCUE condition.

In neither Experiment 1a nor 1b did the rank of the cued attribute influence the probability of making a TTB choice, Experiment 1a: $\chi^2(5) = 5.34$, $p = .38$; Experiment 1b: $\chi^2(5) = 4.39$, $p = .49$. However, in both experiments, we observed an interaction of the cue with the rank of the cued attribute, Experiment 1a: $\chi^2(5) = 74.22$, $p < .001$; Experiment 1b: $\chi^2(5) = 63.70$, $p < .001$. Pairwise comparisons revealed that this finding is an artifact of the research design. Cueing the first attribute always cues the TTB choices as the cued attribute always favors one option over the other. Therefore, cueing the first attribute increased the likelihood of TTB choices compared to the NoCUE condition, whereas cueing all remaining attributes decreased TTB choices compared to the NoCUE condition (all *ps* < .03).

As hypothesized, the proportion of noncompensatory choices varied between the environments in Experiment 1b as indicated by a main effect of environment, $\chi^2(2) = 48.72$, $p < .001$. Paired comparisons with estimated marginal means[6] (EMMs) revealed the most TTB choices in the condition with the highest dispersion of cue validities (i.e., in the J-shaped environment, $EMM_{\text{J-shaped}}=0.77$), followed by the linear distribution ($EMM_{\text{linear}} = 0.75$), and the fewest TTB choices in the condition with the lowest dispersion of cue validities (i.e., in the uniform environment, $EMM_{\text{uniform}} = 0.66$). Neither the interaction of the environment with the

[6] Using the R-package emmeans (Lenth, 2018).

presence of the retro-cue nor the three-way interaction of Cueing condition × Rank × Environment significantly predicted the probability of TTB choices (all *ps* > .11). The influence of the availability of information in memory did not differ between the decision environments. As predicted, both control variables significantly affected the probability of choosing in line with a noncompensatory strategy (all *ps* < .001). Importantly, the effects of the other variables persist while controlling for these variables.

2.3. Discussion

The results of Experiment 1 suggest that visually cueing the position of previously presented product reviews can alter consumer choice and influence what information consumers consider for making a choice. Across all conditions and decision environments, cueing motivated participants to make choices in line with the predictions of a compensatory decision strategy. Behavioral data is not yet sufficient to reveal the underlying attentional processes, reflecting how attention was allocated and how information search differed between CUE and NoCUE trials. Following this line of reasoning, in Experiment 2 we aimed at linking the retro-cue effect to gaze data to explore the underlying attentional processes.

3. Experiment 2

The previous experiment suggested that the retro-cue has a twofold effect on decision making in multiattribute choice tasks: increasing the weight of the cued attribute and shifting decision makers toward more compensatory decision strategies. These findings rest on the assumption that retro-cueing drives attention to a spatial position and subsequently increases the availability of the information in memory that had been presented at the cued position (Souza & Oberauer, 2016; Souza, Rerko, & Oberauer, 2016). However, this has never been tested directly in the context of consumer decision making. At the outset, we used eye tracking as a process-tracing method to test if the retro-cue increases attention to the cued attribute and if this increase in attention moderates the retro-cue effect on choice. We also used eye tracking to verify the retro-cue effect on strategy selection. We assumed that if cueing single attributes during decision making leads to more compensatory strategy use, we should find correspondingly more attribute-wise information search in the conditions with a cue compared to the conditions without a cue. We used the strategy index (SI) to measure the number of option-wise as opposed to attribute-wise transitions (Ettlin, Bröder, & Henninger, 2015; Payne, 1976).

An alternative explanation for the retro-cue effect might be that people use the cue strategically during the decision-making process. In consequence, when using retro-cues in marketing, guiding visual attention alone would not be sufficient. Instead, how consumers interpret the cue, as being benign or biasing their choices, should be controlled for. To test this alternative explanation we included an additional condition in which we warned participants about the cue's distracting effect. If people use retro-cues strategically, the retro-cue effect on choices and strategy selection might disappear when people are warned about its influence.

3.1. Method

3.1.1. Participants

We tested $N = 40$ students of the University of Geneva (60% female, 40% male, M_{age} = 22.5 years) who received CHF 20 ($21) for participating.[7]

3.1.2. Apparatus

We used an Eyelink 1000 eye tracker at a 250-Hz sampling rate to record the gaze data.

[7] We wanted to test 35 students to achieve a power of .99 for a medium-sized effect in a repeated measures analysis of variance; as we expected a higher dropout rate due to noise in the eye-tracking data, we invited 40 participants.

The screen had a size of 24" and a resolution of 1920 × 1080 pixels. The right eye was tracked in remote mode and therefore participants could freely move their heads. The average distance between the head and the screen was 60 cm. To ascertain the precision of the recorded data, the eye tracker was calibrated three times per participant using a 10-point calibration procedure before each block of trials. The experiment was started only if the results of the validation test showed an average fixation error of less than 1° and a maximum fixation error of less than 2° of visual angle. Fixations were detected based on a dispersion-based algorithm (Holmqvist et al., 2011), which is available in the Python library PyGaze Analyser (Dalmaijer, Mathôt, & Van der Stigchel, 2014). Subsequent samples with less than 25 pixels of spatial distance for more than 40 ms were classified as a fixation.

3.1.3. Materials and Procedure

The general procedure followed that applied in the preferential choice task in Experiment 1b. In contrast to the previous experiment, cueing was manipulated block-wise to introduce an additional distractor-cueing condition. The first block of trials did not include cueing (NoCUE condition) to measure unbiased decision making. Next, participants went through a cueing block (CUE) and a distractor-cueing block (DIS). The order of these two blocks was balanced between participants to control for carryover effects. The instructions concerning the cue in the CUE condition were the same as in Experiment 1. In the DIS condition, participants were instructed that the cue “might distract them from the previously presented information.” To make sure that participants understood the cueing instructions, they were asked whether the cue provided additional information. If they agreed, the instructions and the question were repeated. The distribution of cue validities was manipulated block-wise, in randomized order, within each of the cueing conditions. In total, the participants made 288 choices in nine blocks (3 cueing conditions × 3 environments).

Rectangular areas of interest (AOIs) were drawn in each cell of the information board. The resulting AOIs covered 64% of the original cell having the same ratio of sides and the same center as the information board's original cells. Every AOI therefore covered—on average—a horizontal angle of 3.8º and a vertical angle of 2.25º. The vertical distance between the AOIs was 60 mm and the horizontal distance was 106 mm, corresponding to average visual angles of 1.12º and 1.91º.

On the basis of the sequence of fixations in these AOIs, option-wise transitions were defined as two sequential fixations on cells corresponding to the different choice options (i.e., columns in the information board). Attribute-wise transitions describe a sequence of two fixations on different attributes of the same option (i.e., rows in the information board). The two types of transitions define the SI (Payne, 1976), which is the number of option-wise transitions minus the number of attribute-wise transitions divided by the sum of the two types of transitions.

3.2. Results

3.2.1. Retro-Cue Effect on Attention and Choices

Figure 4 shows proportions of fixations on the different rows of the information board. Fixation proportions were calculated as the summed number of fixations on the respective row divided by the total number of fixations during the relevant phase of the trial. The figure illustrates that during the cueing interval, cueing one row of the board guided attention to this and surrounding rows. Importantly, also during the choice phase, the cued and surrounding rows were more likely to be fixated on in both cueing conditions, compared to the NoCUE condition.

The figure also illustrates a gaze bias toward the top half of the screen, since a relatively large proportion of fixations remained on the second and third cue. The large proportion of fixations on the last row during the choice phase was due to the presentation of the choice buttons just below the information board (see Figure 1).

To assess the effect of the retro-cue on attentional allocation, we analyzed proportions of fixations on the cued attribute with a linear mixed model. We included fixed effects for the cue and the rank of the cued attribute as well as their interaction and added by-subject random intercepts. The factor cue consisted of three levels: NoCUE, CUE, and DIS. We found main effects for the factors cue, $\chi^2(2) = 539.60$, $p < .001$, and rank of the cued attribute, $\chi^2(5) = 92.83$, $p < .001$. Furthermore, the two factors interacted, $\chi^2(10) = 36.2$, $p < .001$. Contrast analyses supported the inference based on the visual inspection of the data. That is, attention to the cued attribute did not differ between the two cueing conditions ($EMM_{DIS} = .56$, $EMM_{CUE} = .55$, $p = .13$). However, both conditions significantly differed from the NoCUE condition, $p < .001$. Rerunning the same analysis but only for fixation proportions during the choice phase revealed the same pattern of results.

We next tested whether fixations on the cued attribute moderated the retro-cue effect, illustrated in Figure 5. We first fitted a generalized mixed model to the choice data that included all fixed effects identified in Experiment 1b, that is, the cue, the rank of the cued attribute, the decision environment, and their interactions. This model replicated the result pattern of Experiment 1b. In particular, the retro-cue effect was replicated, $\chi^2(2) = 16.35$, $p < .001$. Testing contrasts revealed that the effect was however larger in the CUE condition compared to the NoCUE and DIS conditions ($ps \leq .01$). Moreover, retro-cueing in the DIS condition did not alter choices as compared to the NoCUE condition (p = .247).

Subsequently, proportions of fixations on the cued attribute (analyzed over the cueing and the choice phase), were included as a fixed effect, as well as the interaction of fixation proportions with all other fixed effects. We observed a significant main effect of fixations on the probability of making a cued choice, $\chi^2(1) = 4.90$, $p = .03$, indicating that the more participants fixated on an attribute, the higher the probability of making a choice in line with this attribute. There was no significant interaction with the factor cue, $\chi^2(2) = .94$, $p = .63$, nor with the rank of the cued attribute, $\chi^2(5) = 9.8$, $p = .08$, or the environment, $\chi^2(2) = .98$, $p = .61$).

The main effect of the cue was not significant either, $\chi^2(2) = 4.80$, $p = .09$, but since the analysis of the behavioral data suggested a difference between the conditions, as hypothesized, we nonetheless conducted contrast tests. These analyses revealed that the proportion of cued choices differed between the DIS ($EMM_{\text{DIS}} = .53$) and the CUE ($EMM_{\text{CUE}} = .56$) condition, as well as the CUE and the NoCUE ($EMM_{\text{NoCUE}} = .52$, $ps < .02$) condition but not between the DIS and the NoCUE condition (p = .42). The rank of the cued attribute did not significantly influence the probability of making a cued choice, $\chi^2(5) = 10.66$, $p = .06$, but the interaction of the rank and the environment remained significant, $\chi^2(12) = 81.35$, $p < .001$. Thus, proportions of fixations on the cued attribute seem to underlie the cueing effect to a large extent. Since the main effect of the cue, as well as the rank of the cued attribute, were not significant anymore when the fixations were included as an additional predictor in the model.

In sum, retro-cueing affected choice behavior only in the CUE condition, in which individuals were not warned about a biasing effect of the cue; fixations on the cued attribute did not differ between the CUE and the DIS conditions. To follow up on this, we investigated whether fixations on the cued attribute would be less predictive of the choice in the DIS compared to the CUE condition. Indeed, the estimated slope of the continuous predictor fixations (the change from not looking at all to all the time on the cued attribute) was smallest in the DIS condition ($\beta_{DIS} = .19$), followed by the NoCUE condition ($\beta_{NoCUE} = .26$), and it was highest in the CUE condition ($\beta_{CUE} = .46$), but this interaction was not significant in the model. Thus, although visual attention per se did not differ between the CUE and DIS conditions, the probability of choosing the cued option did differ between them. In other words, fixations on an attribute were indicative of the weight the attributes received in the decision-making process only if individuals were not warned that visual cues could bias their attention.

3.2.2. Retro-Cue Effect on Information Search and Strategy Selection

Testing the retro-cue effect on TTB choices replicated the effects observed in Experiment 1b. Figure 5B illustrates the average decrease in TTB choices, relative to the NoCUE condition, where on average 64% TTB choices were observed. Retro-cueing decreased TTB choices, $\chi^2(2) = 20.18$, $p < .001$, and contrast analysis showed that *both* the CUE and the DIS condition led to decreased TTB choices compared to the NoCUE condition (*p*s < .001). Given these results, we likewise expected differences in information search between CUE and NoCUE trials. In particular, we expected fewer option-wise transitions following retro-cueing, as indicated by a smaller SI.

Figure 6 illustrates that the average SI in the CUE and DIS conditions was indeed smaller, compared to the NoCUE condition. Testing the SI during the choice phase with a mixed model analysis, including by-subject random intercepts and cue and environment as fixed effects, supported this inference with a significant main effect of the cueing condition, $\chi^2(2) = 55.90$,

$p < .001$. The SI did not differ between the two cueing conditions, CUE and DIS ($EMM_{DIS} = .48$, $EMM_{CUE} = .49$, $p = .18$).

Similar to the analysis of the SI during the choice phase, we also tested if the SI moderates the cueing effect on strategy selection during the cueing phase. There was no significant main effect of SI, $\chi^2(1) = 1.15$, $p = .28$, nor a significant interaction with the factor cue, $\chi^2(2) = 1.81$, $p = .41$, the rank of the cued attribute, $\chi^2(5) = 1.86$, $p = .87$, or the environment, $\chi^2(2) = 2.15$, $p = .34$. The main effect of the cueing condition, $\chi^2(2) = 22.86$, $p < .001$, was again significant, but testing contrasts revealed that the probability of TTB choices did not differ between the DIS and the CUE condition ($EMM_{DIS} = .68$, $EMM_{CUE} = .68$, $p = .83$), but was in both conditions smaller than in the NoCUE condition ($EMM_{NoCUE} = .73$, ps $< .001$).

3.3. Discussion

Analyzing fixations and gaze transitions during the task supported our hypotheses on the retro-cue's twofold effect on decision making. The analyses revealed that cueing increased attention on the position of the cued attribute and additionally guided individuals to scan through the entire memorized information board.

Perkovic et al. (2018) recently showed that the SI, which we used to quantify transitions in the present experiment, can be biased if it is not corrected for random transitions. Here, we still have no reason to assume that random transitions could systematically differ between conditions, and by that distort comparisons between them and consequently our conclusion.

In line with the looking-at-nothing effect (e.g., Ferreira et al., 2008; Richardson & Kirkham, 2004), participants systematically looked at the empty spatial rectangles of the information board that had contained the attribute information during encoding. If the retro-cue was framed as distracting in the DIS condition, choice was not altered to the same extent as in the CUE condition, although visual attention to the cued attribute was the same in the two conditions. To effectively apply retro-cueing in marketing to increase the weight of single product attributes, it is thus necessary to avoid having the cue be interpreted as an attempt to bias consumer choice. To the contrary, irrespective of the interpretation of the cue, using visual cues to increase the availability of memorized product attributes will lead to a more comprehensive comparison of products that can indeed be favorable for products that are superior not on the most valid attributes, but on average across all attributes.

4. Experiment 3

The previous experiments primarily focused on establishing the retro-cue effect and investigating the underlying cognitive processes, whereas the applicability of the results remained untested. On that account, we designed an experiment in accordance with the introductory scenarios about choosing one of two used cars, to generalize the retro-cue effect to a more applied setting. In this experiment, verbal recommendations of either car dealers or previous consumers were used as retro-cues instead of visual cues. Following our previous results, we expected that only the recommendation through previous consumers would influence the weight of the cued attribute, and that the recommendation of the car dealers, who have a less trustworthy stereotype, would not. We still expected both recommendations to increase choices in line with a compensatory decision strategy.

Since the experiment aimed at providing higher ecological validity than the previous experiments, and to outline a possible application of the retro-cueing procedure in practice, several major changes to the previous experiments were implemented: The data were collected with tablets on two university campuses, the timing of the choice task was self-paced, and each participant made only three choices.

4.1. Method

4.1.1 Participants

We aimed for a sample size of 394 participants to achieve a power of .8 for detecting a small effect (d = .2) with a paired t test between any of the cells of the experimental design, and we tested in total N= 415 individuals (65% female, 35% male; 73% were between the ages of 20 and 30 years; 97% were students) on the campuses of the University of Geneva and the University of Zurich.

4.1.2. Apparatus

The experiment was programmed in JavaScript and HTML and conducted online. The task was presented on two different types of tablets: Samsung Galaxy Tab A 6, with a 10.1" display and iPad Air 2, with a 10.5" display.

4.1.3. Materials and Procedure

Participants were presented with a multiattribute choice task in which they were asked to choose which of two used cars they preferred. Screenshots of the task are shown in Figure 7. To inform their choice, pictures of the cars and four attributes were presented to the participants on an information board. We chose cars that were affordable for students in Switzerland, with the attributes adapted to the Swiss online market for used cars. All attributes were expressed in a binary format (price < CHF 5,000: Yes/No; mileage < 100,000 km: Yes/No; initial registration date after 2014: Yes/No; and seat heating: Yes/No) to reduce complexity and increase comparability to the previous experiments. To determine the prediction of the WADD strategy, we set exact values for the attribute validities, representing the importance of the attributes for the choice as the probability that the preferred car had this attribute [90%, 80%, 70%, 60%]. These probabilities were not presented to the participants but were used only to control strategy prediction in the experimental design.

Each participant made three choices in a row. The first choice was in the NoCUE condition; in the two remaining choices, retro-cues were applied. In accordance with the CUE and DIS conditions in Experiment 2, a picture of either a previous consumer (CUE, see Figure 7B) or a car dealer (DIS, see Figure 7C) was presented. One of the attributes was then cued (embedded) in a question presented in a speech bubble (e.g., “Have you considered the seat heating?”). The order of the two cueing conditions was randomized. All rules for balancing the distribution of the attributes’ values and the presented cues that we used in Experiments 1 and 2 were applied in Experiment 3 as well. In contrast to the previous experiments, however, the timing was not fixed. That is, participants could freely decide when they wanted to advance to the next page.

Participants were approached on the universities’ campuses and asked to participate in the study. The consent form, the instructions, and the task were conducted on the tablet. To make sure that participants correctly understood the setup of the task we asked them a test question on an exemplar pair of cars (“which car costs less than CHF 5,000 and was registered after 2014?”). If they did not answer this question correctly, the instructions were presented again.

4.2. Results

The retro-cueing effect differed between the cueing conditions and the order of appearance, as illustrated in Figure 8. If the choice task with recommendation of a previous consumer was presented first, the proportion of cued choices slightly increased, whereas the cueing effect was not present in the remaining conditions.

Testing the retro-cue effect with a mixed model including fixed effects for the cue and the presentation order, as well as their interaction, and participants as random intercept, we still found no evidence against the null hypothesis. Upon closer inspection of the data it became apparent that the cueing effect greatly varied with the cued attribute (see Figure 8C). Cueing of the least important attribute, seat heating, was effective if the attribute was recommended by the previous consumer. If the same attribute, however, was recommended by the car dealer, choices in the opposite direction of the attribute were observed. We tested this effect with the previously used mixed model, including the attribute as an additional fixed effect. Indeed, this analysis revealed a significant interaction of the order of recommendation and the attribute, $\chi^2(3) = 12.44$, $p = .006$. The three-way interaction of the cue condition, the order, and the attribute did not reach statistical significance, $\chi^2(6) = 7.48$, $p = .28$, nor did any other fixed effect in the model.

The results on the decision strategies (see Figure 8B and D) suggest a similar pattern. In the NoCUE condition on average 50% TTB choices were observed that slightly decreased following the recommendation of a previous consumer but increased following the recommendation of a car dealer. Since an increase in TTB choices following a retro-cue stands in stark contrast to our findings in Experiments 1 and 2, we again included the attribute as an additional fixed effect in the mixed model analysis. Figure 8D shows that if the dealer recommended the least important item, seat heating, participants were more likely to make TTB choices. In other words, they were more likely to consider not the recommended but rather the most valid attribute. As for the mixed model analysis of the choices, only the interaction of the order with the attribute reached statistical significance, $\chi^2(3) = 10.32$, $p = .02$. Neither the interaction of the cueing condition and the order nor the three-way interaction reached significance, nor any other fixed effect of the model.

4.3. Discussion

Experiment 3 supports the conclusions drawn based on the previous lab experiments and points toward the application of our results in marketing practice. The results emphasize that framing recommendations as coming from previous consumers can be used to guide consumer choice, whereas framing recommendations as stemming directly from a seller can even have the opposite effect on choice behavior. Although the effects go in the same direction as in the previous experiments, they must be interpreted with caution, since they were comparatively small and did not always reach statistical significance.

Several reasons can potentially explain the decrease in the retro-cue effect and the lack of statistical significance. Since the setting of the initial lab experiments was in a very controlled environment and multiple choices from each participant were collected, noise in the data can be reduced. In contrast, in Experiment 3, individuals were tested in the field and only one choice per condition was collected, which increases the ecological validity of the experiment but also introduces noise in the data and consequentially reduces the test power (Meyvis & Van Osselaer, 2018). On that account our power analysis was probably overly optimistic, and we would have needed a larger sample size to detect the assumed retro-cue effects. Furthermore, the retro-cue was generalized from a visual, spatial cue in the lab Experiments 1 and 2 to a verbal cue in Experiment 3, which may have reduced the effect size as well. Finally, how informative the attributes were for the choice was not explicitly communicated but was implicit in the design of the task. Consequently, participants may have perceived the importance of the attributes differently. For instance, for some consumers having heated seats might be equally important as the gas consumption of the car, although we assumed that seat heating was the least important attribute.

To conclude, that the observed effects were lower than expected based on the previous experiments can be explained by increased noise in the data and reduced strength of the experimental manipulation. Nonetheless, the descriptive results support the existence of the retro-cue effect in a more applied setting. Following this reasoning, Experiment 3 can be regarded as a promising first step for developing a procedure that implements the retro-cue effect in marketing practice.

5. General Discussion

Increasing the availability of product attributes in the consumer's memory can be an effective way to steer decision making. But one should consider that increasing the availability of one attribute influences information search toward more extensive search and subsequently choices in line with a more compensatory decision strategy. Thus, marketers can use retro-cueing to guide decision making in favor of their product as long as the product is superior on several attributes and not only the cued one.

Our results further suggest that how the cue is interpreted is relevant to its effect on choice behavior. Similar to the discussion about the usefulness of attention-grabbing banner ads and similar rather intrusive forms of advertising (Edwards, Li, & Lee, 2002; Lee & Ahn, 2014), our results emphasize that attention to attribute information alone cannot predict subsequent decisions (Horstmann, Ahlgrimm, & Glöckner, 2009).

The behavioral results supported the assumption of the retro-cue's twofold effect on strategy selection on the one hand, and weighting of the cued attribute on the other hand. The latter results on strategy selection contrast with the findings of Platzer and colleagues (2014), who observed a decrease in compensatory strategy use if less valid attributes were cued. In contrast to previous studies, we controlled for the distribution of the attribute values such that the predictions of the strategies and the cue were independent and balanced. This enabled inferences about strategy selection, as well as inferences about the cue's influence on the choice. As a result, we showed that cueing led to an increased use of a compensatory over a noncompensatory strategy. We further corroborated this finding with differences in the information search pattern between the cueing conditions that have been associated with the respective decision strategies (Ettlin et al., 2015; Payne, 1976; Renkewitz & Jahn, 2012). In addition, we presented the information on the attributes for the choice, corresponding to their predictive validities, directly to the participants, whereas they were learned in previous studies. We argue that controlling for the predictions of the strategies and the cue, as well as presenting the predictive validities directly, might have caused our finding to differ from that of Platzer and colleagues (2014).

Drawing attention to one of the attributes in a multiattribute choice task has been shown to increase that attribute's influence on the choice and the decision-making process (Platzer et al., 2014; Renkewitz & Jahn, 2012). It has further been proposed that the availability of information in memory is an important source of influence on judgment and decision making (Lawrence et al., 2018; Platzer et al., 2014). This study builds on both streams of research and explored how the availability of information in memory, which we manipulated by means of attention-grabbing retro-cues (see Souza & Oberauer, 2016), influences preferential choice tasks in the consumer context.

In general, we observed a gaze bias toward the top half of the screen (most fixations were on Attributes 2 and 3). Gaze biases have been shown to occur independently of the applied experimental manipulations (Glaholt et al., 2010). In the present study, the gaze bias may indicate two aspects of attention processes, in particular. First, in two of the three conditions the most relevant pieces of information were positioned in the upper half of the screen (linear and J-shaped environment); subsequently, people were trained to look in this area. This is in line with research showing that people learn to attend to information that allows them to make a correct categorization decision (Rehder & Hoffman, 2005). Second, the gaze bias suggests that people aimed at encoding all information, but due to time constraints, they only had time to process information presented in the top part of the information board. The data of this experiment, however, cannot disentangle the two explanations for the gaze bias toward the top half of the information board. Future research could disentangle the two explanations, for instance, by randomizing the order of the attributes in each trial.

The use of the noncompensatory TTB strategy was relatively high in this study. This frequent use of TTB was previously reported in studies that used a memory-based multiattribute choice paradigm (Bröder & Schiffer, 2003), because inferences from memory in comparison to inferences from givens are more costly in terms of memory retrieval (Gigerenzer & Todd, 1999). The presentation duration during encoding may be another factor that might have increased the use of a noncompensatory decision strategy. Compared to similar studies, showing the information for 3 s is rather short. Reanalyzing the gaze data indicated that—on average—1.4 of the six attributes, the respective AOIs in the middle of the cells on the information board, were fixated on during encoding (*SE* = .95). One could assume that with longer presentation times, participants would potentially fixate on more attributes, thereby using more compensatory decision strategies. Subsequently, cueing will have a smaller influence on strategy selection. In line with this, TTB was less often applied in Experiment 3 under unconstrained information presentation, and the influence on strategy selection could not be replicated. However, other aspects of the task might also influence strategy selection, for example, the length of the experiment, the number of attributes, and the fact that the validities of the attributes were not explicitly communicated. In conclusion, future research should study how the amount of information presented, as well as the time constraints on information encoding, influences the retro-cue effect on strategy use.

In addition to the establishment of the retro-cue effect on decision making, Experiment 3 further outlines the application of the retro-cue effect to a more applied setting. Future research should build on this first step by running experiments in an applied setting to fine-tune a retro-cue technique for application in marketing. Moreover, advances in eye-tracking technologies toward more built-in eye trackers in mobile devices would enable researchers to optimally test the proposed influence of retro-cueing on consumer choice in an applied setting.

In conclusion, our results strongly support the notion that the availability of information in memory is an important contributor to explaining decision-making behavior in multiattribute choice tasks. We further show that increasing the availability via retro-cues can potentially be used to steer consumer choice. These results underline the relevance of retro-cueing to cognitive scientists as well as marketing practitioners.

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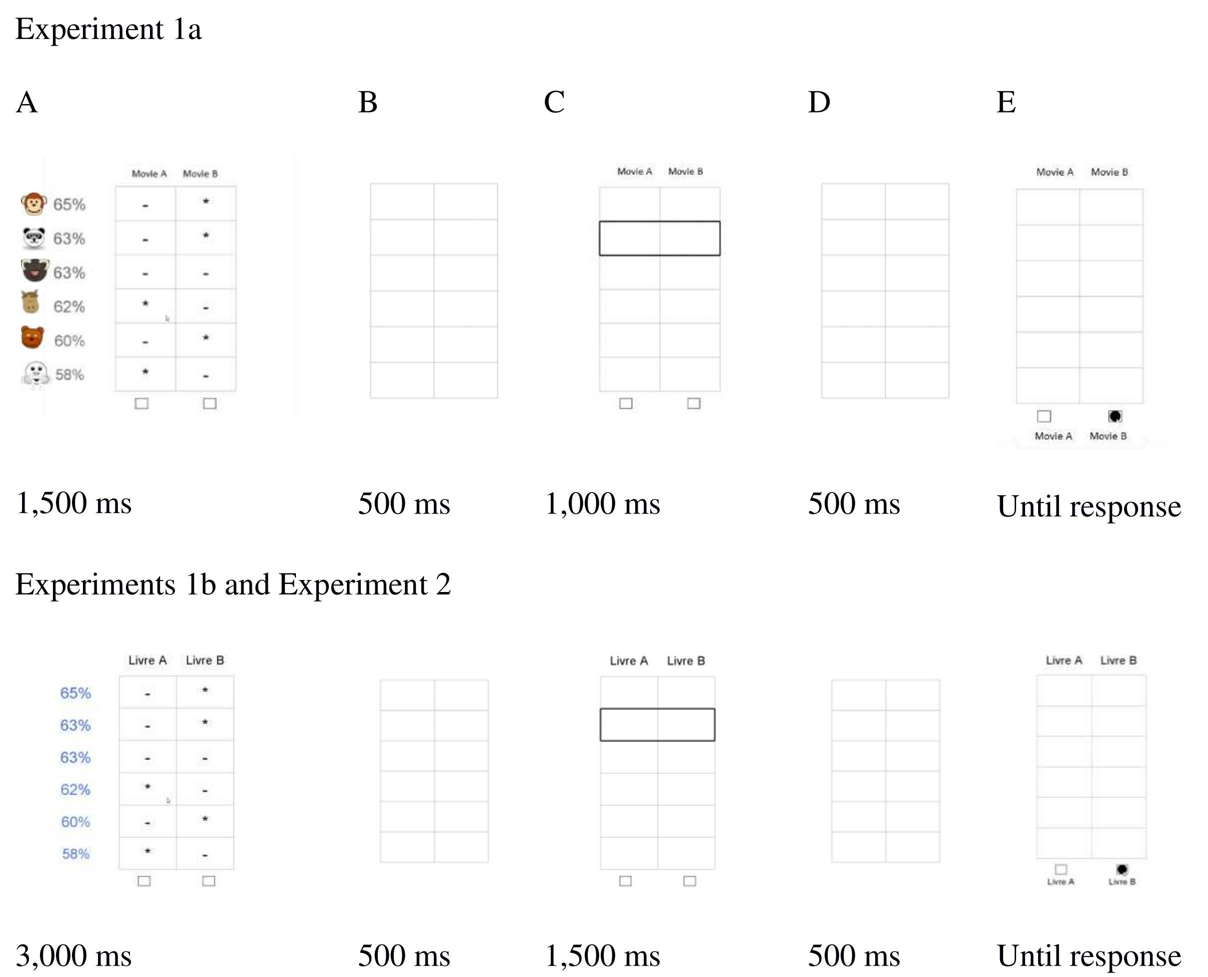


Figure 1. Screenshots of all consecutive screens in Experiment 1a in the top row and Experiments 1b and 2 in the bottom row, in a cued trial: (A) The encoding phase; (B) the first blank grid; (C) the cue; (D) the second blank grid; (E) the choice task. In the condition without cueing, the blank grid (B) remained on the screen for 2,000 ms between encoding (A) and the choice task (E).

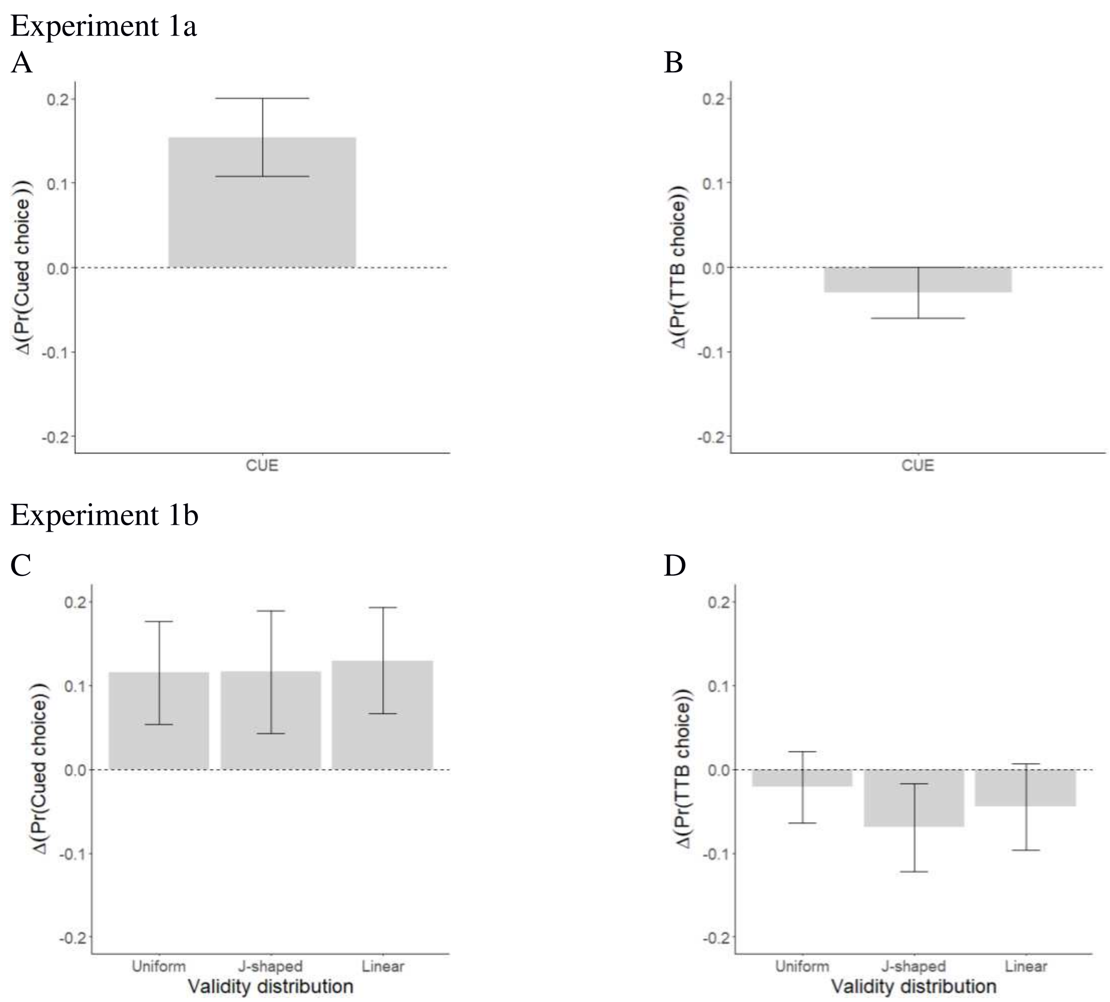


Figure 2. Average retro-cue effect in Experiment 1 on the choice proportions in accordance with the cue (A, C) and the Take-the-Best (TTB) strategy (B, D). $\Delta(\text{Pr (Cued choice)})$ = Difference in the proportions of choices in accordance with a cued attribute in the CUE condition (cued trials), compared to the proportions of choices in accordance with the same attribute in the NoCUE condition (trials without cueing). $\Delta(\text{Pr(TTB choice)})$ = Difference in the proportions of choices in accordance with the TTB strategy in the CUE compared to the NoCUE condition. The error bars indicate 95% confidence intervals around the mean.

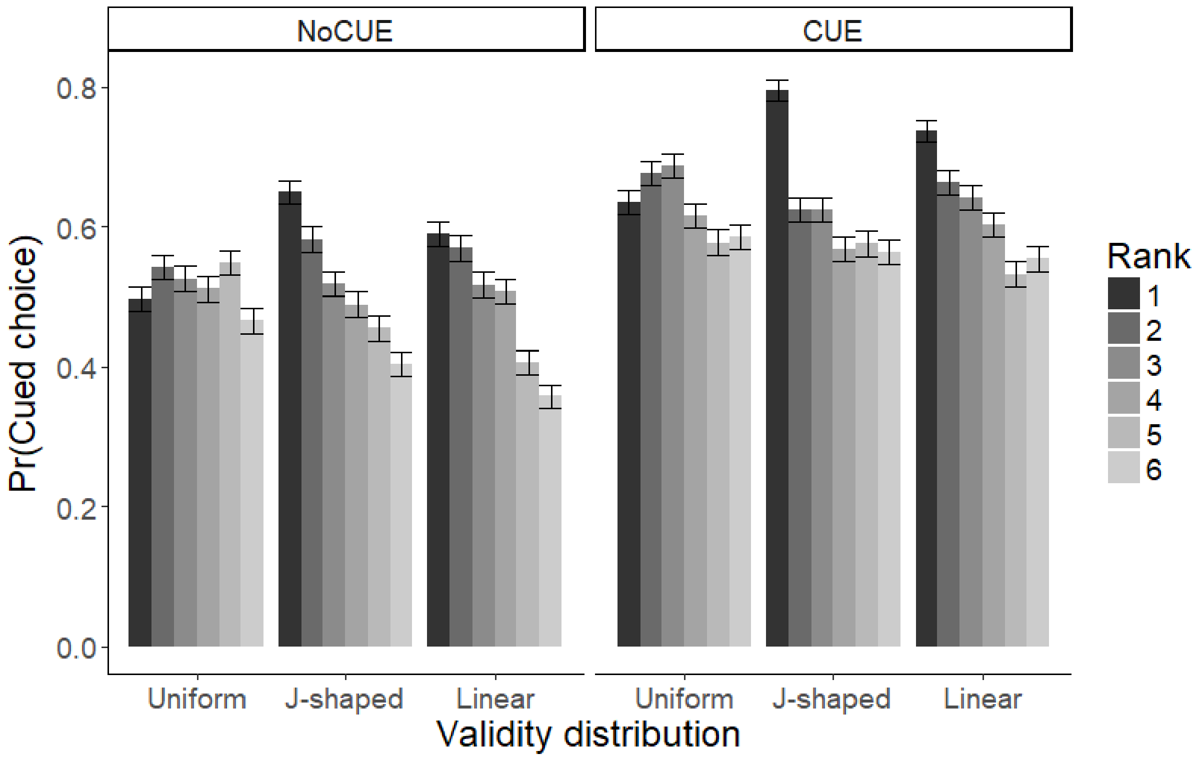
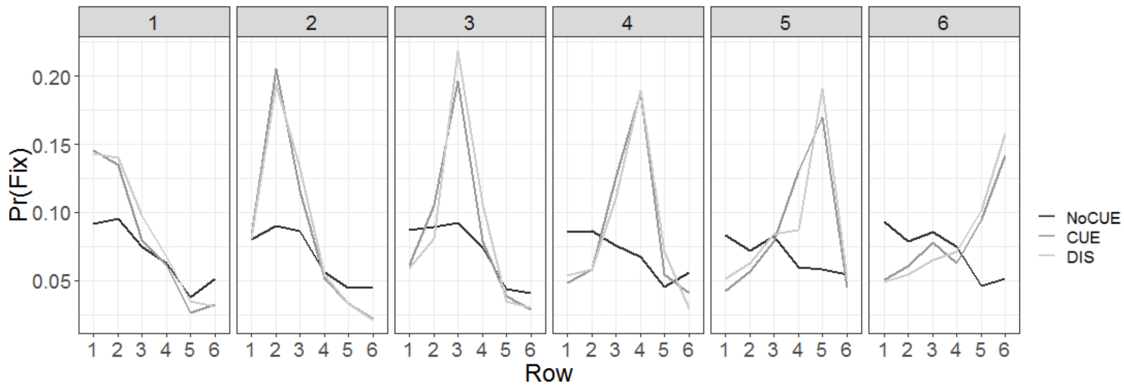


Figure 3. Average proportions of cued choices in Experiment 1b. Pr(Cued choice) = Proportions of choices in accordance with a cued attribute in the CUE condition (cued trials), compared to the proportions of choices in accordance with the same attribute in the NoCUE condition (trials without cueing), as a function of the environment and the rank of the attribute (Rank) in the validity distribution. The error bars indicate 95% confidence intervals around the means.

A Cueing



B Choice

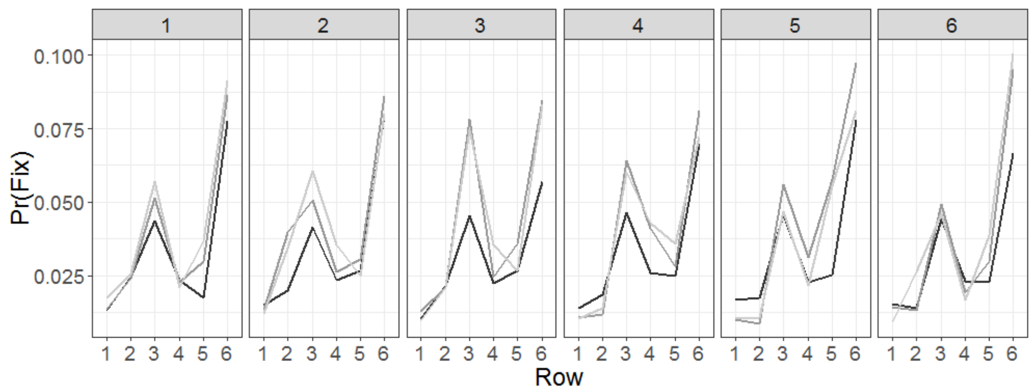


Figure 4. Average proportions of fixations (Fix) in the cueing and choice phases of Experiment 2 on the row areas of interest (*x* axes) representing the reviewers, as a function of the cueing condition (NoCUE, CUE, DIS) and the cued row, indicated by the number above each panel. Fixation proportions are calculated as the summed number of fixations on the respective row in that phase of a trial divided by the total number of fixations in that trial phase. NoCUE = Trials without cueing; CUE = cued trials; DIS = cued trials in which possible distraction of cues was made salient.

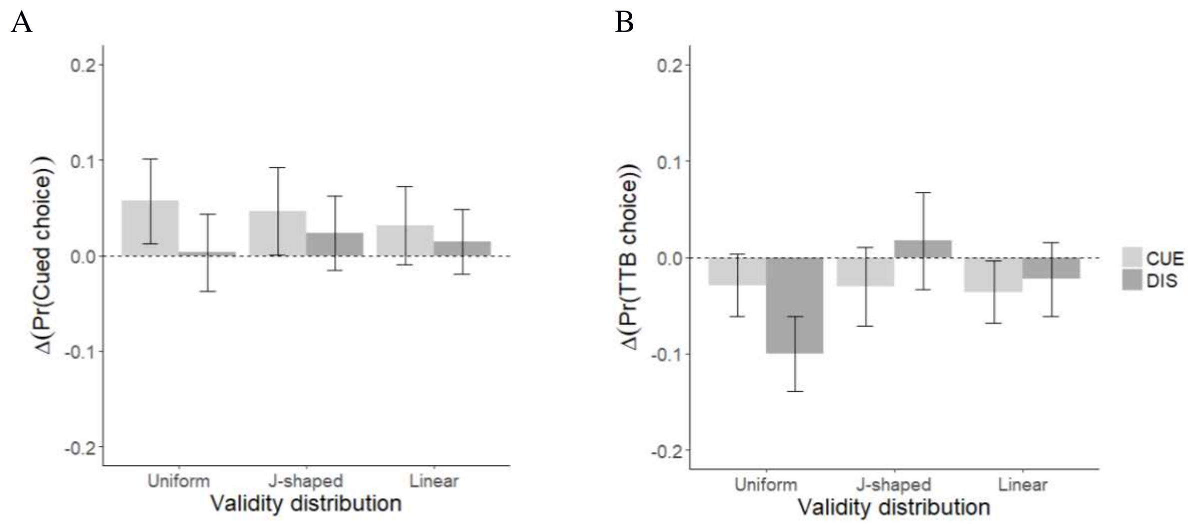


Figure 5. Average retro-cue effect in Experiment 2 on choice proportions in accordance with the cue (A) and the Take-the-Best (TTB) strategy (B) as a function of the validity distribution (uniform, J-shaped, linear) and the cueing condition (CUE, DIS). $\Delta(\mathrm{Pr}(\mathrm{Cued\ choice}))$ = Difference in the proportions of choices in accordance with a cued attribute in the cueing conditions (CUE, DIS) compared to the proportions of choices in accordance with the same attribute in the NoCUE condition. $\Delta(\mathrm{Pr}(\mathrm{TTB\ choice}))$= Difference in the proportions of choices in accordance with the TTB strategy in the cueing conditions (CUE, DIS) compared to the NoCUE condition. The error bars indicate 95% confidence intervals around the mean. NoCUE = Trials without cueing; CUE = cued trials; DIS = cued trials in which possible distraction of cues was made salient.

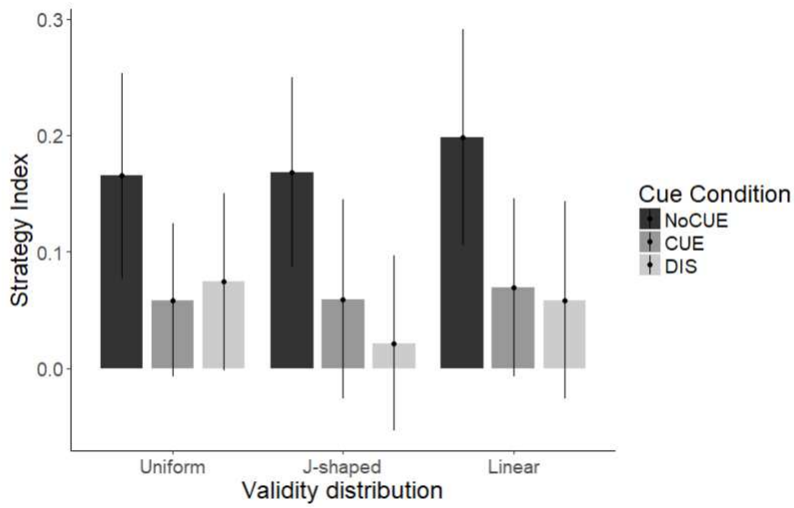


Figure 6. Average Strategy Index during the cue presentation and in the interval following the cue until the participant's response, or the respective blank grid presentation in the NoCUE condition, as a function of the cueing and the validity distribution conditions. A higher SI score indicates more option-wise transitions as often observed for noncompensatory information search strategies such as Take-the-Best. The error bars indicate 95% confidence intervals around the mean. NoCUE = Trials without cueing; CUE = cued trials; DIS = cued trials in which possible distraction of cues was made salient.

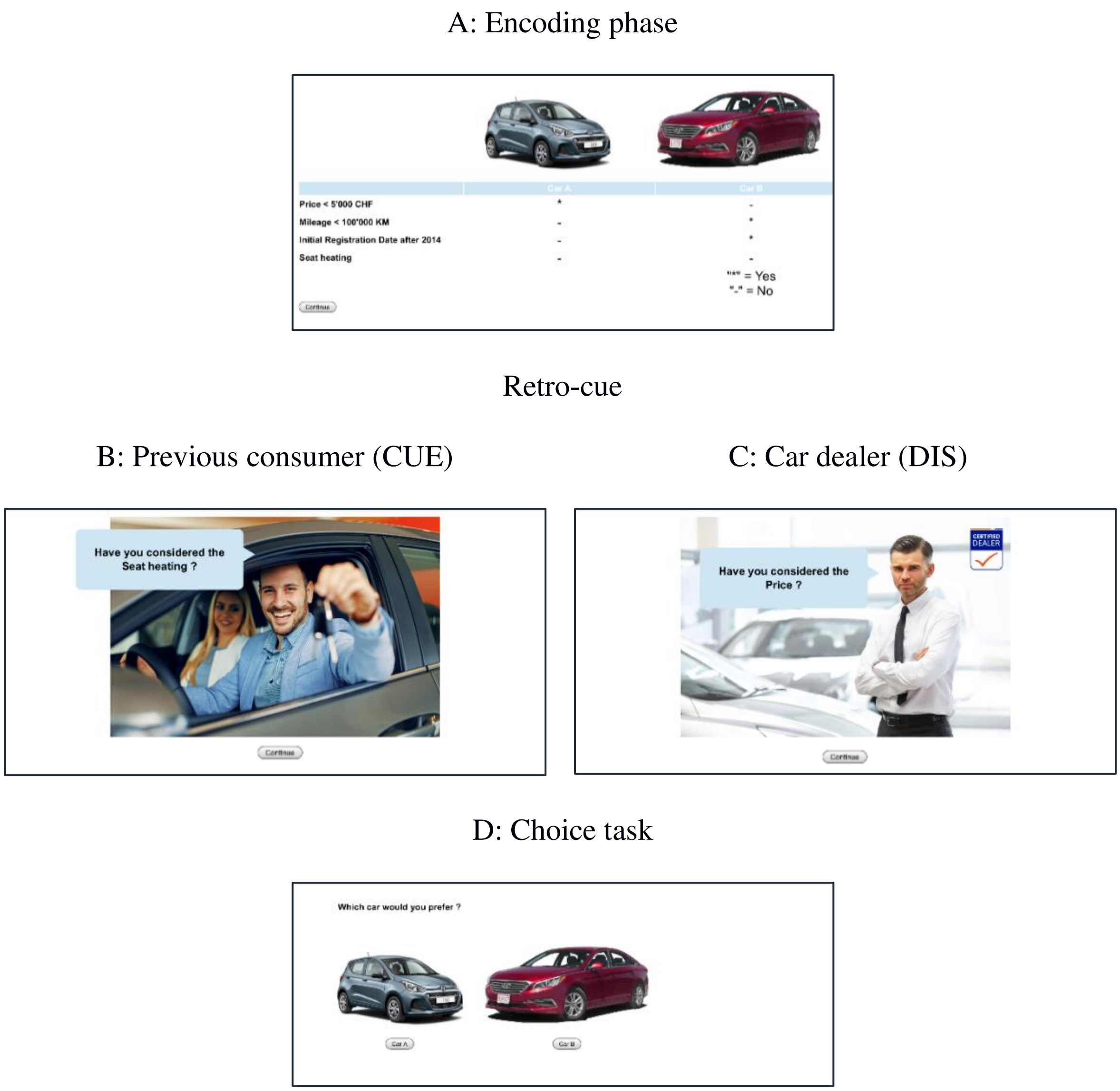


Figure 7. Screenshots of all consecutive screens (arranged from top to bottom) of the choice task in Experiment 3 for a cued trial: (A) The encoding phase; the retro-cue in the (B) CUE condition and (C) DIS condition; (D) the choice task. In the NoCUE condition participants immediately entered the choice task (D) following encoding. NoCUE = Trials without cueing; CUE = cued trials; DIS = cued trials in which possible distraction of cues was made salient.

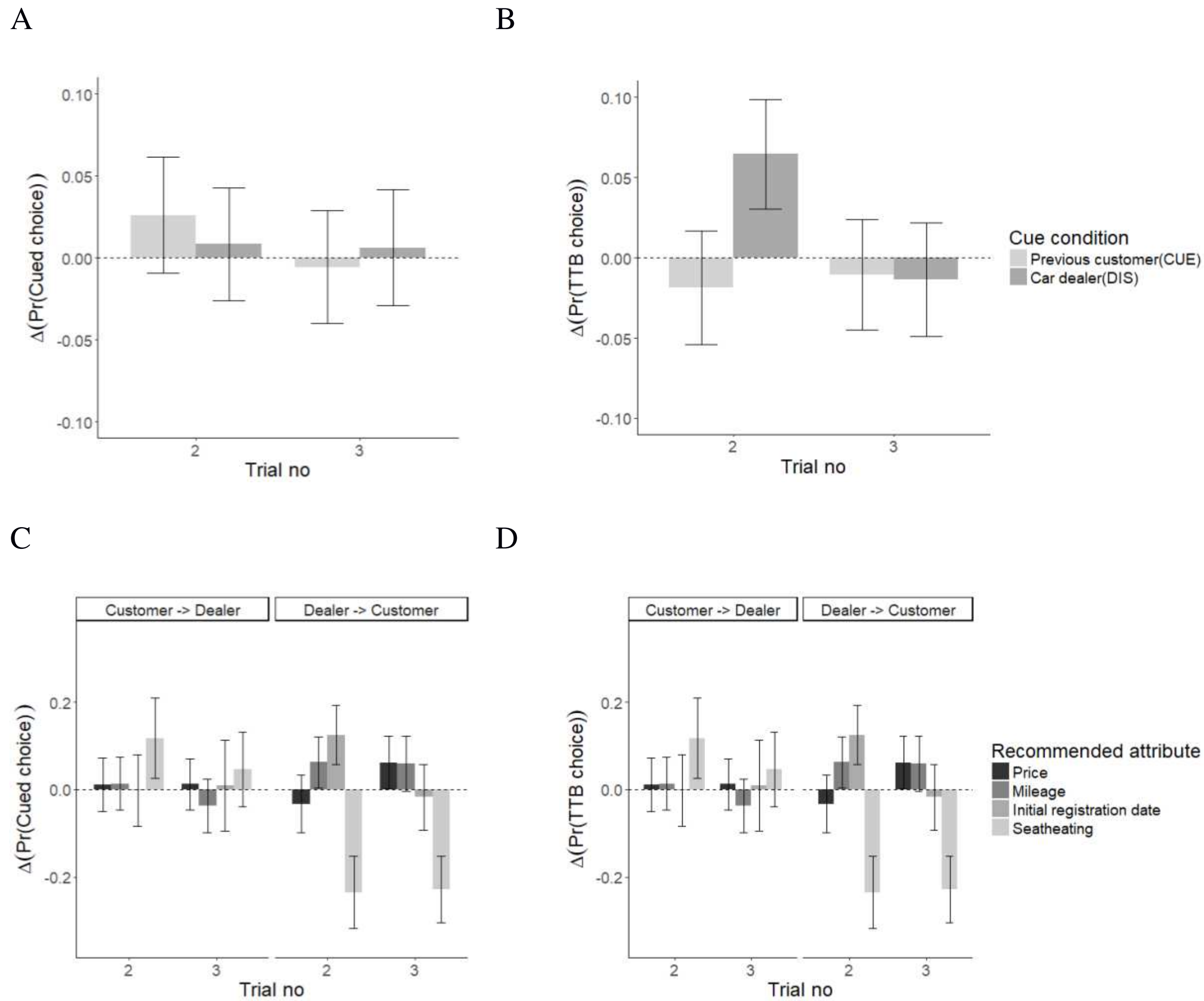


Figure 8. Average retro-cue effect in Experiment 3 on the choice proportions in accordance with the cue (A, C) and the Take-the-Best (TTB) strategy (B, D) as a function of the cueing condition (CUE, DIS). In the top row the effect is averaged across all cued attributes and in the bottom row it is depicted as a function of the cued attribute. $\Delta(\mathrm{Pr}\ (\mathrm{choice}))$ = Difference in the proportions of choices in accordance with a cued attribute in the cueing conditions (CUE, DIS), compared to the proportions of choices in accordance with the same attribute in the NoCUE condition. $\Delta(\mathrm{Pr}(\mathrm{TTB\ choice}))$ = Difference in the proportions of choices in accordance with the TTB

strategy in the cueing conditions (CUE, DIS) compared to the NoCUE condition. The error bars indicate two standard errors around the mean. NoCUE = Trials without cueing; CUE = cued trials; DIS = cued trials in which possible distraction of cues was made salient.