Retro-cueing in multi-attribute choices: The influence of memory availability on strategy
selection and attribute weights

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Abstract

Decision making in multi-attribute choices is adapted to the structure of the task. The availability of information in memory was recently proposed as driving this adaptation. We studied this hypothesis in the context of purchase decisions by using eye tracking and computational modelling in controlled lab experiments. We particularly manipulated memory availability through a retro-cue, thereby highlighting one attribute in a multi-attribute choice task in which participants decided among products (movies, books) based on the recommendations of six reviewers. In three experiments, we observed that the retro-cue has a two-fold effect on subsequent choices. First, cueing the position of one recommendation increased the probability of choosing the recommended product. Second, cueing any recommendation led to an increase of choices in accordance with a compensatory decision strategy. Gaze analyses show that search behavior is indeed changed following the retro-cue. We further propose a computational model for describing and generalizing the effect.

Keywords: consumer behavior; multi-attribute models; choice modeling; adaptive decision making; decision research.

1. Introduction

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

In both examples, the availability of an attribute for the alternatives (in this case, fuel consumption) was increased, because your attention was drawn toward this attribute (i.e. by your friend or the dealer). In the first scenario you would probably decide upon your friend's recommendation, but in the second scenario you might carefully reconsider all 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 – for instance, via visually salient cues – can bias purchase decisions in favor of the product that is preferred by this attribute (Bordalo, Gennaioli, & Shleifer, 2013; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012). However, increasing the availability of one attribute also influences search behavior and subsequently drives choices (Lawrence, Thomas, & Dougherty, 2018; Mandel & Johnson, 2002; Platzer, Bröder, & Heck, 2014). A better understanding of how memory availability influences consumer choices is therefore necessary to make consumer decisions predictable (Wright, 1975) and to avoid unintended consequences.

The following experiments studied how the availability of attribute information in memory affects choices. The present study goes beyond previous research of the availability effect on decision making in a consumer context. We show that increasing the availability of an attribute in memory not only influences the weight, which an attribute receives in the decision making process (Bordalo et al., 2013); it also influences information search behavior per se. In addition to behavioral and gaze data, which support our assumptions, we also put forward a computational model to generalize the observed effects and to better predict – for applying it in consumer research – how availability affects consumers' choices.

1.1. Adaptive Decision Making in Multi-Attribute Choices

Purchase decisions are often described as choices between two or more alternatives, which differ on a couple of attributes (Bettman, Luce, & Payne, 1998). For instance, in the opening example, the different cars are the decision options. Each car can be described according to several attributes, such as fuel consumption, engine type, or kilometers driven. Attributes can also differ according to their predictive value (also referred to as their validity) in relation to the criterion. For example, although fuel consumption may be an important attribute for judging your car's energy efficiency, the color of the car may not.

Decision making behavior in multi-attribute choice tasks is adapted to the task structure and varies between individuals: That is, people adaptively choose strategies to optimize their decisions (Gigerenzer & Todd, 1999; Payne, Bettman, & Johnson, 1993). Whether decision makers apply a compensatory or non-compensatory decision strategy, is a key feature that enables discriminating between different decision making processes. Compensatory means that less valid attributes can overwrite attributes with a higher validity. A well-known example of a compensatory strategy is the “weighted additive heuristic” (WADD). WADD sums up all evidence in favor of an option weighted by the validity of each

attribute. The option with the highest overall sum is chosen. In contrast, non-compensatory means that more valid attributes cannot be overwritten by less valid attributes. An example of non-compensatory strategies is the “take-the-best heuristic” (TTB; Gigerenzer & Todd, 1999). Starting with the most valid attribute, TTB searches for attributes in the order of their predictive validity. If an attribute discriminates between options, the option supported by the attribute is chosen. If the attribute does not discriminate between options, the second best attribute is considered, and so on. Generally, compensatory strategies require an accumulation of more information, whereas non-compensatory strategies rely on only a few – but often the most valid – bits of information.

The Adaptive Toolbox model refers to the notion that individuals have a variety of different decision strategies, which they adaptively apply in different situations (Gigerenzer & Todd, 1999). A typical Toolbox contains at least one compensatory and one non-compensatory decision strategy. The Toolbox is a proven, valid model of decision making in multi-attribute choice tasks (for a discussion, see Bröder & Newell, 2008). By implementing the Adaptive Toolbox model in a computational modelling framework (see Scheibehenne, Rieskamp, & Wagenmakers, 2013), the Adaptive Toolbox was better able to describe individuals’ choices than a competing accumulator model (Krefeld-Schwalb et al., in press). Furthermore, a simple Toolbox, consisting of only one compensatory and one non-compensatory decision strategy, described individuals’ choices better than a more complex toolbox containing multiple strategies (Scheibehenne, Rieskamp, & Wagenmakers, 2013).

The extent to which a decision maker applies either a compensatory or non-compensatory decision strategy depends upon several factors, such as the affect richness of the choices (Suter, Pachur & Hertwig, 2016), incidental emotions (Scheibehenne & von

Helversen, 2015), and the pay-off structure (Rieskamp & Otto, 2006). The selection of the appropriate strategy also depends on the search costs: “Inferences from memory” (Gerd Gigerenzer & Todd, 1999) are more costly in terms of memory retrieval than inferences “from givens” and therefore they lead to more non-compensatory decision making (see Bröder & Schiffer, 2003). In a similar vein Maity, Dass and Kumar (2018) showed recently, how search cost influence information search of consumers. The distribution of attribute validities is another factor, which influences strategy use. More non-compensatory strategy use has been observed in decision-making environments in which one attribute has a much higher validity than the other attributes. In contrast, uniformly distributed attribute validities – that is, all information is almost equally valid – leads to more compensatory strategy usage (Krefeld-Schwalb, Donkin, Newell, & Scheibehenne, in press; Mata, Schooler, & Rieskamp, 2011). Interestingly, this highly adaptive behavior can even be observed when participants have received neither training nor feedback (Krefeld-Schwalb et al., in press).

Recent research points toward another factor, which influences strategy use, namely the amount of attention directed toward attribute information. For instance, Platzer, Bröder, and Heck (2014) showed that spatial cueing of an option's attribute value – after the participants have encoded information about the different decision options into their memories – increase the influence of this attribute on inferential choices. The memory literature has extensively explored the fact that cueing the spatial location of previously presented information increases visual attention to this position and the likelihood of this information being retrieved from memory (Souza & Oberauer, 2016). Recent research showed that this retro-cue effect also applies to verbal material (Krefeld-Schwalb, 2018) and can best be described as a shift of attention between representations stored in memory (Scholz, Klichowicz, & Krems, 2018). Beyond that, Platzer et al. (2014) showed that retro-

cueing even affects choice behavior in multi-attribute inferences from memory. The authors argue that the retro-cue increases the weight, which a cued attribute receives during the decision making process and the decision strategy. This means that cueing valid information supports the use of non-compensatory strategies, whilst cueing less valid information increases the motivation to search for more information in memory, and thus increases the use of compensatory decision strategies. It must be noted, however, that the authors did not systematically control for the predictions flowing from the different strategies and the retro-cue: In most cases, the attributes of higher validity are also more likely to make a prediction in line with the TTB strategy and therefore this study could not differentiate whether cueing of highly valid cues is generally more efficient or whether it leads to more TTB choices.

Another recent study points toward the importance of taking memory processes into account when explaining multi-attribute decision making (Lawrence et al., 2018). The authors showed that the availability of attributes in memory influences the extent to which they were used in the decision making process. By using a computational model, which describes the hypotheses generation process (HyGene, see Thomas, Dougherty, Sprenger, & Harbison, 2008), the authors showed that memory retrieval underlies attribute usage during decision making.

This study aims to continue this line of research by simultaneously excluding alternative explanations, which previous research has not addressed. In three experiments, we study how the availability of information in memory affects consumer choices and the strategies used. We therefore apply the retro-cueing paradigm (Souza & Oberauer, 2016) to a multi-attribute binary choice task in which attribute information has to be retrieved from memory. In the Experiment 1 we aim to replicate the retro-cue effect, which was found in a

previous study (see Platzer et al., 2014) about an inferential choice task. However, since there is often no right or wrong when it comes to consumer choice, we study preferential choices instead in Experiments 2 and 3. In Experiment 2, we manipulate the decision environments, which are defined by the distribution of the cue validities. Different environments lead to different decision strategy usage. As a result, also the expected retro-cue effect may differ between environments. In Experiment 3, we test whether the retro-cue effect is only due to an increase in the availability of information held in memory. Alternatively, it may occur, because the retro-cue is interpreted as providing additional useful information for the choice task. In order to also trace the attentional dynamics closer, we use eye-tracking as a process tracing tool (Orquin & Mueller Loose, 2013; Renkewitz & Jahn, 2012; Schulte-Mecklenbeck, Kühberger, Gagl, & Hutzler, 2017). In all three experiments, we control for the predictions flowing from compensatory and non-compensatory decision strategies, as well as the information emphasized with the retro-cue, since this may change the results. Based on the experiments' results we further propose and test a computational model that relies on the Adaptive Toolbox approach (Krefeld-Schwalb et al., in press; Scheibehenne, Rieskamp, & Wagenmakers, 2013) to describe the observed effects and to link cognitive modelling with process measures.

1.2 . General Overview of the Experiments

In the following experiments we combined a multi-attribute choice task – which is frequently used to study decision making processes (Payne, 1976; see also Scheibehenne & von Helversen, 2014) – with a retro-cue paradigm, which is mostly used in memory research (Souza & Oberauer, 2016).

We implemented a multi-attribute choice task with two options and six attributes in the following experiments. Figure 1 illustrates the task's general procedure. All the

information, including the predictive validities of the options' attributes, were presented at the beginning of each trial on an information board in the center of the screen (see Figure 1A). Subsequently, only the grid of the board remained on the screen and the participants were asked to perform a memory-based choice (see Figure 1E). Furthermore, in certain trials one of the attributes was cued between the presentation of the information and the choice task. A black frame particularly emphasized one of the board's rows, thereby corresponding to one of the attributes (see Figure 1C). The attribute's values or its validity was not presented again; only the black frame cued the position of the previously presented information. The data and coder for running the following analyses is in the supplementary material to this article¹.

Figure 1. Screenshots of all consecutive screens in a cued (MCue) trial: The encoding phase (Panel A), the first blank grid (Panel B), the cue (Panel C), the second blank grid (Panel D), and the choice task (Panel E). In the NoCue condition the blank grid (Panel B) remained on the screen for 2000ms between encoding (Panel A) and the choice task (Panel E).

2. Experiment 1

The Experiment 1 studied how the cue influences the choice probabilities, as well as the strategy selection proposed by Platzer et al. (2014). We hypothesize that cueing one attribute will increase the probability of choosing the option, which is preferred by the cued

¹ <https://osf.io/ke7az/>

attribute. We also hypothesize that cueing increases the use of non-compensatory decision strategies.

2.1. Method

2.1.1. Participants

We tested 58 students from the University of Geneva (Female = 48%, $M_{\text{age}} = 21.7$) who received course credits for their participation.

2.1.2. Apparatus

The following experiments were programmed in python by using functions from the PsychoPy library (Peirce, 2007). The tasks were presented on 24" screens with a 1920×1080 pixel resolution.

2.1.3. Material and Procedure

The participants were presented with a multi-attribute choice task in which they were asked to choose one out of two hypothetical movies, which they think will be more successful at the cinema box offices (Scheibehenne & von Helversen, 2014). In order to inform their choices, the participants received recommendations from six hypothetical movie critics. These critics differed in their probability to recommend the more successful movie. The critics' recommendations represent the cue values (recommendation versus no recommendation) and the probabilities represent the cue validities. The validities were uniformly distributed across the critics [65%, 63%, 63%, 62%, 60%, 58%] so that all the information was almost equally important for the choices, but still not identical, thereby increasing the external validity of the task. Since we were interested in studying the applied decision strategies, we balanced trials in which a non-compensatory heuristic (TTB) and a compensatory heuristic (WADD) made either the same or different predictions. The latter trials help estimate the proportion of choices in accordance with TTB or WADD. Thereby,

trials in which both strategies make the same prediction enable us to estimate the proportion of choices, which are not in accordance with either of the strategies.

All the information was presented on an information board in the center of the screen; asterisks illustrated the recommendations and hyphens illustrated no recommendations. In addition, the critics were visualized with cartoon animal icons on the left side of the information board. The validities were expressed as percentages between the icons and the board. The information was ordered such that the critic with the highest validity appeared at the top of the information board and the one with the lowest validity at the bottom.

Every cell of the information board covered 10% of the screen's height and 10% of the screen's width – therefore 5.3 cm × 3 cm. In total, the information board together with the percentages in the animal icons covered 24% percent of the screen. With an average distance of 70 cm between the participant's eye and the screen, the information board covered a horizontal visual angle of 10° and a vertical visual angle of 26°.

The complete information board was shown for 1.5 sec, following, all the information was deleted from the board and only the grid remained on the screen. After 500 ms – in 50% of the trials – one row of this grid was emphasized with a black frame for 1 sec. The row was randomly chosen among the critics who distinguish between the options. The trials were balanced between trials in which the cued critic's recommendation was in accordance with either the non-compensatory or the compensatory decision strategy. The recommendation was not shown again; only the frame of the information board's row was emphasized. In justifying this cue to the participants, they were instructed that it might help them memorize the previously shown information. Subsequently, the frame disappeared, and the grid remained on the screen for another 500 ms until the choice task started. With a mouse click,

the participants could choose either Movie A or Movie B. We refer to cued trials with MCue versus complementary NoCue trials of the same duration, but without cueing.

All the participants made a total of 63 choices in two blocks, preceded by 8 practice trials. Due to experimenter error, these blocks were not equally sized; the first block consisted of 32 trials and the second block consisted of 31 trials. Furthermore, the cueing 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.

Figure 2. Average choice proportions in Experiment 1 in accordance with the cue (Panel A) and the TTB strategy (Panel B). $\text{Pr}(\text{Cued Choice})$ = proportions of choices in accordance with a cued attribute in the MCue condition, compared to the proportions of choices in accordance with the same attribute in the NoCue condition. $\text{Pr}(\text{TTB Choice})$ = proportions of choices in accordance with TTB strategy as a function of the cue. The error bars indicate 95% CI around the mean.

2.2. Results

2.2.1. Choices

First, we wanted to understand whether the cue alters the choices. As shown in the study by Platzer et al. (2014), the cue certainly has a significant influence on the choice proportions. The participants were more likely to follow a critic's recommendation if the position of the critics' recommendations on the information board were highlighted through the retro-cue than when it was not highlighted (69% cued trials vs. 53% in cued trials, p

$< .001$, $BF_{10}^2 > 1000$, see Figure 2A). In order to investigate the cueing effect – while simultaneously controlling for the validity of the cued recommendation and the correspondence of the recommendation with either of the decision strategies – we randomly selected one row in all the trials. In the MCue condition, this row was cued, but in the NoCue trials it only served as a random counter for pairing NoCue with MCue trials to compare choice proportions and strategy use. $\text{Pr}(\text{Cued Choice})$ therefore refers to the recommendation of the critic who was cued in the MCue trials, but not in the NoCue trials.

A generalized linear mixed modelling analysis (GLMM³) supported the cueing effect, but also showed that the critic's validity did not influence the cueing effect. The model was implemented with a logit link to the choice, which was – or was not – in accordance with the cued information (Cued Choice). The cue, as well as the validity of the cued critic and their interaction, were introduced as fixed effects in the full model and the trials and subjects as random effects. From all possible models derived from the full model, we selected the model with the smallest AIC. The best fitting model, which compromises only the retro-cue effect, is depicted in Table 1, together with the best fitting models of the following experiments.

2.2.2. Strategies

Second, we were interested in the strategies that people used. We therefore tested the amount of choices in accordance with the non-compensatory TTB heuristic. We found that TTB choices became less likely in cued trials (55% MCue trials vs. 58% in NoCue trials, $p = .01$, $BF_{10} = 1.7$ see Figure 2b). In order to control for the influence of the cue corresponding with the strategies – and to also control for other features of the trial – we tested this effect in a second set of GLMM analyses. We added two additional factors, which influence the

² Bayes factors were calculated by using the R-package BayesFactor (Morey & Rouder, 2014)

³ The mixed models were fitted by using the R-package lme4 (Bates, Mächler, Bolker, & Walker, 2015).

number of TTB Choices in cued and non-cued trials. The first factor indicated whether TTB and WADD made the same or different predictions. This is relevant, because trials in which TTB and WADD make the same prediction, the TTB choices compromise the WADD choices and are thus more likely to occur than in trials where both strategies make different predictions. The second factor indicated whether the cue and TTB make the same prediction. If the cue and TTB make the same prediction, choices in accordance with the cue cannot be distinguished from choices in accordance with TTB. Table 2 summarizes the best fitting model of the GLMM analysis. Controlling for the predictions of the two strategies, as well as predictions of the cue and the TTB strategy, showed that cueing actually decreased TTB choices across all trials.

2.3. Discussion

Experiment 1 replicates the retro-cue effect on choices, as well as the underlying decision making process in memory-based choice. Our data suggest that – across all trials – cueing motivated participants to recall and consider all the information, which was previously presented, by using a compensatory WADD strategy.

In contrast to previous studies on the cueing effect, the participant did not have to learn the validities of the attributes – here framed as the predictive validities of the critics, – because they were shown to the participants as percentages. We controlled the distribution of the attribute values such that the predictions of the strategies and the cue were independent and balanced. This enables inferences about strategy usage, as well as inferences about the cue's influence on the choice. As a result, we showed that cueing certainly led to an increased use of a compensatory over a non-compensatory strategy. This result stands in contrast to those reported by Platzer and his colleagues (2014) who observed a decrease of compensatory strategy use. We argue that this may be due to controlling for the predictions of the strategies and the cue.

In the current task implementation, the validities of the attributes were very similar. This potentially increased the effect of cueing on one of the attributes concerned with the choice and strategy selection. This may be due to compensatory strategy use in environments with a low dispersion of validities being more likely than in environments with a higher dispersions of validities (Krefeld-Schwalb et al., in press; Mata et al., 2011). As a result, an adaptation to different environments, which are defined by the dispersion of the attributes' validities, might interact with the retro-cue's effect on strategy selection.

3. Experiment 2

Experiment 1 tested the general retro-cue effect in an inferential task, in a decision environment in which the attributes had almost equal predictive validity for the choice. However, decision making differs between environments. Furthermore, in many real-life decision making situations information is not uniformly distributed. Instead, certain attributes have more predictive validity than others. For example, not all the attributes of a product are equally important for the probability to purchase the product. The dispersion of the attributes' validities in a choice task further influences which strategy will be used (Krefeld-Schwalb et al., in press; Mata et al., 2011). Experiment 2 studied how the retro-cue effect interacted with the influence of different decision environments – both in terms of strategy use and with choices.

Since we were also particularly interested in the relevance of the retro-cue's effect for consumer behavior, we changed the task to a preferential choice task. Framing the task as a preferential choice – particularly a purchase decision for yourself – does not provide an objectively evaluable choice.

We asked participants to make preferential choices between two books. Similar to online selling platforms, they received the recommendations of six hypothetical reviewers.

However, instead of a continuous or a five-star rating, the recommendations were presented as binary values. The ratios how the reviewers' recommendations have helped other clients in the past, represented the validities. This is information that amazon.com, for example, provides about reviewers.

3.1. Method

3.1.1. Participants

We tested $N = 28$ students from the University of Geneva (Female = 54%, $M_{age} = 22.8$) who received course credits for participating in the experiment.

3.1.2. Apparatus

We used exactly the same setup as in Experiment 1.

3.1.3. Materials and Procedure

In a multi-attribute choice task similar to the task used in Experiment 1, the participants were asked to choose one out of two books for themselves, based on the recommendations of six reviewers. As in Experiment 1, all the information was shown in an information board in the center of the screen. The validities were framed as ratios showing how the reviewers' recommendations helped other clients in the past. Note that online platforms, such as amazon.com, definitely provide this information about reviewers. In addition to manipulating the absence or presence of the cue, we further manipulated the distribution of the validities in three blocks between a uniform [65%, 63%, 63%, 62%, 60%, 58%], a j-shaped [90%, 69%, 68%, 66%, 63%, 60%], and a linear distribution [90%, 83%, 76%, 69%, 62%, 55%]. In order to give the participants more time to completely encode the information board, we also changed the timing of the trials. After showing a fixation cross for 500 ms, the information board, including the recommendations and validities, were shown for 3000 ms. Then, only the grid of the empty information board was shown for another 500 ms.

In half of the trials one row on the board was then emphasized with a black frame for 1500 ms. After showing of the blank information board for another 500 ms, the open-ended choice task started.

After 8 practice trials, 64 trials were conducted in every validity condition, thereby leading to 192 experimental trials per participant in total.

Figure 3. Average choice proportions in Experiment 2 in accordance with the cue (Panel A) and the TTB strategy (Panel B) as a function of the validity distribution and the cue conditions. The error bars indicate 95% CI around the means.

3.2. Results

3.2.1. Choices

As in Experiment 1, we found a retro-cue effect in the uniform condition. Figure 3A illustrates that the retro-cue effect also occurred in the j-shaped and the linear environments. In every validity condition, cueing the location of one reviewer increased the probability that the choice was made in accordance with this reviewer, compared to not cueing the reviewer (63% vs. 51 % in the uniform condition, 63% vs. 51% in the j-shaped condition, 62% vs. 49% in the linear condition, all $p < .001$, $BF_{10} > 1000$).

The same GLMM as in Experiment 1 – but with the validity distributions added as additional fixed effect – was run to study this result. See Table 1. In addition to the cue's fixed effect, the analysis showed an interaction and main effects of the cued reviewer's validity and the

validity distributions. However, neither the cued reviewer's validity nor the validity distributions interacted with the cueing effect. Figure 4 plots the probability of choosing the cued option as a function of the cued attribute's validity or of corresponding non-cued attributes and the distribution of the validities. The plot illustrates that cues with a higher validity have a stronger influence on the choices, because the probability to choose in accordance with these attributes increases with their validity. Not only the rank in the distribution influences the choice; the exact validity is also influential, since the distribution of choice proportions reflects the distributions of the attribute validities. Cueing the attributes further increased the probability of choosing the favored option.

Figure 4. Average proportions of cued choices in Experiment 2. $\text{Pr}(\text{Cued Choice})$ = proportions of choices in accordance with a cued attribute in the MCue condition, compared to the proportions of choices in accordance with the same attribute in the NoCue condition, as a function of the validity distribution condition and the rank of the attribute in the validity distribution. The error bars indicate 95%CI around the means.

3.2.2. Strategies

Similarly, the cue's effect on strategy selection was replicated in all environments,

which were tested in Experiment 2 (60% vs. 62 %, $p = .20$, $BF_{10} = .19$, in the uniform condition, 66% vs. 73% $p < .001$, $BF_{10} > 1000$ in the j-shaped condition, 65% vs. 70% in the linear condition, all $p = .004$, $BF_{10} = 5$); see Figure 3b. The GLMM, which is summarized in Table 2, shows that – in contrast to the retro-cue effect on choice – the retro-cue effect on strategy selection interacted with the validity distributions. As hypothesized, TTB choices varied between the validity distributions, with the most TTB choices in the condition with highest dispersion of cue validities (i.e., in the j-shaped environment) and the least TTB choices in the condition with the lowest dispersion of cue validities (i.e., in the linear environment). Cueing decreased the use of the non-compensatory decision strategy, especially in the conditions with j-shaped and linear validity distribution.

3.3. Discussion

Experiment 2 replicated and extended the results of Experiment 1 in a preferential choice task. Moreover, the retro-cue effect was also observed in choice environments with a more disperse distribution of validities. In the latter environments, individuals tend to use more non-compensatory decision strategies. However, retro-cueing nonetheless increased the probabilities to apply compensatory strategies in these conditions. This increase was even more significant than in the condition with the uniform distribution of validities. The results therefore support the assumption of the retro-cue's two effects. Retro-cueing increases the weight of the cued option, because it augments the probability of choosing the options preferred by the cued attribute. In other words, it appears that retro-cueing adds a certain weight to the validity of the option, which is favored by the cued attribute. Retro-cueing also seems to influence strategy selection such that it leads to more compensatory decision making strategies.

The beneficial effect of retro-cues on memory retrieval has been explained via

attentional processes. More precisely, the item that is cued prior to testing is focused in memory, thereby leading to an increased availability of this information for further processing. However, Souza and Oberauer (2016) also note that the retro-cue effect depends on the cue's reliability – that is, people use the cue strategically to modulate the encoded information. If the effect, which we observed in Experiments 1 and 2, is indeed caused by a strategic allocation of attention to information that is stored in memory, the retro-cue effect should disappear when people are warned about the cue's distracting effect.

We also based our inferences about strategy usage only on the behavioral choice data; we could not investigate the underlying attention processes, which reflect how information search differs between compensatory and non-compensatory decision strategies in the previous experiments. However, recent research has shown that eye movements are indicative of information search processes in memory, which differ between decision strategies (Renkewitz & Jahn, 2012).

4. Experiment 3

The previous experiments suggested that the retro-cue has a two-fold effect on decision making in multi-attribute choice tasks. Above all, it was assumed that retro-cueing drives attention to a spatial position and subsequently increases the availability of this information in memory that had been presented at a cued position (Souza & Oberauer, 2016; Souza, Rerko, & Oberauer, 2016). However, instead of increasing attention and – subsequently – the activation of information in memory, the retro-cue benefit might only arise, because people use it strategically during the decision making process.

Furthermore, although the experimental design enabled us to investigate strategy selection with choice data, the choices remain only proxies of the decision making processes (also see Schulte-Mecklenbeck, Kühberger, Gagl, & Hutzler, 2017). We have not yet studied

whether search behavior in compensatory decision strategies actually differs from search behavior in non-compensatory decision strategies, and whether the same subsequently also applies to the MCue and NoCue conditions.

We addressed these issues in Experiment 3. At the outset, we included an additional condition whereby we warned the participants about the cue's distracting effect. If the retro-cue effect that we observe in decision making is the same as the one observed in memory research, we expect that the cue's effect on the choices should disappear when people do not use the cue strategically to inform their decisions. Next, we recorded gaze data during the task with an eye tracker to study information search in memory. Studying eye movements has proven to be a useful tool for tracing retrieval processes from memory (the so-called “looking-at-nothing”-behavior, e.g., Richardson & Kirkham, 2004; Richardson & Spivey, 2000) during judgment and decision making (Renkewitz & Jahn, 2012; Scholz, Krems, & Jahn, 2017; Scholz, von Helversen, & Rieskamp, 2015). Not only the number of fixations to more or less attributes (Wästlund, Otterbring, Gustafsson, & Shams, 2015), but also gaze transitions are informative of information search. For instance, Renkewitz and Jahn (2012) showed that compensatory WADD strategy usage leads to more gaze transitions within an option (henceforth referred to as attribute-wise transitions). As a result, using the non-compensatory TTB heuristic leads to more transitions between options (henceforth referred to as option-wise transitions). If cueing attributes during decision making leads to more compensatory strategy usage, we should also find more attribute-wise information searches in the conditions with a cue compared to the conditions without a cue. We used the SI index to measure the amount of option-wise – as opposed to attribute-wise – transitions (Ettlin, Bröder, & Henninger, 2015; Payne, 1976).

4.1. Method

4.1.1. Participants

We tested $N = 40$ students of the University of Geneva (Female = 60%, $M_{age} = 22.5$) who received 20CHF (\$21) for participating.

4.1.2. Apparatus

We used an Eyelink 1000 eye tracker at 250 Hz sampling rate to record the gaze data. The screen had a size of 24" and a resolution of 1920×1080 pixels. The right eye was tracked in remote mode and therefore the participants could freely move their heads. The average distance between the head and the screen was 60 cm. In order to ascertain the precision of the recorded data, the eye tracker was calibrated three times per participant by using a 10 point calibration procedure, before every cueing block as described in more detail below. The experiment was only started 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° . Fixations were detected based on a dispersion based algorithm (Holmqvist, Nyström, Andersson, Dewhurst, Jarodzka, van de Weier, 2011), which is available in the python library PyGaze Analyser (Dalmaijer, Mathôt, & Van der Stigchel, 2014). Subsequent samples with less than 25 pixels spatial distance for more than 40 ms were classified as a fixation.

4.1.3. Material and Procedure

The general procedure followed the procedure applied in Experiment 2. 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 in this block of the experiment. Then, the participants conducted a “memory” (MCue) and a “distractor” cueing block (DCue). The order of these two blocks was balanced between the participants to control for carryover effects between the blocks. The instruction concerning the cue in the MCue condition was the

same as in Experiments 1 and 2. In the DCue condition, the participants were instructed that the cue “might distract them from the previously presented information.” Then, they were instructed – in both conditions – that the cue provides no additional information concerning the choice. In order to make sure that the participants were not misinterpreting the cue, they were asked on a subsequent page whether the cue provided additional information. If they agreed, the instructions and the question were repeated. Similar to Experiment 2, the distribution of the validities was manipulated blockwise in randomized order within each of the cueing conditions. The participants were therefore faced with trials in the j-shaped, linear, and uniform validity distribution condition in each cueing condition: NoCue, MCue, and DCue. In total, the participants conducted 288 experimental trials in 9 blocks.

A rectangle in every cell of the information board, as well as equally sized cells around the validities of every attribute, were defined as areas of interest (AOI). 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 3.8° and a vertical angle of 2.25° . The vertical distance between the AOI was 60 mm and the horizontal distance was 106 mm, thereby corresponding to average visual angles of 1.12° and 1.91° .

Based on the sequence of fixations in these AOIs, option-wise transitions were defined as two sequential fixations in cells, which correspond to the different choice alternatives. Attribute-wise transitions describe complementary gaze movements – thus, a sequence of two fixations in different attributes, which is different rows on the information board. The two types of transitions – taken together – define the strategy index (Payne, 1976), which is the number of option-wise transitions minus the number of attribute-wise transitions divided by the sum of these two types of transitions per trial.

4.2. Results

4.2.1. Choices

How the retro-cue affects the choice proportions was replicated in the MCue condition in which the participants were instructed that the cue might help them to memorize the presented information (56% vs. 52%, $p < .001$, $BF_{10} > 1000$). Contrarily, the choice proportion in the DCue condition did not differ from the conditions in which no cue had been presented (53%, $p = .09$, $BF_{10} < 1$) – see Figure 4A. The median response time in the choice task was .998 sec ($SD = 1.11$) and 93% of all response times were less than 2 sec. We conducted the same GLMM analysis as in Experiment 2, with the retro-cue effect now measured separately as the effects of the MCue and the DCue condition. The MCue's effect could be replicated. However, the distractor-instruction removed the retro-cue effect in the DCue condition. Similar to Experiment 2, the retro-cue effect in both cueing conditions did not fluctuate between the validity conditions, nor did it interact with the validity of the cued information (see Table 1).

Figure 5. Average choice proportions in Experiment 2 in accordance with the cue (Panel A) and the TTB strategy (Panel B) as a function of the validity distribution and the cue conditions indicated by the grey shade. The error bars indicate 95% CI around the means.

4.2.2. Strategies

Contrary to the results for the choices, an analysis of strategy use showed that *both* the MCue and DCue cueing conditions led to a decreased use of non-compensatory decision strategies (64% vs. 61%, $p < .001$, $BF_{10} = 165$ and 64% vs. 61% , $p < .001$, $BF_{10} > 1000$) – see Figure 5B and the summary of the corresponding most fitting GLMM in Table 2.

4.2.3. Eye movements and strategies

Based on our analyses of the gaze transitions, we expected that a more compensatory information search in the cueing conditions should also lead to more attribute-wise transitions. We used a mixed model analysis, including the subject and the trial as random effects, to test –how the cueing conditions and the validity distributions influence SI. The best fitting models included only the cueing conditions as fixed effects. Adding the validity distribution or their interaction did not improve the model fit in terms of a smaller AIC. As expected, cueing was associated with a decrease in SI since the presentation of the cue, as indicated by negative regression coefficients of both the MCue and DCue conditions ($B_{MCue} = -.12$, $SE = .02$, $p < .001$; $B_{DCue} = -.13$, $SE = .02$, $p < .001$, $BF_{10} > 1000$) – see Figure 6. A decrease in SI indicates more attribute wise search that has been associated with more compensatory information search.

Figure 6. Average Strategy Index (SI) during cue presentation and in the interval following the cue until the participants' response, or the respective blank grid presentation in the NoCue condition, as a function of the cueing and the validity distribution conditions. The error bars indicate 95%CI around the mean.

The SI did not differ between the two cueing conditions, MCue and DCue ($t(39) = .52, p = .60, BF_{10} < 1$). Likewise, the proportion of fixations to the cued attribute ($t(39) = -.69, p = .5, BF_{10} < 1$) and the cued option ($t(39) = -.05, p = .96, BF_{10} < 1$) did not differ between the two conditions ($t(39) = 1.25, p = .22, BF_{10} < 1$). Proportions were calculated as the number of fixations in the respective AOI relative to all fixations.

Figure 7. Average proportions of fixations in the encoding, cueing, and choice phases of Experiment 3 to the AOI in the different rows (x-Axis) representing the reviewers, as a function of the cueing condition (line color) and the cued row, indicated in the grey bar above the single plots. Proportions are calculated according to the number of fixations on the respective rows in a particular trial phase divided by the total number of fixations in that trial phase.

Figure 7 plots the fixation proportions on the different rows of the information board. It plots the fixations to the attributes, based on the cueing condition and the cued row, separately for the encoding, the cueing, and the choice phases. The plot illustrates that during encoding, most fixations remained on the second and third cue. Subsequently, cueing

attracted attention to the cued row. Importantly, the MCue condition is not distinguishable from the DCue condition during this phase. The fixation proportions during the choice show the fixation pattern of the encoding and the cueing phases. The participants again fixated the third row and in the cueing conditions they also fixated the cued row, as well as the surrounding rows. The large proportion of fixations on the last row is due to the choice task being shown below the information board – see Figure 1.

Eye gaze – that is, transitions between attributes and options – only mirrored information search behavior and thus supported our inferences about the retro-cue effect strategy used. Fixations, however, did not mirror the effect on the choices. Although the retro-cue effect was only observed in choices in the MCue condition and not in the DCue condition, fixations on the cued row – during the cue and the choice – did not differ between the two conditions.

4.3. Discussion

Recording the participants' eye gaze supported our inferences concerning strategy selection based on the choice data of Experiments 1 and 2. Retro-cueing led to an increase of compensatory strategy use, which was characterized by an increase of attribute-wise search behavior – regardless whether the participants were warned about the cue or not. However, cueing only affected the choice proportions in accordance with the cued attribute if the participants were not warned about the cue's distracting effect.

These results further support the assumption that retro-cueing certainly has two distinct effects on decision making: It affects the weight attributes received during decision making and it influences strategy selection. The former, however, depends on the strategic use of the cued information. The cue in the MCue condition was framed as benign, helping memorize the information, contrarily, the cue was framed as distracting in the DCue

condition. However, regarding the cue-guided information search in memory – and thus the strategy selection in both cueing conditions – retro-cueing did not increase the probability of choosing the option recommended by the cued reviewer in the DCue condition.

5. Modelling

It has been established that the Adaptive Toolbox model can describe choice behavior in multi-attribute decisions very well. In particular, a Toolbox containing a compensatory WADD and a non-compensatory TTB decision strategy can explain multi-attribute choices better than an adjustable spanner model, which assumes individual evidence accumulation thresholds (Krefeld-Schwalb et al., in press; Scheibehenne et al., 2013). However, the implementation of this Toolbox model has not yet modelled how an increased availability of certain attributes influences decision making, for example via retro-cueing. This study provides the empirical data for adapting previous instantiations of the Toolbox for implementing the observed cueing effects.

Figure 8. Flow diagram of the retro-cue Toolbox model. θ = Mixing parameter, probability

of TTB, δ = Retro-cue effect on strategy selection, $cue = \text{Retro-cue}(0,1)$, ε = Trembled error, probability to guess, γ = Retro-cue effect on options weight, val_c = validity of attribute_c $[.5,1]$, $Att_c = \{\text{Attribute value } A_c(0,1), \text{Attribute value } B_c(0,1)\}$, $Att_{cue} = \{\text{Cued attribute value } A_c(0,1), \text{Cued attribute value } B_c(0,1)\}$, Δ = Difference between the attributes values times the retro-cue effect of A and B.

The original Toolbox model has two parameters: The mixing parameter θ , which indicates the probability of using the non-compensatory TTB strategy over the compensatory WADD strategy and the error parameter ε , which indicates the probability of guessing between the options. In order to describe the pattern of results that followed a retro-cue in the previously reported experiments, we propose two additional parameters: A parameter δ , which indicates the decreased use of non-compensatory decision strategies in the presence of a retro-cue and another parameter γ , which indicates the increased weight of the cued option if the retro-cue is not interpreted as distractive. The model is illustrated as a flow diagram in Figure 8.

As a first step – referring to the diagram in Figure 8 – θ together with the retro-cue effect on strategy selection δ indicate the probability by which a strategy is chosen. If there is no retro-cue in the trial $cue = 0$, the probability of using TTB is driven by θ only. In the presence of a retro-cue, θ is multiplied with δ , which remains between 0 and 1. Then, the effect of the cue – in both strategies – is either 0, $cue = \{0,0\}$ if the participants were warned about the cue's distracting effect or the weights of all attributes (of the cued option) multiplied by the retro-cue effect γ , which remains between 1 and 2. Cueing can therefore reduce the probability of using TTB to zero if $\delta = 0$ and maximally double the cued option's weight if $\gamma = 2$.

If the TTB strategy is used, a choice is made if the best available attribute – the attribute with the highest validity – differentiates between the options under consideration of the potential cueing effects. If the attribute does not discriminate (i.e., if the difference

between the attribute values is zero), the second-best attribute is considered, and so on, until a decision can be made. If no attribute discriminates between the options (i.e., if the options have an identical cue pattern), TTB reverts to guessing, and therefore to a random choice between the options. If WADD is used, all available evidence is considered and all cue values are weighted with their validities, multiplied with potential cueing effects, and summed up. The option with the highest weighted sum is then chosen. If the weighted sum of both options is equal, the model selects either option with equal probability. Both strategies predict the probability of choosing option A that is either 0, .5, or 1. However, in combination with the mixing parameter and the trembled hand error, the likelihood as indicated in the white box at the bottom of the flow diagram in Figure 8 can take on any value between 0 and 1. In sum, the complete Toolbox model has four free parameters: the mixing parameter θ , the trembling hand error ϵ , the retro-cue effect on strategy selection δ , and the retro-cue effect on the attributes weights γ .

5.1. Model Selection

In order to test this model – particularly the added parameters – we fitted the original Toolbox model, including the error and mixing parameters, two models with contained additionally either of the proposed parameters δ and γ , as well as the full model, to the data of all three experiments. The models were fitted for each individual and in every validity distribution condition via grid search and likelihood maximization.

Comparing the models via BIC (see Table 4) shows that only if the model includes both parameters, will the adapted Toolbox model provide better fits than the original Toolbox model. Table 5 summarizes the original and best fitting model in more detail. Applying the adapted Toolbox increases the model's fit in both cueing conditions, while the fit in the NoCue condition is equal for the two models – although the best fitting parameter values of θ

and ε differ between the two models.

5.2 Linking model parameters with gaze transitions

We also compared the validity of the two models by comparing the estimates of θ between the validity distribution conditions and calculating the correlation of θ with the average SI in the respective conditions. In both models, θ was smaller – but not significantly smaller in the condition with uniform distribution of validities – compared to the conditions with linear and j-shaped distribution of validities, thereby indicating less non-compensatory strategy use in conditions with a uniform distribution of validities.

Furthermore, the individual parameter θ of the adapted models were – in all cueing conditions – significantly correlated with the average SI in the respective validity condition ($r_{NoCue} = .26, p < .001, r_{MCue} = .23, p = .02, r_{DCue} = .31, p < .001$). Figure 9 shows the scatterplots of the best fitting θ along with the individuals' SI. The same parameter of the original model was similarly correlated with SI, thereby indicating that the mixing parameter of the toolbox – the individual probability of using TTB instead of WADD – is indeed mirrored in gaze transitions.

Figure 9. Scatterplot of the best fitting individual parameters θ and the average SI in the different cueing conditions. The black line indicates the linear regression coefficient with

the grey area illustrating 95%CI around the estimate.

6. General discussion

Recent research has 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 these results and extends them to preferential choice tasks, which are frequently studied in consumer research. We also studied how the availability of information in memory, which we manipulated by means of retro-cues (see Souza & Oberauer, 2016), interacts with different decision environments (i.e., varying distributions of attribute validities). We applied a multi-method approach, which combines choice data with process tracing – that is, with eye movements and cognitive modeling. Our main results show that cueing the position of a previously presented attribute in a multi-attribute choice task increases the probability that the option recommended by the respective attribute is chosen (retro-cue effect on choices). Furthermore, cueing the position of any attribute increased the probability that the participants used a compensatory, instead of a non-compensatory, decision strategy (retro-cue effect on strategies). However, the retro-cue effect on choices could only be observed if people used it strategically to inform their decisions, but not if they thought that the cue would distract them from making their choices.

These results suggest that marketers should consider unintended consequences when they use attention grabbing methods for a specific feature of a product in an advertising campaign. Marketers should first ascertain that costumers do not interpret the increase in awareness of a specific feature as an attempt to distract them – for instance, to bias the purchase decision to their favor. Our results suggest that guiding attention to a specific product feature will also lead people to reconsider all the other attributes of the product. Thus, if a product is specialized on one specific attribute, for example a car with specifically

low fuel consumption, this product might not necessarily profit from drawing additional attention to this feature. However, a car that is less specialized on optimizing a specific attribute, can profit more from increasing the awareness about one of its attribute in an advertising campaign.

The retro-cue effect in the memory literature has been explained via attentional processes. More precisely, the item cued prior to testing is focused in memory. Focusing attention has at least three consequences for the item stored in memory. The focused item is strengthened, it is prevented from interference, and it is selected for further processing (Souza and Oberauer, 2016). That means that the availability of the cued attribute is increased. In the context of memory-based multi-attribute decisions this increased availability in memory manifests itself as an increased weight – not only of this attribute, but of the complete option favored by the respective attributes as shown in the cognitive modeling exercise. However, this is only the case when the cue is interpreted as being benign to the task. If the participants were warned about the cue's distracting function, the retro-cue effect on choices diminished. People can therefore strategically use the available information in memory. The retro-cue does not have an automatic effect per se on an option's weight.

Drawing attention to one of the attributes in a multi-attribute choice task has been shown to increase that attribute's influence on the choice and the decision making process (Orquin & Mueller Loose, 2013b; Platzer et al., 2014; Renkewitz & Jahn, 2012). In contrast with previous studies, we show that by controlling for the correspondence of the predictions concerning the strategies and the cued information, cueing leads to increased use of compensatory decision strategies. This result is based on the choice data of all three reported experiments and also on gaze transitions: That is, the participants showed more attribute-wise transitions when the cue was shown than when it was not. More attribute-wise information

search has been associated with more compensatory decision making (Ettlin et al., 2015; Payne, 1976; Renkewitz & Jahn, 2012).

Gaze data in a multi-attribute choice task has been used to trace attentional processes and infer strategy use (Renkewitz & Jahn, 2012; Scholz, von Helversen, & Rieskamp, 2015; Scholz, Krems, & Jahn, 2017; for a review, see Orquin & Mueller Loose, 2013). In that context, the ratio of attribute-wise and option-wise transitions have been associated with compensatory and non-compensatory strategy use, respectively (Ettlin, Bröder & Henninger, 2015; Renkewitz & Jahn, 2012). However, Perkovic, Kaptan, and Bown (2018) recently showed that especially the strategy index can be biased if it is not corrected for random transitions. Contrarily, the authors propose sequences of transitions as an alternative to indicating a decision strategy. In the present study, instead of interpreting strategy use based on the absolute value, we investigated how the conditions differed in the strategy index. We have no reasons for assuming that the random transitions could systematically differ between conditions and therefore they should not influence the difference of SI between the conditions.

We also did not study strategy use with gaze data only. Instead, we used a multi-method approach consisting of gathering choice data, gaze data, and using cognitive modeling. The results of all those measures converge with the observation that – compared to trials without a retro-cue – the retro-cue leads to increased compensatory strategy use..

The use of the non-compensatory TTB strategy was relatively high in the present experiments. This relatively frequent use of TTB was previously reported in studies, which used a memory-based multi-attribute 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 non-compensatory decision strategy. Compared to similar studies, showing the information for 3 sec is rather short. Re-analyzing 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 during encoding ($SE = .95$). With longer presentation time, the participants potentially fixate more attributes and apply more compensatory decision strategies. Subsequently, cueing will have a smaller influence on strategy selection. Nonetheless, the TTB strategy in Experiment 1, in which the information was only presented for 1.5 sec, was not used more often than under the respective conditions in Experiments 2 and 3. However, other aspects of the task might also influence strategy use, for example the length of the experiment. In conclusion, future research should study how encoding duration influences the retro-cue effect on strategy use.

The Adaptive Toolbox model is only one possible model to describe decision making in multi-attribute choice tasks. Alternatively, for example, models assuming a continuous accumulation of evidence (Busemeyer & Townsend, 1993; Newell, 2005) can equally be implemented in this environment. A rigorous model comparison has, however, shown that the Toolbox model is the better fitting model in similarly designed multi-attribute choice tasks (Krefeld-Schwalb et al., in press). For instance, the authors showed that individuals provide higher situational flexibility in decision making than assumed in the current implementation of accumulator models. Nonetheless, we believe that implementing other possible choice models would lead to similar conclusions. Most decision making models assume adaptive decision making that can be described through differences in the amount of evidence that is considered for a decision (Busemeyer & Townsend, 1993; Newell, 2005). Likewise, non-compensatory versus compensatory decision strategies differ in the amount of information that is considered in a given decision making situation. Therefore, the increased use of

compensatory decision strategies can potentially also be described by related concepts in other models, such as a higher threshold of evidence accumulation (Newell, 2005). The present experiments, however, were specifically tailored for implementing and testing the Adaptive Toolbox model so that choices were maximal informative for strategy use. However, correlating the Toolbox's mixing parameter with the strategy index, calculated on the gaze transitions, further suggests that the Adaptive Toolbox is indeed a valid model for similar multi-attribute choice tasks.

Based on the behavioral results observed in the experiments, we propose an adaptation of the Toolbox model's computational implementation that considers whether an attribute's availability is increased. We adapted the Toolbox to consider both distinct effects, which we observed with two independent parameters in the data. It is indeed so that only if the model contains both these parameters and implement each of these effects, it provides a better model fit, with regard to BIC considering model complexity than the original Toolbox across all three experiments.

Our results strongly support the notion that increasing the availability of information held in memory during multi-attribute choices tasks is an important contributor that helps explain decision making behavior in these kinds of tasks. By using a multi-method approach, we found that the availability of information held in memory had a two-fold effect on decision making, namely the cued option's increased weight and an increase in more compensatory information search behavior. This result corresponds with a growing number of studies, which emphasize the role of memory during judgment and decision making (Lawrence et al., 2018; Platzer et al., 2014; Renkewitz & Jahn, 2012) and therefore it is highly relevant to both cognitive and applied researchers who are interested in understanding judgment and decision making processes. It is especially relevant to marketers who aim to

presenting products to their customers in a manner that optimizes their profit.

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Table 1

Summary of the best fitting generalized mixed effects model predicting choices in accordance with the cued attribute

McFadden R ²	Cued Choice								
	Experiment 1			Experiment 2			Experiment 3		
	.03			.03			.10		
	B	SE	<i>p</i>	B	SE	<i>p</i>	B	SE	<i>p</i>
Intercept	.14	.07	.042	.16	.11	.15	-.09	.11	.41
Cue									
MCue	.70	.07	<.001	.53	.06	<.001	.26	.05	<.001
DCue							-.08	.05	.13
Cue Val	-			-.05	.03	.12	.11	.03	<.001
Val distr									
j-shaped				.36	.13	.004	.48	.11	<.001
linear				.31	.13	.013	.38	.11	<.001
j-shaped * Cue val				-.14	.04	.001	-.20	.04	<.001
Linear * Cue val				-.15	.04	<.001	-.17	.04	<.001

Note. Hyphens indicate fixed effects, which were included in the complete, but not in the best, fitting model. B = Regression coefficient, SE = Standard error.

Table 2

Summary of the best fitting generalized mixed effects model predicting choices in accordance with the TTB strategy

	TTB Choice								
	Experiment 1			Experiment 2			Experiment 3		
	McFadden R ²								
	B	SE	p	B	SE	p	B	SE	p
Intercept	-1.15	.13	<.001	-.87	.17	<.001	-.85	.21	<.001
Cue									
MCue	-.45	.15	.003	-.47	.16	.004	-.60	.11	<.001
DCue							-.52	.11	<.001
TTB = Cue	.40	.13	.001	.10	.11	.37	.18	.10	.06
TTB = WADD	2.99	.15	<.001	3.40	.15	<.001	3.17	.12	<.001
Val distr									
j-shaped	-			.84	.14	<.001	.47	.07	<.001
linear				.62	.14	<.001	.50	.07	<.001
MCue * TTB = Cue	1.65	.18	<.001	1.50	.16	<.001	.70	.13	<.001
MCue * TTB = WADD	-1.21	.18	<.001	-1.13	.17	<.001	.01	.14	.94
MCue * j-shaped	-			-.41	.18	.03	-		
MCue * linear	-			-.24	.18	.19	-		
DCue * TTB = Cue	-			-			.23	.13	.08
DCue * TTB = WADD	-			-			.38	.14	.005
DCue * j-shaped	-			-			-		
DCue * linear	-			-			-		

Note. B = Regression coefficient, SE = Standard error.

Table 4
Model fits of the original and adapted Toolbox models for
Experiments 1 -3

BIC	Toolbox (θ, ϵ)	Toolbox (θ, ϵ, δ)	Toolbox (θ, ϵ, γ)	Toolbox ($\theta, \epsilon, \delta, \gamma$)
Experiment 1	4036	4082	4094	3484
Experiment 2	4840	4882	4924	4293
Experiment 3	9834	9796	9519	9480

Table 5

Parameter estimates and model fit of the original and best fitting Toolbox model

	Toolbox (θ, ϵ)			Toolbox ($\theta, \epsilon, \delta, \gamma$)			
BIC	9774			9385			
	θ	ϵ		θ	ϵ	δ	γ
	Mean(SD)	Mean(SD)		Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)
Uniform	.27 (.33)	.27 (.24)		.34 (.32)	.24 (.22)	.43 (.43)	1.11 (.21)
J-shaped	.39 (.30)	.22 (.24)		.46 (.28)	.19 (.22)	.59 (.39)	1.15 (.28)
Linear	.37 (.28)	.21 (.26)		.44 (.28)	.18 (.24)	.66 (.36)	1.17 (.27)
	Mean(L)	-LL	MSE	Mean(L)	-LL	MSE	
NoCue	.73	1642	.14	.73	1642	.14	
MCue	.72	1770	.15	.77	1381	.11	
DCue	.74	1597	.13	.76	1428	.12	

Note. L = Likelihood, -LL = negative summed log Likelihood, MSE = Mean squared error.