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Learning affects top down and bottom up modulation of eye movements in decision making

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Abstract

Repeated decision making is subject to changes over time such as decreases in decision time and information use and increases in decision accuracy. We show that a traditional strategy selection view of decision making cannot account for these temporal dynamics without relaxing main assumptions about what defines a decision strategy. As an alternative view we suggest that temporal dynamics in decision making are driven by attentional and perceptual processes and that this view has been expressed in the information reduction hypothesis. We test the information reduction hypothesis by integrating it in a broader framework of top down and bottom up processes and derive the predictions that repeated decisions increase top down control of attention capture which in turn leads to a reduction in bottom up attention capture. To test our hypotheses we conducted a repeated discrete choice experiment with three different information presentation formats. We thereby operationalized top down and bottom up control as the effect of individual utility levels and presentation formats on attention capture on a trial-by-trial basis. The experiment revealed an increase in top down control of eye movements over time and that decision makers learn to attend to high utility stimuli and ignore low utility stimuli. We furthermore find that the influence of presentation format on attention capture reduces over time indicating diminishing bottom up control.

Keywords: eye tracking, top down, bottom up, learning, information reduction, decision strategy.

1 Introduction

Human decision behavior is consistently inconsistent in its tendency to change over time and over repeated decisions, yet these changes are mostly seen as a nuisance factor or even treated as a theoretical anomaly. In economics the static view of decision making is reflected in the assumption about stability of preferences (McFadden, 2001) while in psychology a similar assumption is often made about the stability of decision strategies over time (Riedl, Brandstätter, & Roithmayr, 2008). While both assumptions have been challenged on different occasions (Kahneman, 2003; Svenson, 1979) many studies implement them implicitly by aggregating choice and process data over time. In this paper we propose that temporal dynamics in decision making are more than a nuisance factor. Rather, they are informative to decision research for two reasons. First, temporal dynamics in decision making pose a theoretical challenge to strategy selection models of decision making. This challenge makes these dynamics a topic worthy of study. Second, understanding temporal dynamics calls for a previously neglected perspectives on decision making. We recently argued that decision research to a large extent has ignored attention processes and that a better integration of visual cognition into decision research could help account for a large number of observations (Orquin & Mueller Loose, 2013). Here we expand our argument by examining temporal dynamics in decision making, more particularly how decision making changes over the course of repeated decisions. We explore two competing explanations of temporal dynamics in decision making, one derived from strategy selection theory and one derived from vision research.

1.1 Can strategy selection account for temporal dynamics?

Among the many findings on temporal dynamics three have emerged as particularly robust: Over time decision makers become faster in making decisions (Meißner & Decker, 2010; Mueller Loose & Orquin, 2012), use less information in making their decisions (Payne, Bettman, & Johnson, 1988), and at the same time increase the accuracy of their decisions (Carlsson, Mørkbak, & Olsen, 2011; Hess, Hensher, & Daly, 2012; Payne et al., 1988). The simultaneous reduction in decision time and information use with an increase in decision accuracy seems

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counter-intuitive at first, but can mean only that decision makers become better or more efficient at making decisions over time. According to a strategy selection view of decision making, which in general terms posits that decision makers first select a decision strategy and then implement it in a given decisions task (Glöckner & Betsch, 2008), the increased efficiency could result either from a more efficient application of one particular decision strategy or from selecting a decision strategy that is more efficient in the given decision environment.

If decision makers become more efficient in applying a decision strategy, we would expect a decrease in decision time and perhaps also a reduction in the amount of information that is re-fixated. One could, for instance, imagine that decision makers become faster in reading and remembering information which would lead to shorter fixation durations and fewer re-fixations. On the other hand, we would not expect any changes as to what or how the information is searched, since the decision strategy itself specifies what information is needed and the order in which it should be acquired (Costa-Gomes, Crawford, & Broseta, 2001). However, this account of decision efficiency conflicts with studies showing that decision makers often change their search pattern over the course of repeated decisions (Meißner & Decker, 2010; Patalano, Juhasz, & Dicke, 2010). Even though decision makers may become more efficient over time in applying one particular decision strategy, this change merely accounts for some of the observations on temporal dynamics. The change in search pattern could, on the other hand, indicate that decision makers are likely to change their decision strategy over time.

If decision makers learn over repeated decisions to select strategies that are more efficient to the decision environment we would expect a reduction in decision time, an increase in decision accuracy, and a change in the information search pattern because each decision strategy predicts qualitatively different search patterns (Riedl et al., 2008). Although this view seems promising, as it could potentially explain the general observations from studies using repeated decision trials, it has one major problem: There is most likely no order for which decision makers could select their decision strategies, for each decision, so that over time they would decrease in information use, decision time and increase in accuracy. In Figure 1 we compare a typical pattern of observed decision time and accuracy (compare this to Appendix 2) with the predicted decision time and accuracy of nine different decision strategies. The predicted decision times and accuracies are borrowed from Payne and colleagues (Payne et al., 1988, Table 1 column 4) who simulated the performance of nine decision strategies under different environments. The simulation reports the number of operations which we use as a proxy for decision time following (Johnson & Payne, 1985). The decision time and accuracy measures are fitted to the same scale for the sake of comparison.

The figure illustrates that there is no ordering of decision strategies that can produce or approximate the observed pattern. The predicted decision times and accuracies are positively correlated across decision strategies while the observed pattern indicates a negative correlation. Although the comparison is neither a mathematical nor empirical proof, it does point us to a theoretical challenge to the strategy selection view of decision making: It seems impossible to account for the development of decision time and accuracy in repeated decisions by switching between decision strategies. To account for temporal dynamics through strategy selection one could, for instance, relax the assumptions about what defines a decision strategy or about how decision strategies are mapped to process measures such as information acquisition, decision time and choice accuracy (see the discussion). In the following section we pursue an alternative view of temporal dynamics which accounts for the behavioral observations mainly through attentional and perceptual processes.

1.2 Temporal dynamics and perceptual efficiency

In the previous section we examined whether the strategy selection paradigm could account for temporal dynamics in decision making, such as the development in decision time, information search patterns, and decision accuracy. The comparison between observed and predicted decision time and accuracy suggested that the strategy selection paradigm cannot account for temporal dynamics except by relaxing the assumptions about what defines a decision strategy or by introducing new strategies. As an alternative account, we propose that at least part of the change in decision time, information search, and decision accuracy could be driven by increased efficiency in attentional and perceptual processes. Such a view has previously been expressed in the information reduction hypothesis (Haider & Frensch, 1999), which accounts for expertise across different domains in terms of perceptual efficiency. The theory posits that experts are more efficient than novices because they have learned to fixate task relevant information and ignore task redundant information—hence the term "information reduction". Information reduction effects has been demonstrated in various domains, and a recent meta-analysis of the effect of expertise on attention to visualizations (Gegenfurtner, Lehtinen, & Säljö, 2011) concludes that experts have more fixations to task-relevant areas and fewer fixations to task-irrelevant areas. Information reduction has also been demonstrated in repeated-trial experiments showing that practice increases fixation likeli-

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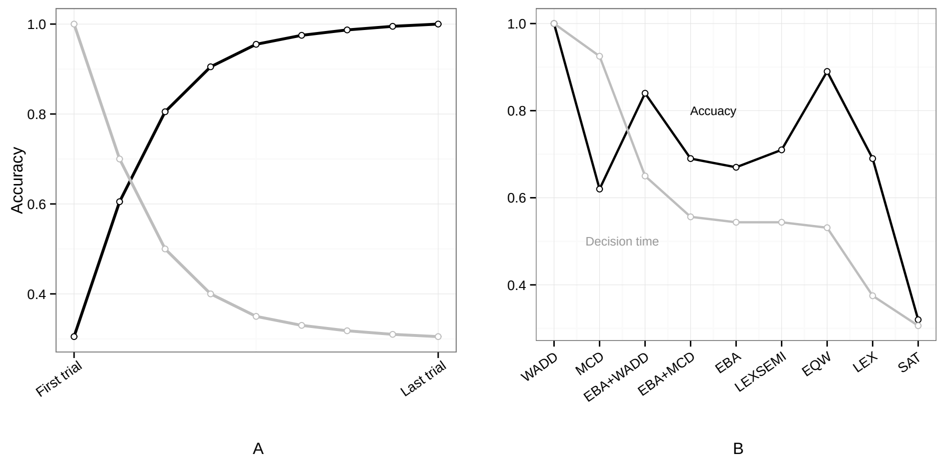
Figure 1: A: Typical pattern of observed decision time and accuracy in a repeated choice task. B: Ordering of decision strategies in accordance with their predicted decision times and accuracies (Payne et al., 1988). The y-axis represents normalized values for both decision time and accuracy. WADD = weighted additive, EQW = equal weight, EBA = Elimination by aspects, MCD = majority of confirming dimensions, SAT = satisficing, LEX = lexicographic, LEXSEMI = lexicographic semi-order, EBA+WADD elimination-by-aspects plus weighted additive, EBA+MCD = elimination-by-aspects plus majority of confirming dimensions.



hood and fixation duration to important stimuli, and reduces fixation likelihood and duration for irrelevant stimuli (Droll, Gigone, & Hayhoe, 2007; Hegarty, Canham, & Fabrikant, 2010; Jovancevic-Misic & Hayhoe, 2009; Lee & Anderson, 2001). In decision making, similar observations have emerged, indicating that decision makers become more likely to fixate high utility attributes over the course of repeated decision trials (Meißner & Decker, 2010; Mueller Loose & Orquin, 2012). Decision makers also reduce the number of fixations per trial over the course of repeated-measures experiments (Fiedler & Glöckner, 2012; Knoepfle, Wang, & Camerer, 2009; Toubia, de Jong, Stieger, & Füller, 2012). Although none of these studies address information reduction directly, the increased attention to high utility information and the overall reduction in information search indicates that information reduction is likely to happen in repeated decision making.

If decision makers reduce information in a manner predicted by the information reduction hypothesis this could potentially explain the development in decision time, information search, and accuracy. Whereas the strategy selection theory shows a positive correlation between decision time, information search, and accuracy across decision strategies the information reduction hypothesis posits a negative correlation, i.e., the more accurate you are the less information you look at, and the faster you are.

However, even if decision makers reduce information as suggested above, one problem remains; the information reduction hypothesis does not account for the underlying cognitive mechanism that leads to information reduction. Accounting for temporal dynamics by information reduction is therefore no different than giving the problem a new name. To avoid this logical loop the following section attempts to integrate information reduction into a broader theoretical framework and derive hypotheses concerning the development of visual attention in repeated decision tasks.

1.3 Top down and bottom up control of attention

An alternative way of viewing information reduction/perceptual efficiency is to see it as a consequence of top down and bottom up processes, i.e., goal and stimulus driven processes (Corbetta & Shulman, 2002; Theeuwes, 2010). According to this terminology, the findings above strongly suggest that practice, whether in the form of years of expertise in a particular field or as practice in repeated-trial experiments, increases top down control of attention. The claim follows logically from the propositions that top down control is defined as attention to task relevant stimuli, and that practice in multi-trial experiments increases attention to task relevant stimuli. However, the process through which practice increases top down modulation is by no means clear.

One possible explanation is that increasing top down control is a consequence of perceptual learning, i.e., an improved ability to identify and discriminate between sensory inputs. It has, for instance, been demonstrated that playing certain video games can improve spatial resolution (Green & Bavelier, 2007) and target detection (Green & Bavelier, 2006) so that experienced video game players become better at identifying objects in visually cluttered environments. This may lead to enhanced top down control of eye movements (West, Al-Aidroos, & Pratt, 2013), and reduced bottom up attention capture by distractors (Chisholm, Hickey, Theeuwes, & Kingstone, 2010). Perceptual learning could therefore explain perceptual efficiency in situations where the target stimulus is difficult to identify or categorize, such as in comprehending visualizations (e.g., Gegenfurtner et al., 2011) or when performing tasks under time pressure (e.g., Chisholm et al., 2010; West et al., 2013). However, in the walking experiment by Jovancevic-Misic and Hayhoe (2009) and in the choice experiment by Meißner and Decker (2010), the stimuli were easy to discriminate and categorize, and the participants were not under time pressure, which questions the role of perceptual learning.

Another perspective on increasing top down control would be the reward-based model of gaze allocation advocated by Hayhoe and colleagues (Hayhoe & Rothkopf, 2011; Tatler, Hayhoe, Land, & Ballard, 2011). According to their theory, gaze allocation is crucially dependent on reward systems so that eye movements are guided by the reward value of gazing at a particular stimulus. Reward value is understood here as consisting of both primary reinforcers such as foods and secondary reinforcers such as money. It has, for instance, been demonstrated that monkeys are willing to trade-off food rewards for visual information about members of their social group (Deaner, Khera, & Platt, 2005), and studies on humans indicate similar trade-off patterns (Dai, Brendl, & Ariely, 2010). Trommershäuser and colleagues have also noted that most brain areas dedicated to the control of eye movements are sensitive to rewards, and that neural computations during visual search in humans and primates are similar to those activated when eye movements are extrinsically rewarded (Trommershäuser, Glimcher, & Gegenfurtner, 2009). According to this view, top down control develops in a feedback loop between the agent and the environment. Certain gaze behaviors are selected because they lead to rewarding outcomes, such as avoiding collisions with other pedestrians or completing a decision task successfully.

The question is, of course, what type of feedback decision makers can rely on in a repeated decision task in which no explicit feedback is given? One possibility is that decision makers monitor their own decision process in terms of how effortful the decision is and how confident they feel about it (Anzai & Simon, 1979; Payne et al., 1988). Such process feedback could potentially serve to guide learning of top down control both within and across decision trials. Given that decision makers generate some form of process feedback we therefore hypothesize the following, in accordance with the reward-based model of gaze allocation (Hayhoe & Rothkopf, 2011; Tatler et al., 2011), and the information-reduction hypothesis (Haider & Frensch, 1999):

H1 Learning during repeated decision trials increases top down modulation of attention, leading to higher fixation likelihood for important attributes and lower fixation likelihood for unimportant attributes.

The hypothesis poses another question: What is the role of bottom up modulation during the development of top down modulation? In line with the biased competition theory of selective attention (Desimone & Duncan, 1995) we suggest that, in a situation with weak top down modulation, the competition between stimuli will be based on bottom up processes. A similar view is proposed by Theeuwes (2010), who argues that selective attention is initially completely driven by bottom up processes and only later (a few hundred msec after stimulus onset) by top down processes. Both theories suggest that in the absence of top down control we should expect a stronger influence of bottom up control. If H1 is correct and top down control increases over repeated decisions we would expect that bottom up control has a relatively larger influence in the beginning of the experiment when top down control is still relatively weak.

However, the important question is what will happen later in the learning process when top down modulation becomes relatively stronger? One possibility is that increasing top down modulation will diminish bottom up control. It has, for instance, been shown that top down factors, such as semantic or contextual cues about a visual scene, feature based attention, object representations, task demands, and rewards for task performance, all override the effect of visual saliency (Kowler, 2011). Alternatively, it has been suggested that changes in the balance between the two processes over time will favor the process that makes more efficient use of cognitive resources (Nyamsuren & Taatgen, 2013; Salvucci & Taatgen, 2008). According to this view, both top down and bottom up modulation could in fact increase over time if both processes contributed to higher perceptual efficiency. Such interaction effects between top down and bottom up processes have been demonstrated on attention capture (Nyamsuren & Taatgen, 2013) and encoding to short term memory (Nordfang, Dyrholm, & Bundesen, 2013). Although interactions between top down and bottom up control are theoretically possible in laboratory experiments, studies on naturalistic tasks often show a limited role of bottom up and interaction processes in gaze allocation.

According to our previous proposition, strong top down modulation should reduce bottom up modulation except in the special case in which an interaction between the two processes leads to higher perceptual efficiency (Nyamsuren & Taatgen, 2013). Given that there is no interaction or that the interaction between top down and bottom up processes remains constant, we therefore hypothesize the following:

H2: Bottom up modulation of attention is stronger in the beginning of the experiment and diminishes over time as a consequence of increasing top down modulation.

1.4 Experimental approach

In order to examine Hypotheses 1 and 2, we decided for an experimental approach combining measured within-subjects and manipulated between-subjects independent variables. Top down factors were operationalized as individual level attribute importance, while bottom up factors were operationalized through information presentation formats. Combining measured and manipulated independent variables has the main advantage that it disentangles top down and bottom up modulation. Earlier studies have shown that important attributes gain higher fixation likelihood over time (Meißner & Decker, 2010), but it is in principle impossible to rule out that the effect could have been caused by bottom up factors or interactions between top down and bottom up factors, i.e., the important attributes could have been more salient than the less important attributes.

The importance of attributes can also be directly manipulated through task instructions, which, for instance, increases the utility of the attribute in one situation but lowers it in another (Bialkova & van Trijp, 2011; van Herpen & van Trijp, 2011; Visschers, Hess, & Siegrist, 2010), however, a more subtle approach is to derive it from individual level estimates of part-worth utilities. By taking a measurement approach to attribute importance it should be possible to show that participants who assign a higher level of importance to an attribute will increase their fixation likelihood for that attribute, compared with participants who assign a lower importance.

Regarding bottom up factors, one common approach in decision research has been to manipulate the format in which the information is presented using, for instance, verbal matrices or more naturalistic product representations (Huang & Kuo, 2011; Smead, Wilcox, & Wilkes, 1981; Söllner, Bröder, & Hilbig, 2013; van Raaij, 1977). Although this method involves less control over individual bottom up factors, such as saliency, size and position of information elements, one can think of all these factors as captured across presentation formats. In this experiment, the product representation format varies in, for instance, the saliency and size of attributes relative to a verbal or visual matrix presentation. Using this approach, the strength of bottom up modulation on gaze allocation is observable as the differences among attributes in fixation likelihood between the presentation formats as well as in the effect size of the presentation format model terms. If an increasing top down modulation competes with bottom up modulation, we therefore expect that attribute differences in fixation likelihood across presentation formats diminish over the course of repeated decisions.

In line with H1, we expect that learning over the course of the experiment will increase top down modulation, leading to a larger effect size of attribute importance over time and to increasing fixation likelihood when attributes are high, rather than low, in importance. We also expect, in line with H2, that increasing top down modulation will diminish the effect of bottom up modulation, leading to diminishing differences in fixation likelihood between the presentation formats and a smaller effect size of presentation format over time.

2 Method

2.1 Participants

Sixty eight participants were recruited on campus (62% male, mean age 25.6 years). To qualify, participants had to have normal vision and had to buy and eat fruit yoghurt at least once a month.

2.2 Experimental design

We conducted a discrete choice experiment in which participants made choices between four alternative fruit yoghurts and a no-choice alternative. Each participant saw 48 choice sets in which six product attributes varied on four levels according to a D-optimal design, which maximizes the differences in attribute levels between choice alternatives (Street & Burgess, 2007). Accordingly, all four choice alternatives in a set differed in those attributes with four levels (brand, flavor, fat percentage, and price), while attributes with two levels (organic and health claim) were present twice in each choice set. The presentation order of the choice sets was randomized across participants. As an additional between-subjects factor, the choice set presentation format varied between a verbal information matrix ($N = 22$), a visual information matrix ($N = 24$), and a realistic product representation ($N = 22$) (Mueller, Lockshin, & Louviere, 2010).

2.3 Materials and measures

The three stimulus presentation formats were operationalized as follows: For the verbal and visual matrix formats the attributes were presented in six rows and the alternatives as four columns within the rows. The attributes were, from top to bottom: brand, flavor, fat percentage, organic claim, health claim, and price. The product representation format was operationalized as individual products presented next to each other. The attributes were inserted on the products with the brand at the top of the product followed by the flavor, fat percentage, organic claim in the lower right and health claim in the lower left of each product, and price at the very bottom below each product. The verbal information matrix was based on written descriptions of the attribute levels. Each attribute description was kept to a minimum number of letters stating only the name of the attribute level, such as "strawberry" or "peach" for the flavor attribute or "Arla" or "Cultura" for the brand attribute.

The position of the attributes remained constant throughout the experiment. Two of the attributes, organic and health claim, had two levels (absent or present). The absence of either the organic or health claim on an alternative was operationalized as an empty cell in the verbal and visual matrices or as empty space in the product representation format. A pre-test ensured that all attribute levels were sufficiently large to be easily readable in all three presentation formats at a distance of 60 cm from the screen (the optimal distance for the Tobii 2150 eyetracker system used in the study).

Assuming a distance of 60 cm from the screen, individual attributes were separated by an average angle of 2.3° for the verbal and visual matrices and 2° for the product representation format. The spacing of attributes was chosen so that it would be impossible for participants to foveate more than one attribute at the time.

The yellow highlighted areas in Figure 2 represent the rank of product attributes by visual saliency as assessed by the Itti-Koch algorithm (Itti & Koch, 2001). The algorithm predicts a visual scanpath based on a computation of visual saliency, i.e., the color, intensity, and orientation of stimuli, and gives an impression of how attention would be distributed in the absence of top down modulation. There were no systematic differences in visual saliency between product attributes in the verbal information matrix (lower left of Figure 2). In the visual information matrix (lower middle of Figure 2), the health claim had the highest visual saliency followed by brand (top row), flavor (second row), and organic claim. In the product representation format, the attribute flavor had the highest visual saliency followed by brand. The relative size of the attributes also differed between the product representation and the two information matrices.

Eye movements were recorded using a Tobii 2150 eyetracker (21 in, 50 frames per sec). Respondents' choices were recorded as mouse clicks on the chosen product.

2.4 Procedure

Upon entering the laboratory, participants were seated in front of the eye tracker and randomly assigned to one of the three presentation format conditions. After calibration, each participant completed 48 choice sets. Before each choice set, respondents had to click on a calibration cross that centered their gaze between the two middle choice alternatives. The first fixation of each choice set was discarded from further analysis as this fixation is a direct consequence of having fixated on the fixation cross immediately before stimulus onset. The first fixation is therefore driven neither by top down nor bottom up processes which makes it of little interest to the analysis.

2.5 Analytical plan

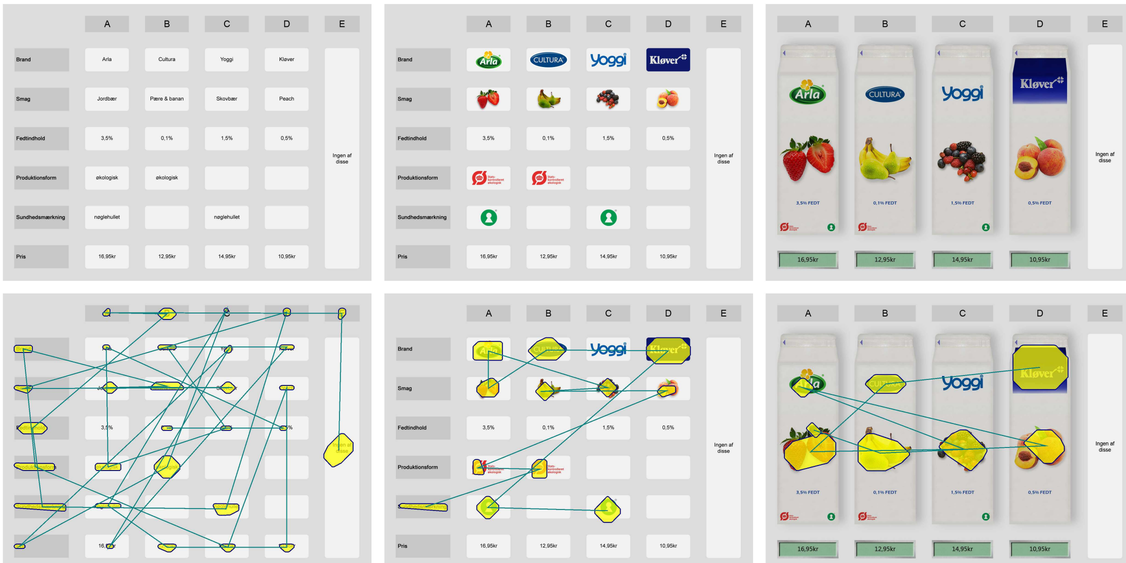
The analysis unfolded in four steps: First we assessed the stability of preferences over time. This is an important prerequisite, as any conclusion regarding learning effects on attention would be valid only if the participants did not change their preferences during the experiment. The first step was carried out by splitting the choice sets into three bins of 16 choice sets, separately estimating individual level choice models for each of the bins and checking for any differences within participants across the three bins. In the second step we modelled choices across all 48 choice sets for each participant at a time, thus providing individual level estimates of part-worth utilities and attribute importance. In the third step we merged the individual level choice data with the attention data and analysed attention selection as a function of trial order, attribute importance, and presentation format. To assess changes in top-down modulation we computed the correlation between fixation likelihood and attribute importance for each trial. To assess bottom-up modulation we plotted the fixation likelihood for all six attributes across the presentation formats. In the fourth step, we calculated effect sizes for top down, bottom up, and interaction components separately for each of the 48 trials to assess changes in modulatory strength over time.

3 Results

3.1 Step 1. Analysis of stability of preferences

In the first step of the analysis, participants' choices were analyzed individually for three consecutive bins of 16 choice sets based on random utility theory (Louviere,

Figure 2: Top row from left to right: Examples of experimental stimuli for the verbal information matrix, visual information matrix and product representation format. Bottom row: Examples of the visual saliency of attributes for the three presentation formats.



Hensher, & Swait, 2000), according to which subjects choose the alternative that maximizes their subjective utility. Utility is defined as:

$$U_i = V_i + \varepsilon_i \tag{1}$$

where U_i is the utility of the choice alternative i, V_i is the observable or systematic utility component, which is a function of its attributes, and ε_i is the random utility component. The systematic component V_i is assumed to be an additive and linear function in the attributes X. The systematic component is defined as:

$$V_i = \sum_s \beta_s X_{is} \tag{2}$$

where X_{is} is the value of alternative i with attributes $s(s = 1, \ldots, 6)$, and β_s are part-worth utilities to be estimated. Under the assumption that the random error terms ε_i are independently and identically extreme value distributed, the choice probability of alternative i being chosen from all the alternatives in choice set T follows the closed form expression of the multinomial logit (MNL) model

$$P(i) = \frac{\exp(V_i)}{\sum_{i' \in T} \exp(V_{i'})} \tag{3}$$

Parameters are estimated with maximum likelihood where likelihood is given by:

$$L = \prod_{n=1}^{N} \prod_{i \in C_n} P_n(i) f_{in} \tag{4}$$

where N represents the number of choice observations and f_{in} is a dummy variable such that $f_{in} = 1$ if alternative i is chosen and $f_{in} = 0$ if an alternative is not chosen from the choice set.

Attribute importance was approximated for each participant and each choice set bin with the share of variance explained by each attribute, assuming that the presented attributes determine 100% of the choice process (Lancsar, Louviere, & Flynn, 2007; Louviere & Islam, 2008). All choice models were run in Latent Gold Syntax 4.5 (Statistical Innovations Corp.).

Differences in attribute importance were calculated on an individual level between the first and second as well as the second and third bin. T-tests were performed to test if these changes in attribute importance differed significantly from zero. Only brand differed significantly between the first and second choice set bin ($t = -3.038$, $p = 0.003$), while all other attributes were not significantly different from zero. Accordingly, results overall suggested that participants did not change preferences over the course of the experiment.

3.2 Step 2. Analysis of choice data

Because preferences were confirmed to be stable during the experiment, participants' choices were analyzed individually for all 48 choice sets according to equations (1) to (4), resulting in individual level importances [0;100] for all six product attributes. A summary of average attribute importance is provided in Table 1.

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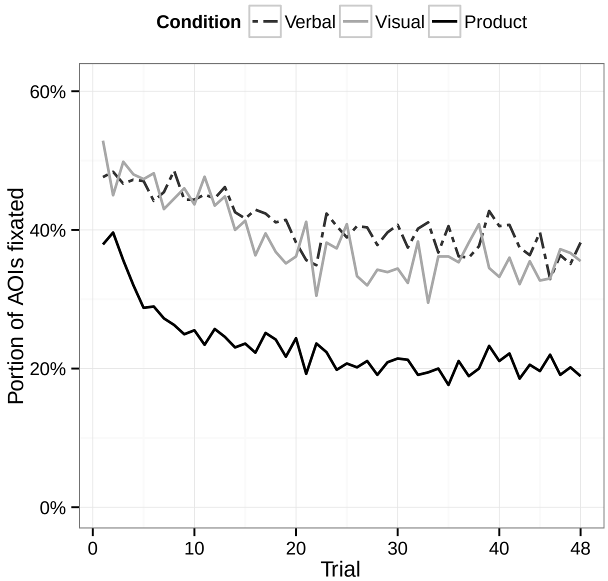
Table 1: Average attribute importance in percent (N = 68).

Attribute	Mean	SD
Flavor	36.63	26.83
Price	19.48	19.20
Fat	14.54	14.19
Organic claim	9.93	11.04
Brand	9.90	10.42
Health claim	5.58	7.94

Note: Attributes are sorted by decreasing average importance.

Figure 3: Proportion of AOI's fixated across presentation formats.



3.3 Step 3. Analysis of fixation likelihood

Before analyzing fixation likelihood we first inspected the proportion of attributes fixated per trial as a complete or very high degree of fixation or non-fixation would go against the purpose of the analysis. The inspection revealed that roughly 50% of the attributes are fixated in the beginning of the experiment for the verbal and visual information matrices and less than 40% are fixated in the product representation format. The proportion of attributes fixated furthermore declines throughout the experiment (see Figure 3).

In the third step of the analysis, individual level attribute importances were merged with the eye tracking data. We estimated fixation likelihood by means of a generalized linear mixed model (GLMM), using fixation selection as the dependent variable (0 indicating no fixation to the attribute and 1 indicating that the attribute was fixated at least once during a trial). Four independent variables were included in the model: presentation format (verbal information matrix, visual information matrix, and product representation), attribute (flavor, price, brand, fat percentage, organic claim, and health claim), attribute importance derived from individual level estimates, and experimental trial order.

Data from all 68 participants and 48 choice sets were used to estimate the model. The GLMM assumed a binomial distribution for the dependent variable with a log link function and a random intercept for participants to capture individual differences in fixation likelihood. The model was estimated by means of maximum likelihood estimation with quadrature approximation. This approximation was used to obtain log likelihood values for model comparison and effect size measurement (Schabenberger, 2007; Stroup, 2013).

We estimated a full factorial model and compared it to reduced models. Model comparison (LR tests) revealed that the full factorial model provided the best fit, and that model was therefore used for interpretation. Table 2 shows the type III test of fixed effects.

All effects in the final model were significant indicating that trial order, presentation format, attribute importance, and attribute type as well as their interactions contribute to explain fixation likelihood. In relation to the hypotheses we were mainly interested in the interaction terms between trial and importance and between trial and presentation format which would indicate changes in top down and bottom up attention capture over time.

Table 2 shows that the model terms trial$\times$importance and trial$\times$importance$\times$attribute are significant which means that the influence of attribute importance on fixation likelihood changes over time. Similarly, the significance of the interaction terms trial$\times$format and trial$\times$format$\times$attribute means that the influence of presentation format on fixation likelihood changes over time. It is important to observe that the interpretation of the interaction terms between importance and format is limited because the two main effects might not be causally independent.

In order to interpret the changes in top down processes over time we computed the observed correlation between fixation likelihood and attribute importance for each trial across participants, attributes, and presentation formats. The correlations are plotted in Figure 4. We also fitted a linear function across the correlation values showing that the development was significantly different from zero ($t = 6.212, p < 0.001$). The figure shows that the observed correlation between fixation likelihood and importance increases over time, which in relative terms means that important attributes are more likely and unimportant

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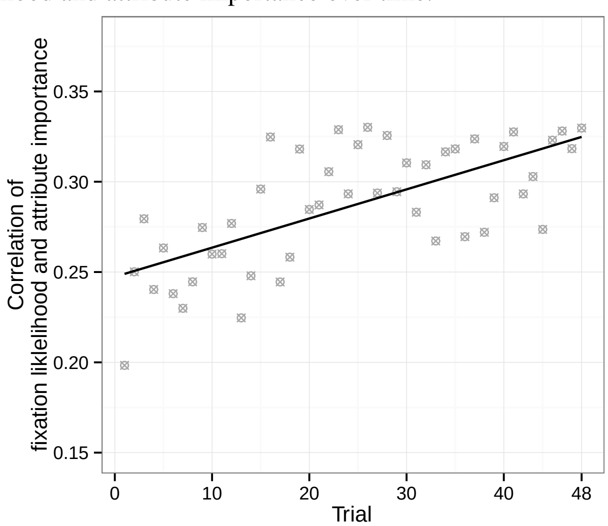
Table 2: Fixation likelihood as a function of presentation format (format), attribute, trial, and importance.

Effect	Num *Df*	Den *Df*	F-Value	$Pr > F$
Format	2	3125	14.41	$< .0001$
Attribute	5	3125	154.31	$< .0001$
Trial	1	3125	362.63	$< .0001$
Importance	1	3125	134.48	$< .0001$
Format×Attribute	10	3125	14.09	$< .0001$
Trial×Format	2	3125	4.57	0.0105
Trial×Attribute	5	3125	29.20	$< .0001$
Importance×Attribute	5	3125	47.58	$< .0001$
Trial×Importance	1	3125	35.94	$< .0001$
Trial×Format×Attribute	10	3125	7.73	$< .0001$
Trial×Importance×Attribute	5	3125	4.89	0.0002
Importance×Format	2	3125	23.25	$< .0001$
Importance×Format×Attribute	10	3125	9.69	$< .0001$
Trial×Importance×Format	2	3125	4.34	0.0132
Trial×Importance×Format×Attribute	10	3125	5.05	$< .0001$

Notes: Variance random intercept $= 0.7439$ (std. err. 0.1341). -2 Log Likelihood $= 78043.17$, $R^2 = 0.1624$, Generalized $\chi^2 = 79207.63$, Generalized $\chi^2/Df = 1.01$.

Figure 4: Observed correlation between fixation likelihood and attribute importance over time.



attributes are less likely to be fixated in the end, rather than in the beginning, of the experiment in accordance with the information-reduction hypothesis. The predicted fixation likelihood as a function of attribute importance is shown in the Appendix 1.

To interpret the change in bottom up processes over time we plotted the predicted fixation likelihood for each attribute per presentation format across trials (see Figure 5). The plots revealed that, for the attributes brand, fat percentage, organic claim, and health claim the slopes are fanning in over the course of the experiment, while for flavor the slopes fan out and for price there is no clear development. One way to interpret the plots is that the fanning in of slopes means that the presentation formats become more similar over time with regards to fixation likelihood while slopes fanning out means that the presentation formats become more dissimilar. With the exception of flavor and price, the plots suggest that the three presentation formats become more similar over time. The diminishing difference between the presentation formats could indicate a reduced modulatory influence of bottom up control over time.

3.4 Step 4. Analysis of top down and bottom up modulatory strength over time

To determine how the modulatory strength of top down and bottom up processes change over time we computed the effect sizes of top down and bottom up components across trials. The idea is that if top down and bottom up modulation changes over time this would be reflected in the effect size of the model terms corresponding to the two cognitive processes. Separate models were estimated for each of the 48 trials and effect sizes were determined with partial generalized R-Squares by stepwise integra-

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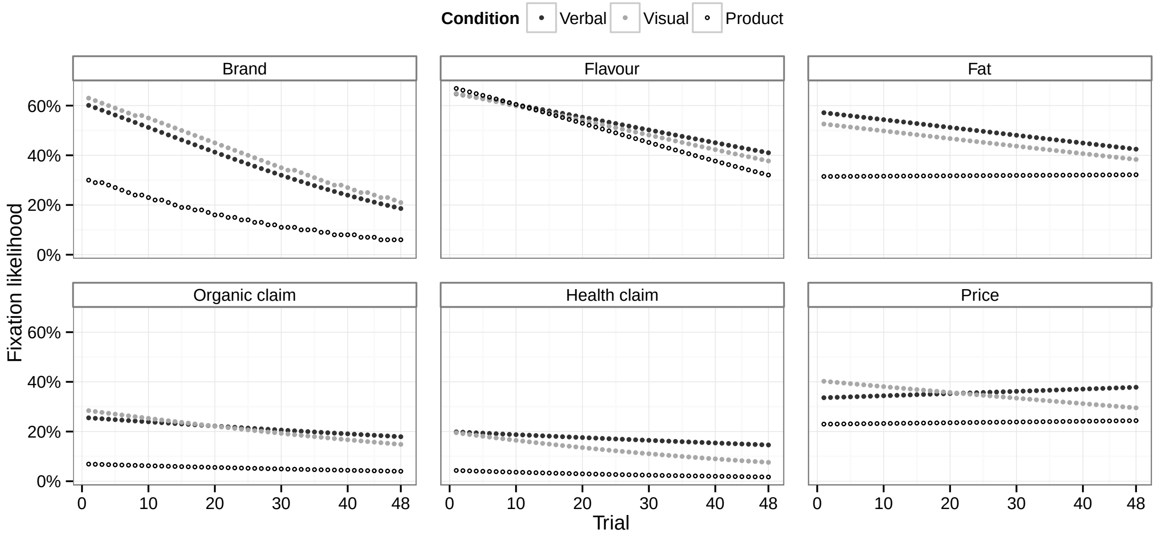
Figure 5: Fixation likelihood for the six attributes across presentation formats.



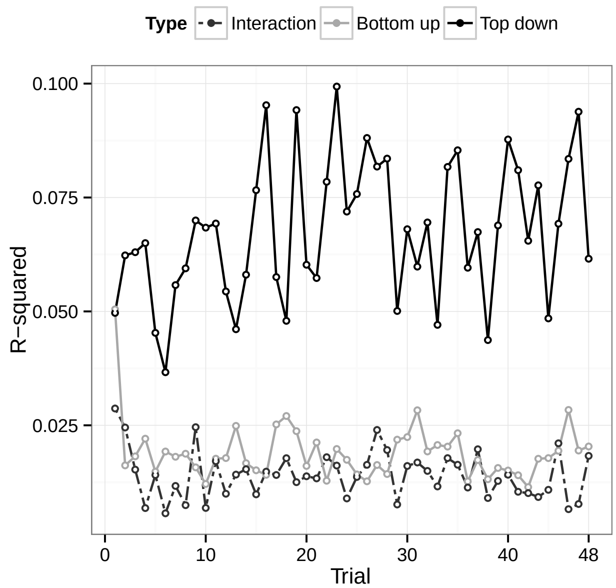
tion of parameters into the model (Aerni, Scholderer, & Ermen, 2011). An example of the computation is provided in Table 3.

The model terms were divided into top down factors (importance and attribute×importance), bottom up factors (format and format×attribute), and interaction factors (importance×format and importance×format×attribute). By adding up the partial effect sizes for the top down, bottom up, and interaction factors, total effect size components were calculated for the top down, bottom up, and interaction components in each trial. The total effect size components were analyzed by regressing trial order on each component. The slope of the top down component was significantly different from zero ($t = 2.212, p = .032$), meaning that over time the effect of top down modulation on fixation likelihood increases. The slope of the bottom up component was not significantly different from zero ($t = -1.192, p = .239$), which suggests that the modulatory strength did not change over time.[1]

The slope of the interaction component between top down and bottom up factors was not significantly different from zero ($t = -1.040, p = 0.304$). As for step 3 of the analysis, it is important to observe that the interpretation of the interaction component is limited since we cannot assume that the two main effects are causally independent.

[1]In order to test if the significance level could be due to low statistical power (48 observations) we bootstrapped the data increasing the number of observations to 200. By bootstrapping the slope became significantly different from zero.

Figure 6: Bottom up, top down and interaction effect sizes over time.



4 Discussion

4.1 Summary of results

In line with the reward-based model of gaze allocation (Hayhoe & Rothkopf, 2011; Tatler et al., 2011) we hypothesized that top down modulation is learned through interaction with the environment and that modulatory strength increases as participants become more experienced with a task or situation. The modulatory increase will lead to higher fixation likelihood for task relevant

Table 3: Example for goodness-of-fit and effect size statistics (Trial 1). No. indicates the model number.

			Goodness-of-fit statistics					Model comparison statistics			
No.	Effects entered	Effect type	$\ln L$	$LR\chi^2$	df	p	R^2	$LR\Delta\chi^2$	Δdf	p	ΔR^2
0	None		−1028.56								
1	Format	Bottom up	−1026.44	4.24	2	.120	.002	4.24	2	.120	.002
2	Attribute		−756.77	543.57	7	.000	.264	539.33	5	.000	.263
3	Importance	Top down	−728.66	599.79	8	.000	.292	56.22	1	.000	.037
4	Format×Attribute	Bottom up	−693.40	670.31	18	.000	.326	70.52	10	.000	.048
5	Attribute×Importance	Top down	−684.72	687.68	23	.000	.334	17.37	5	.004	.013
6	Importance×Format	Interaction	−682.44	692.24	25	.000	.337	4.56	2	.102	.003
7	Importance×Format×Attribute	Interaction	−665.13	726.86	35	.000	.353	34.62	10	.000	.025

stimuli and lower fixation likelihood for task redundant stimuli consistent with the information reduction hypothesis (Haider & Frensch, 1999). This prediction was expressed in H1. Furthermore, we hypothesized that an increase in top down modulatory strength would reduce bottom up attention capture as the two processes have been shown to compete for control over eye movements (Desimone & Duncan, 1995; Theeuwes, 2010). This prediction was expressed in H2.

In order to examine the hypotheses we conducted a repeated-choice experiment manipulating three different presentation formats. In the first step of the analysis we compared the choice models based on bins of the first, middle and last groups of choice sets. The analysis revealed that participants were largely stable in their preferences throughout the experiment, supporting an assumption required for conclusions about learning effects. In the second step of the analysis we modeled individual level estimates of attribute importance. In the third step we merged the individual level estimates with the attention data to model and analyze the effect of top down and bottom up factors over time. The analysis revealed significant interaction effects between trial order and attribute importance and trial order and presentation format, indicating a change over time in top down and bottom up processes. To interpret the direction of effects, we computed the correlation across trials between fixation likelihood and importance. Plotting the correlations revealed a positive slope demonstrating that fixation likelihood increases over time when an attribute is of high importance to the decision maker relative to when the attribute is of low importance to the decision maker. In order to interpret the direction of effects for bottom up processes, we plotted the predicted fixation likelihood for all six attributes across the three presentation formats. The plots revealed that, for the most part, the slopes were fanning in, indicating that the fixation likelihoods became more similar across presentation formats over time.

In the fourth step of the analysis we tested the modulatory strength of top down and bottom up processes over time. In order to do so, we estimated the effects sizes of importance and presentation format factors for each trial separately. The analysis revealed an increase in the effect size of importance over time, suggesting that top down modulation increases over time, thus confirming H1. The results for bottom up modulation were less clear, as the effect size of presentation format factors did decrease over time but not significantly. Future experiments with more observations are required to further test changes in effect sizes in order to test H2.

4.2 Alternative interpretations of our data

So far, we have mainly focused on one interpretation of our data in accordance with the information reduction hypothesis (Haider & Frensch, 1999) and the reward based model of gaze allocation (Hayhoe & Rothkopf, 2011; Tatler et al., 2011). However, it is worth considering at least a few alternative interpretations of the data. Although the information reduction hypothesis considers developments in perceptual efficiency, it is worthwhile to consider whether developments in cognitive efficiency could help to explain the results. If we think of cognitive efficiency in terms of cognitive skill acquisition, there are at least four possible interpretations (Lee & Anderson, 2001): The decrements in fixation proportions and fixation likelihood could have been driven by cognitive skill acquisition through a) transforming or collapsing the individual components of the procedure, b) strengthening the components of the procedure, or c) changing the procedure altogether. Finally we can also conceive of cognitive skill acquisition as a process of becoming familiar with the task requirements thereby reducing initial task confusion.

The first view of cognitive skill acquisition is to see it as a result of transforming or collapsing a multi-step procedure into one or more macro procedures (Newell & Rosenbloom, 1981). One could, for instance, hypothesize that the decrease in proportion of fixations would stem from participants collapsing smaller process steps such as scanning alternatives for an overview, comparing alternatives or attributes, checking chosen alternative and so forth into larger process steps. One possibility could, for instance, be to collapse two binary comparison steps into one trinary comparison (on binary and trinary comparisons see Russo & Leclerc, 1994) thereby decreasing the time and number of fixations needed to complete the decision task. Based on our class of analysis we cannot exclude the possibility that participants were collapsing process steps and thereby decreasing the number of fixations and decision times. Future studies might address this question using different classes of scanpath analyses (Holmqvist et al., 2011). It would, for instance, be interesting to ask whether there is a shift in binary to trinary comparisons over time or whether other steps in the decision process are being transformed over time.

A second view of cognitive skill acquisition is to see it as resulting from increased efficiency in performing the individual task components (Anderson, 1982). Although this particular view is strongly associated with the notion of "strengthening" in Anderson's ACT theory, we could also think of efficiency in terms of automaticity. It seems plausible that individual process steps will require more deliberation in the early trials, while the later trials might be characterized by a more automatic execution. Another possibility is that participants will rely increasingly on memory retrieval, for instance, when searching for acceptable attribute levels. Because of the D-optimal design all attribute levels were present in every choice set which would allow participants to retrieve the last attribute level from memory after having fixated the first three levels. Such a mixed visual search and memory retrieval approach would lead to a decrease in the number of fixations needed to complete the decision task and perhaps also a reduction in decision time. Based on our analyses, we cannot exclude the possibility that participants became more efficient in terms of automaticity, nor can we do so by simply inspecting individual fixation durations over time, as fixation durations might not be closely related to deliberate versus automatic decisions (Horstmann, Ahlgrimm, & Glöckner, 2009). Future studies might examine such processes by analyzing changes to the scanpath over time or by examining multiple process measures (Glöckner, 2009).

A third view of cognitive skill acquisition is to see it as resulting from selecting a faster method or strategy (Crossman, 1959). In a decision task this could mean that participants change from one decision strategy to another that is faster, such as going from a weighted additive strategy to a lexicographic or satisficing strategy (see the Introduction). If we qualitatively compare individual participants' scanpaths from the first and the last trials it does, in fact, seem like the participants are changing their decision strategy dramatically. While the first few trials are characterized by participants fixating many or most of the attributes, the last trials are often characterized by the participants fixating only one or two rows of attributes. Such a simple inspection suggests that participants over time go from a slower strategy involving more fixations to a faster strategy involving fewer fixations. The only problem with this claim is that the change in strategy would have to occur gradually, which is in conflict with the way decision strategies are currently specified. If we adhere to the view that decision strategies are qualitatively different and discrete processes then the gradual change in fixation patterns can suggest two things: a) either participants use the same decision strategy throughout the experiment but the way it is implemented in a search process changes (concerning instability of search patterns (Costa-Gomes et al., 2001; Svenson, 1979) or b) participants simply do not use decision strategies in the form or to the extent they have been specified in the decision literature (for a related discussion see Orquin & Mueller Loose, 2013). In the case of participants maintaining a stable decision strategy but changing their fixation pattern over time, it is unlikely that we can either confirm or reject the hypothesis based on the choice and fixation data alone, but future studies might look into this question using other techniques. Regarding the second implication, one can either reach the conclusion that decision makers do not rely on decision strategies or that decision strategies are not discrete entities. Future studies might wish to relax the assumption about discrete and deterministic decision strategies and look into probabilistic or stochastic specifications instead (Bergert & Nosofsky, 2007). Given a relaxed assumption about discrete decision strategies, we cannot exclude the possibility that participants changed their strategy during the experiment and that this strategy change explains the development in proportion of fixations and fixation likelihood. However, we can exclude the possibility that participants made discrete changes in their decision strategies, since our data reveal a gradual change in fixation patterns.

Another possible view of our data is to see the decline in fixation proportions and fixation likelihood as a consequence of task-level familiarization, or in other words a reduction in task-confusion. This hypothesis suggests that participants during the first few trials are uncertain about the task requirements, and this uncertainty would increase the number of fixations because additional time and effort is spent on becoming familiar with the task. If participants are confused about the task requirements during the first few trials, we should also expect them to be less consistent in their choices. Inspecting the development in choice consistency over time indicates that participants are, in fact, less consistent in the beginning of the experiment. However, two aspects speak against participants being confused: First of all, choice consistency increases gradually throughout the experiment, albeit with the strongest increase in consistency in the beginning of the experiment (see Appendix 2). Second, even in the first trial participants are highly consistent, with more that 70% choosing the highest utility alternative. The high degree of consistency suggests that participants cannot be confused about the task requirements. Although it is plausible that participants experienced a certain degree of confusion in the first couple of trials it is difficult to say whether this could explain the development in proportion of fixations or in top down and bottom up control. Future studies could look into this process by more directly manipulating task confusion and test whether it amplifies, for instance, bottom up control of attention.

5 Implications and future research

The study has several implications for research on decision making, as well as research on eye movements and attention. Firstly, we replicate findings from prior studies on top down and bottom up effects in decision making (Orquin & Mueller Loose, 2013), and extend these findings by showing that the modulatory processes change over time. The study lends support to the reward-based model of gaze allocation (Hayhoe & Rothkopf, 2011; Tatler et al., 2011) by showing that learning increases top down modulation of attention. Furthermore, we present evidence suggesting that top down and bottom up processes compete for influence over eye movements, and that increases in top down modulation could diminish bottom up modulation. However, based on this experiment alone, we cannot say whether the likely reduction in bottom up modulation is caused by the increase in top down modulation. Another possibility could be that bottom up modulation decreases over time even when top down modulation remains equal. On the other hand, both theoretical reasons (Desimone & Duncan, 1995) and empirical findings (Kowler, 2011) suggesting that the two processes influence each other in what could be a competition for control over eye movements. Future studies should address this issue and examine the circumstances under which top down and bottom up processes compete, and when they interact to amplify attention capture (e.g., Folk, Remington, & Johnston, 1992).

Furthermore, due to the experimental approach, several bottom up factors were manipulated simultaneously across the three presentation formats. Although we could demonstrate separate effects of top down and bottom up processes with this approach, it leaves open the question of what particular bottom up processes were acting on attention capture. Future studies could take advantage of a more structured approach in which bottom up factors, such as visual saliency, size, and position, are manipulated separately.

The study also lends support to the information reduction hypothesis (Haider & Frensch, 1999), by showing that participants learn over time to fixate important information and ignore less important information. The results imply that participants in choice experiments become more efficient at a perceptual level over time, which could explain how decision time decreases and accuracy increases over the course of repeated-trial experiments. We do not wish to say that no gains occur at a cognitive skill level, which most likely is the case, however our findings suggest that increased perceptual efficiency plays an important role in the observed reduction in decision time and increase in accuracy. An interesting question for future research is, therefore, to examine the degree to which faster decision time and higher accuracy are explained by gains in perceptual efficiency and cognitive skill level.

Another implication from our findings relates to process tracing studies, particularly studies measuring eye movements. The fact that attention processes change with learning should matter to most experimenters, since the vast majority of eye tracking studies in judgment and decision making are based on repeated-trials experiments, which must lead to learning effects of the sort we have demonstrated. Our data show that learning occurs rapidly right from the beginning of the experiment. Particularly the effect of bottom up modulation is subject to a steep decline in the first 3–4 trials (see Figure 6). It could be problematic to aggregate process measures over time, particularly if the goal is to improve choice models based on process measures (Balcombe, Fraser, & McSorley, 2011; Hensher, Rose, & Greene, 2005; Meißner, Musalem, & Huber, 2012; Scarpa, Zanoli, Bruschi, & Naspetti, 2013). Assuming that temporal changes in top-down and bottom-up processes is problematic for the estimation of choice models, one could possibly counteract or at least diminish this change by randomizing the position of attributes within-subjects. It has, for instance, been shown that randomizing the position of information elements from trial to trial diminishes information reduction (Haider & Frensch, 1999). However, randomizing the attribute position within-subjects may lead to other effects besides diminishing information reduction, and more studies would be needed to examine the effects of such a manipulation on top-down and bottom-up processes.

Last but not least, throughout the study we have argued that temporal dynamics constitute a theoretical challenge to the strategy selection view of decision making.

In the introduction we demonstrated that no plausible ordering of decision strategies leads to a decrease in decision time and increase in accuracy. In the previous section we discussed different possibilities for relaxing the assumptions about decision strategies and whether this could explain our observations. Although relaxing the assumptions about strategy selection and what defines a decision strategy would fit the theory better, we suggest that a more promising approach would be to reconsider the role of visual processes in decision making.

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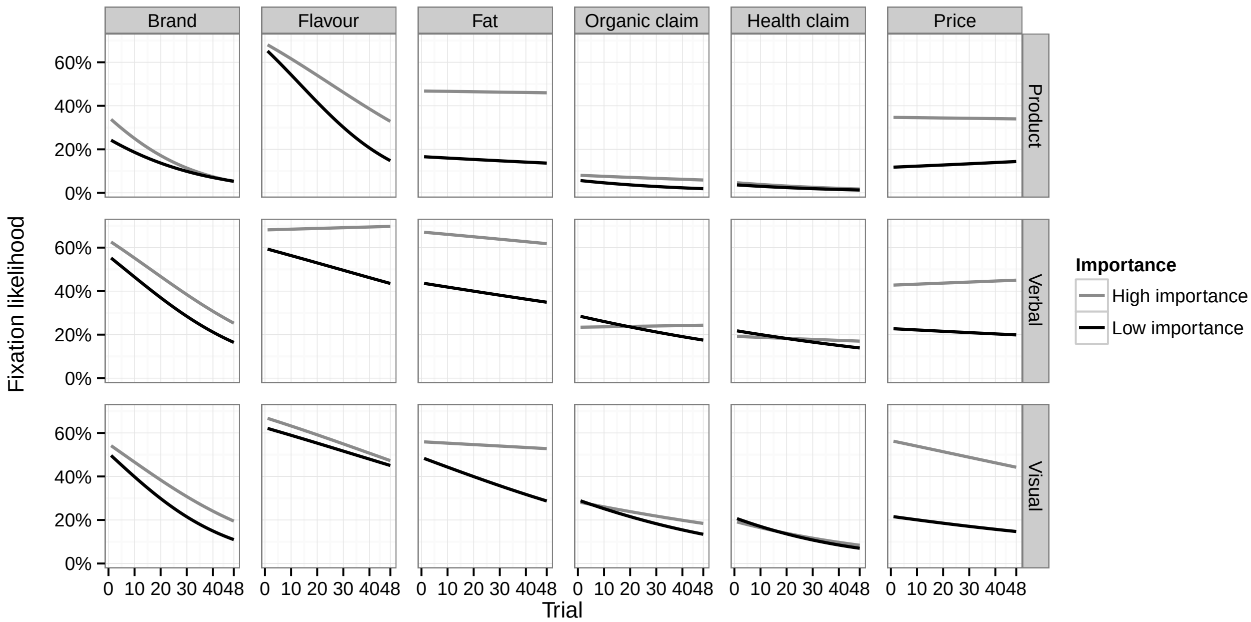
Appendix 1

Fixation likelihood for the six attributes across presentation formats as a function of trial for high importance and low importance. The upper and lower quartiles were used as measures of high and low importance respectively.



Appendix 2

Decision time a) and hit rate b) as function of trial. The hit rate is the percentage of participants who choose the alternative with the highest utility according to their own preferences. The hit rate indicates the degree of choice consistency and is conceptually similar to the measure of choice accuracy in Payne et al. 1988.