Cognition 132 (2014) 44–56

Contents lists available at ScienceDirect

Cognition

journal homepage: www.elsevier.com/locate/COGNIT

In the attraction, compromise, and similarity effects, alternatives are repeatedly compared in pairs on single dimensions

Takao Noguchi *, Neil Stewart

Department of Psychology, University of Warwick, Coventry, CV4 7AL, UK

A R T I C L E   I N F O

Article history:
Received 8 August 2013
Revised 11 March 2014
Accepted 17 March 2014
Available online 21 April 2014

Keywords:
Multi-alternative decision making
Eye-tracking
Context effects
Attraction
Compromise
Similarity

A B S T R A C T

In multi-alternative choice, the attraction, compromise, and similarity effects demonstrate that the value of an alternative is not independent of the other alternatives in the choice-set. Rather, these effects suggest that a choice is reached through the comparison of alternatives. We investigated exactly how alternatives are compared against each other using eye-movement data. The results indicate that a series of comparisons is made in each choice, with a pair of alternatives compared on a single attribute dimension in each comparison. We conclude that psychological models of choice should be based on these single-attribute pairwise comparisons.

1. Introduction

In the domain of choice between multiple alternatives, the attraction, compromise, and similarity effects demonstrate some puzzling behaviours. Together these effects demonstrate that an individual does not choose by selecting the alternative with the highest value or utility. Instead, an individual chooses as if the value or utility of an alternative is temporarily affected by the other alternatives in the choice set they face. This is puzzling because how much an individual enjoys the car she or he buys, for example, should be independent of the cars he or she does not buy. These context effects are often interpreted as indicating that a choice is reached by comparing available alternatives. This study investigated how alternatives are compared, using eye movement data collected while people make a series of three-alternative choices.

To illustrate the attraction, compromise, and similarity effects, suppose an individual is choosing among different cars. Available cars are described in terms of the two attributes, quality and economy, where Car A is better on the quality dimension but Car B is better on the economy dimension (Fig. 1). The attraction effect is produced by adding Car D to the choice of Cars A and B. Car D is inferior to Car A in both quality and economy dimensions and should thus be discarded but, after adding this decoy, Car A becomes more likely chosen and Car B becomes less likely chosen (Huber, Payne, & Puto, 1982). Adding Car C to a choice between Cars A and B produces the compromise effect. Car C has extremely good quality but poor economy. Importantly, Car C makes Car A a compromise between the other cars, and with Car C's presence, Car A becomes more likely to be chosen than Car B (Simonson, 1989). The similarity effect is produced by adding Car S instead. Car S is similar to Car B, and Car S's introduction results in the higher probability of Car A being chosen than Car B (Tversky, 1972).

* Corresponding author. Tel.: +44 (0)24 76523158; fax: +44 (0)24 765 24225.

E-mail address: t.noguchi@warwick.ac.uk (T. Noguchi).

http://dx.doi.org/10.1016/j.cognition.2014.03.006
0010-0277/© 2014 The Authors. Published by Elsevier B.V.

For the non-chosen alternative to influence a choice as described above, an individual has to be comparing alternatives in making a choice (e.g., Simonson, Bettman, Kramer, & Payne, 2013). Here we explore the nature of these comparisons, and consider models involving attribute-wise comparison, alternative-wise comparison, and attribute-and-alternative-wise comparison (see Table 1 for a list of the models).

According to attribute-wise comparison models, one attribute dimension is attended at one moment and all the available alternatives are simultaneously evaluated. In the above car example, an individual may attend, for instance, on the quality dimension of available cars at one moment, and evaluate how advantageous each of the three cars is. Then at the next moment, the individual may attend the economy dimension and evaluate all three cars. This attribute-wise comparison is implemented in multi-alternative decision field theory (Roe, Busemeyer, & Townsend, 2001) and the leaky competing accumulator model (Usher & McClelland, 2001) to explain the three context effects.

In contrast, alternative-wise comparison models assume that all the attributes are integrated before comparison: one pair of alternatives is attended, attribute dimensions are integrated within each alternative, and then the pair of alternatives are compared on their integrated values. In the above example, an individual may integrate the quality and economy dimensions for, for instance, Car A, and also integrate these dimensions, separately, for Car B. Then, the individual compares the integrated value for Car A with Car B. At the next moment, the individual may select a new pair of alternatives, Cars A and S, and repeat the integrate-then-compare process. This integration of information across attributes is commonly assumed in models of two-alternative choice, including models where risk and reward information are integrated into a single expected-value-like measure such as cumulative prospect theory (Tversky & Kahneman, 1992) and the transfer of attention exchange model (Birnbaum, 2008). In the domain of multi-alternative choice, the comparison-grouping model (Tsuzuki & Guo, 2004) implements a mixture of attribute-wise and alternative-wise comparisons to explain the context effects.

Lastly in the attribute-and-alternative-wise comparison, one attribute dimension and also one pair of alternatives are attended at one moment, and two alternatives are compared against each other on the attended attribute dimension. For instance, an individual may attend on the quality dimension and compare Cars A and B at one moment. Then, at the next moment, the individual may focus on the economy dimension and compare Cars A and D. This comparison is assumed in the decision by sampling model (Stewart, Chater, & Brown, 2006), which has been applied to context effects in risky and intertemporal choice (Stewart, Reimers, & Harris, in press) and could potentially be extended to account for the three context effects. The attribute-and-alternative-wise comparison has also been employed in the 2N-ary choice tree model (Wollschläger & Diederich, 2012), and the multi-attribute linear ballistic accumulator model (Trueblood, Brown, & Heathcote, in press).

This study examined predictions made by the three types of comparison model. In particular, we tested predictions concerning transitions of attention during choice and effect of random fluctuations in the attention on choice.

Table 1
A list of models discussed.

Comparison	Model
Attribute-wise	Multi-alternative decision field theory
	Leaky competing accumulator model
Alternative-wise	Comparison-grouping model
Attribute-and-alternative-wise	Decision by sampling
	2N-ary choice tree model
	Multi-attribute linear ballistic accumulator model

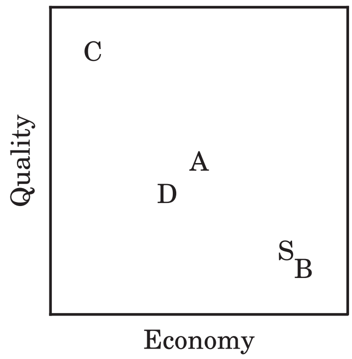


Fig. 1. Illustration of various alternatives. The probability of A being chosen over B can be affected by the presence of D, C or S.

1.1. The pattern of attention transition

In attribute-wise comparison, all of the available alternatives are simultaneously compared on a single attribute dimension. Therefore, an individual is likely to fix attention to one attribute dimension and shift their attention back and forth between alternatives to make comparisons. Thus we should see transitions of attention between alternatives within a single attribute dimension more frequently than, or at least equally frequently to, transitions within a single alternative between attribute dimensions. This same pattern of transitions is predicted by the attribute-and-alternative-wise comparison.

In contrast in the alternative-wise comparison models, all the attributes are used simultaneously in each comparison. Therefore, an individual is likely to fix attention to one alternative, shift their attention within the alternative to integrate attribute values, and then make a comparison. Thus we should see transitions of attention between attributes within a single alternative more frequently than, or at least equally frequently to, between alternatives.

1.2. The influence of stochastic fluctuations in attention on choice

When attribute dimensions are weighted equally so that each attribute dimension is equally likely to be attended at any moment, there will still be trial-to-trial variations in the number of times each attribute dimension is attended. This is due to the stochastic nature of the allocation of attention, and the relative frequencies of the observed split in attention are given by the binomial distribution. For example, with two equally weighted dimensions and with 10 allocations, the number of times each dimension is attended would follow the binomial distribution. So we would see a 5/5 split 24.6% of the time but, just by random chance, we would see the unequal splits (0/10, 1/9, 2/8, 3/7, or 4/6) 75.4% of the time.

Thus, for a particular trial, one attribute dimension will often be attended more frequently than another, even when attribute dimensions are weighted equally. These trial-by-trial fluctuations will increase the probability of selecting the alternatives high on the more attended dimension. To illustrate this prediction, we simulated the multi-alternative decision field theory. In this simulation, a choice is reached after 1,000 comparisons and dimensions are weighted equally. We explored how the choice probabilities change with the number of times the quality dimension is attended. The results are summarised in the left panel in Fig. 2 (see Appendix A for the details). This figure illustrates that, for example, when 490 comparisons are made on the economy dimension and 510 comparisons are on the quality dimension, probability of choosing Car A is .69 with the presence of Car D in the choice set. Generally when Car D or S is included in a choice set, more sampling of the quality dimension predicts higher probability of Car A to be chosen.

We also considered attention fluctuating over pairs of alternatives in the alternative-wise comparison models. One pair of alternatives will more frequently be compared against each other even with an equal weighting of all the pairs. This stochastic bias towards one pair of alternatives results in these alternatives being more likely to be chosen. For example if an individual more frequently compares Cars B and C, the individual is more likely to choose Car B or C and less likely to choose Car A. To illustrate this prediction, we simulated a modified version of the comparison grouping model. This modified version assumes that all the pairs of alternatives are equally weighted and that an alternative is chosen after 1,000 alternative-wise comparisons (see Appendix B for the details). We manipulated the number of comparisons made between Cars B and D, C, or S, and summarised the results in the right panel of Fig. 2. The figure shows that the probability of choosing Car A decreases with the frequency of comparisons between Cars B and D, C, or S.

Finally, in the attribute-and-alternative-wise comparison models, bias towards one pair of alternatives affects choice. But here, attention to an alternative pair interacts with attention towards an attribute dimension: In the car example, an individual is more likely to choose Car A over B if the individual more frequently compares Cars A and B on the economy dimension. In contrast, frequent comparison of Cars A and B on the quality dimension should lead to the choice of Car B.

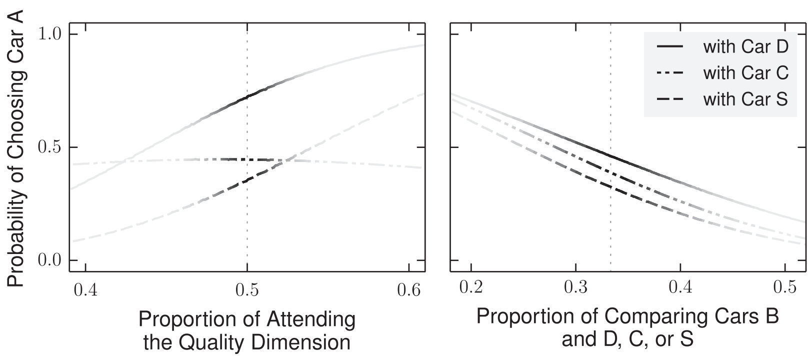
In summary, the three types of model predict different patterns of attention transition and make competing claims on how a stochastic attention bias explains choice. These claims were examined using eye-movement data in the following experiment.

2. Method

Following Simmons, Nelson, and Simonsohn (2012)'s recommendation, we report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

2.1. Participants

One hundred undergraduate students were recruited through the participant panel at the University of Warwick and were paid £5.00 for participating. We decided in advance of collecting the data to test exactly 100 participants. Our previous work indicated that this would give us reasonable statistical power to replicate the attraction, compromise, and similarity effects. Seven participants could not complete the experiment due to failure in tracking their eyes (e.g., lazy eyes), leaving 93 (34 males and 59



(a) Attribute-wise Comparison: A Decision Field Theory Simulation

(b) Alternative-wise Comparison: A Comparison Grouping Model Simulation

Fig. 2. Simulated choice probability. The darkness of the line corresponds to the likelihood of the attention frequency given the equal weighting, and vertical dotted line represents most likely attention split.

females) participants. Their ages ranged from 17 to 49 (median = 21.0).

2.2. Procedure

Participants made 40 choices. At the beginning of each choice, participants were given information about the two attributes involved. After displaying the fixation point until participant fixated it for at least 500 ms, the experiment program presented three choice alternatives: one at the lower left corner of the screen, another at the top middle area, and the other at the lower right corner of the screen. This presentation ensures that the three alternatives are equally distant from each other on the display. An example screen shot is given in Fig. 3. Participants made a choice by pressing one of the left, up, or right arrow keys.

The 40 choices comprised 10 attraction, 10 compromise, 10 similarity, and 10 catch choices. The catch choices always had one dominant alternative on both attribute dimensions. We used participants' responses to the catch choices to assess whether they were engaged in the task. Each of the other 30 choices appeared in one of two versions, one favouring Alternative A and another favouring B. The two versions are summarised in Fig. 4.

The left panel in Fig. 4 displays the alternatives for the two versions of the attraction choices. One version involved Alternatives A, B and D_A (the decoy to Alternative A), and the other involved Alternatives A, B, and D_B (the decoy to Alternative B). The middle panel displays the alternatives for the compromise choices. One version involved Alternatives A, B, and C_A (making Alternative A the compromise), and the other involved Alternatives A, B, and C_B (making Alternative B the compromise). The right panel displays alternatives for the similarity choices: one version involved Alternatives A, B, and S_A (adding an alternative similar to Alternative B), and the other involved Alternatives A, B, and S_B (adding an alternative similar to Alternative A). The allocation of versions was counterbalanced between participants.

Each of 40 choices involved a different cover story (e.g., cars, laptops, and TV sets), and the same cover story was used for the two version of choices. Thus, all the participant made a choice between cars in an attraction choice, regardless of the version to which they were assigned. The order of the choices was randomised and the four types of choices were interleaved. The locations of alternatives and attributes on the screen were randomised for each choice.

Throughout the experiment, participants' eye-movements were recorded at 500 Hz using an EyeLink 1000 (SR Research). The eye-tracker was placed right under the 19 in. monitor, and the distance between participant's eye and the eye-tracker was kept between 50 cm and 55 cm. Also, the eye-tracker was calibrated just before the experiment and also after every 10 choices during the experiment.

3. Results

Out of 93 participants, 44 participants did not choose the dominant alternative in one or more of the catch choices. These less-engaged participants may have been unable to differentiate the attraction and similarity choices, where the detection of dominance is crucial. Thus, the analysis below includes engagement as a factor, noting where it matters.

3.1. The attraction, compromise, and similarity effects were replicated

We computed the proportion of times each alternative was chosen for each choice type for each participant. The choice proportions from the engaged group of participants are plotted in Fig. 5. The filled circles with the solid line represent the version of choices which favours Alternative A, and the empty squares with the dashed line represent the one which favours Alternative B.

The left panel in Fig. 5 shows a replication of the attraction effect: Alternative A is most often selected from the D_A version while Alternative B is most frequently chosen from the D_B version. The middle panel shows a replication of the compromise effect: The compromise alternatives are most often to be chosen in both C_A and C_B versions. The right panel shows a replication of the similarity effect: Alternative A has a higher proportion of choice in the S_A version compared to the S_B version and Alternative B has a higher

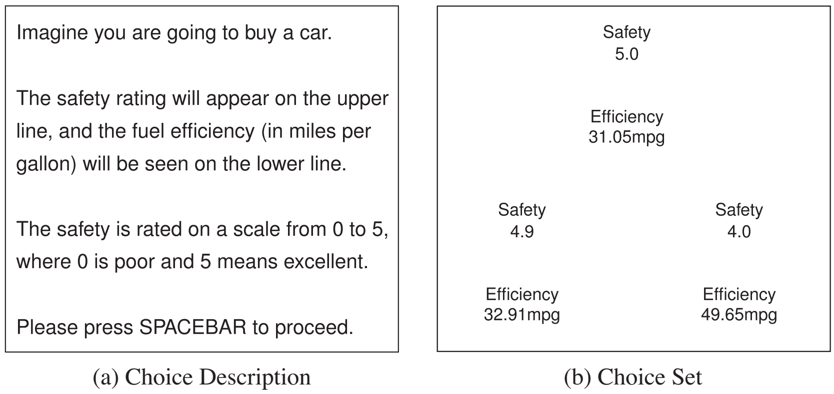


Fig. 3. Example screen-shots. This example depicts a choice between cars in an attraction choice. Font size is enlarged for this illustration.

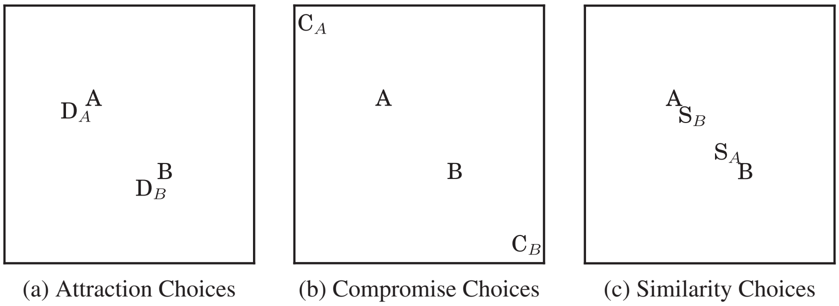


Fig. 4. Locations of the alternatives used in the experiment.

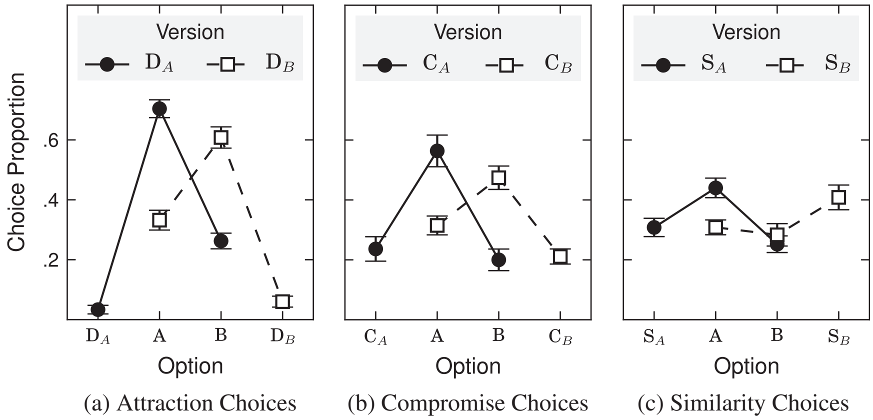


Fig. 5. Mean choice proportions of the engaged participants. Error bars are standard error of the mean.

proportion, albeit only slightly, in the S_B version compared to the S_A version.

We explored the significance of these effects using a mixed-effect model. The proportions for Alternatives A and B are logit-transformed after multiplying with 0.9 to handle ones and adding 0.05 to handle zeros. Then the transformed proportions are entered into a linear mixed-effect linear model. The model had fixed effects for alternative (A or B), version (whether the version favours Alternative A or B), choice-type (attraction, compromise, or similarity), and participant group (engaged or less-engaged). The model also had by-participant slopes and intercepts as random factors.

The model fit indicates that the effect of the three-way interaction depends on participant engagement: the four-way interaction is significant, $\chi^2(2) = 17.92$, $p < .001$. When the same model is fit only to the engaged group of participants, the three-way interaction effect indicates that the effect of choice alternative on the choice proportion depends on the choice type and the version: $\chi^2(2) = 28.84$, $p < .001$. Thus, we fit the same mixed-effect model to the attraction, compromise and similarity choices separately for the group of engaged participants.

For the attraction choices, the interaction effect is significant, $\chi^2(1) = 44.47$, $p < .001$, indicating that the choice proportions for Alternatives A and B are different between the D_A and D_B versions. The interaction effects are also significant for the compromise choices, $\chi^2(1) = 19.90$, $p < .001$, and for the similarity choices, $\chi^2(1) = 4.11$, $p = .043$. These interaction effects indicate that the attraction, compromise and, similarity effects are replicated in this study.

For the group of the less-engaged participants, the three-way interaction is also significant: $\chi^2(2) = 51.81$, $p < .001$. The attraction and compromise effects are confirmed: $\chi^2(1) = 34.23$, $p < .001$ and $\chi^2(1) = 27.37$, $p < .001$. However, the similarity effect does not reach significance: $\chi^2(1) = 0.11$, $p = .738$.

3.2. Eye movements

For the fixation data, we defined non-overlapping regions of interest to identify to which alternative and attribute dimension the participant fixated his or her eye on. Due to noise in the detecting fixation locations, fixations were not registered for some of the displayed attributes in 153 out of the total of 2,790 (=30 choices × 93 participants) trials. These trials are removed from the analysis. Then, each choice was recoded to match the labels in Fig. 1. So for the D_A version of the attraction choices, D_A was relabelled D. For the D_B version, D_B was relabelled D and labels for A and B were swapped. In addition, the attribute dimensions were switched when relabelling the alternatives in the D_B version. Similar relabelling was done for the compromise and similarity choices.

3.3. Stages of decision making

Previous studies which analyse eye-movement often assume three stages of decision making: initial screening, evaluation and comparison, and validation prior to making a choice (e.g., Glaholt & Reingold, 2011; Russo & Leclerc, 1994). Glöckner and Herbold (2011) review evidence that the duration of fixations increases with processing difficulty, and so differences in fixation duration over time may indicate different processing stages.

To examine the stages of decision making, we segmented the sequence of fixations into three blocks. Each block has the equal number of fixations, but when the number of fixations is not dividable by three, we added the reminder to the last block. Then the mean fixation duration is computed for each block for each participant and displayed in Fig. 6. This figure illustrates that the fixation tends to be longer in the first block.

The fixation durations were examined with a mixed-effect model. Fixed effects are fixated alternative (A, B, or the third alternative), fixated attribute dimension, block (1, 2, or 3), and choice-type (attraction, compromise, or similarity). Random effects are by-participant intercept and slope for block. The interaction effects indicates that the fixation duration does not differ between the alternatives or the attribute dimensions (*ps* > .066), but that the difference between blocks depends on the choice-type ($\chi^2(4) = 13.48, p = .009$). Thus, we fit the mixed-effect model separately for each choice-type. Although the strength of the effect may differ between the choice-types, the effect of block is significant for all the three choice-types ($\chi^2(2) = 49.34, p < .001$ for the attraction choices; $\chi^2(2) = 44.92, p < .001$ for the compromise choices; $\chi^2(2) = 37.37, p < .001$ for the similarity choices), indicating that the fixation duration is significantly longer in the first block.

The longer fixation in the first block may indicate a qualitatively different stage of decision making. Therefore, we examined effects of the block in the following analysis, although the results hold if the block is not included in the analysis.

3.4. The pattern of attention transitions

According to the attribute-wise and attribute-and-alternative-wise comparison models, transitions of attention between alternatives on a single attribute should be more frequent than, or at least equally frequent to, transitions between attributes within a single alternative. In contrast, according to the alternative-wise comparison models, transitions of attention within a single alternative should be more frequent than, or at least equally frequent to, transitions between alternatives.

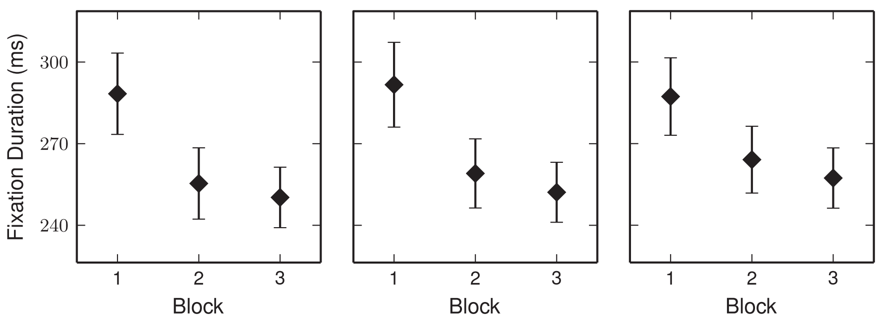
The difference between the number of transitions between alternatives and within an alternative is displayed in Fig. 7. The between-alternatives transitions include only those on a single attribute dimension, excluding the between-alternatives, between-attributes transitions. Thus, the between-alternative transitions are underestimated, which should favour the prediction from the alternative-wise comparison. However, between-alternatives transitions are more frequently observed than within-alternative transitions, consistent with the attribute-wise and attribute-and-alternative-wise comparison models.

These transitions are examined with a mixed-effect model, whose fixed effects are participant group (engaged or less-engaged), choice-type (attraction, compromise, or similarity), and block (1, 2, or 3), and the random effects are by-participant slopes and intercepts. The three-way and two-way interaction effects indicate that the effect of transition-type does not differ significantly between the participant groups or the blocks: *ps* > .064. The main effect of choice-type is significant: $\chi^2(1) = 6.87, p = .032$. When the mixed-effect model was fit to each choice-type, the estimated intercept indicates the scores are significantly different from zero: $\beta = 0.48$ (95% CI [0.29, 0.68]) for the attraction choices; $\beta = 0.33$ (95% CI [0.12, 0.53]) for the compromise choices; $\beta = 0.52$ (95% CI [0.31, 0.73]) for the similarity choices. These results suggest that the effect differs quantitatively but not qualitatively across the choice-types.

Thus, the attention transitions more frequently between alternatives on the same attribute dimension than within an alternative. This pattern of attention transition supports the attribute-wise and attribute-and-alternative-wise comparison models and rejects the alternative-wise comparison models.

3.5. The influence of stochastic fluctuations in attention on choice

Before examining the influence of attention bias on choice – the subject of the simulations above – we need



(a) Attraction Choices (b) Compromise Choices (c) Similarity Choices

Fig. 6. Fixation duration as a function of time. Error bars are standard error of the mean.

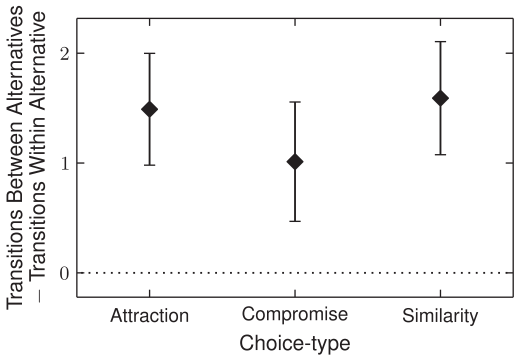


Fig. 7. Difference in transitions. Error bar are standard error of the mean.

to consider the gaze-cascade effect (Shimojo, Simion, Shimojo, & Scheier, 2003). In the gaze cascade effect a developing preference for an alternative causes more frequent eye-movements to that alternative and vice versa, in a positive feedback loop. This gaze-cascade effect is considered independent of the comparison process and could artificially favour one prediction over another. Thus, we quantified the gaze-cascade effect and used it as a control variable.

Specifically, we counted the number of transitions *towards* an alternative and the number *away from* the alternative. According to Bird, Lauwereyns, and Crawford (2012), transitions towards an alternative increase the probability of selecting that alternative, and transitions away from an alternative decrease the probability of selecting that alternative. Importantly, once the number of transitions towards and away from an alternative is controlled for, there is no overall effect of the total number of fixations in predicting a choice.

As the number of transitions towards an alternative is highly correlated with the number of transitions away from the alternative, we took the difference as the gaze-cascade score. By definition, the number of transitions towards an alternative must be one less than, equal to, or one more than the number of transitions away from that alternative, and so the gaze-cascade score for an alternative was always −1, 0, or +1. When tested alone in a mixed-effect logistic regression with by-participant intercept and slope as random factors, the gaze-cascade score for Alternative A significantly predicts the choice of Alternative A: $\beta = 0.52$ (95% CI [0.45, 0.59]), $\chi^2(1) = 144.27, p < .001$. The gaze-cascade score for each alternative was entered as both fixed and by-participant random factors to all the models to predict choices we used below.

Attribute-wise comparison. In the attribute-wise comparison models, a stochastic bias in attention towards one attribute dimension over the other should predict a choice of the alternative on which that attribute is highest, as in the simulation described above. To examine this prediction, we counted differences in the numbers of fixations and also summed the duration of fixations between the attribute dimensions within each trial. We first examined whether fixation counts and durations varied over the time course of a trial before testing whether fixation counts and durations were related to choices as the attribute-wise comparison models predict.

To examine whether these fixation counts and duration differ between the blocks, we used a mixed-effect model. Fixed factors are block (1, 2, or 3), participant group (engaged or less-engaged), and choice-type (attraction, compromise, or similarity), and random factors are by-participant slopes and intercepts. While we tested the counts and durations in the separate models, the total fixation duration is correlated with the fixation counts, as the average duration of each fixation does not differ significantly between alternatives or attributes (see the analysis in Section "Stages of decision making"). As a result, the model with fixation duration yielded essentially the same results as the model with the fixation counts. The model fits suggest that the counts and the duration do not differ significantly between blocks, participant groups or choice-types ($ps > .066$). Thus, we summed the counts and durations across the blocks to explore their relationship to choice.

The fixation counts and durations were then entered into mixed-effect logistic regressions to predict the choice of Alternative A. The fixed effects include participant group (engaged or less-engaged) and choice type (attraction, compromise, or similarity), and the random effects are by-participant slopes and intercepts. The three-way and two-way interaction effects indicate that the effect of attention bias over attribute dimensions, in both counts and durations, does not depend on the participant group or the choice-type: $ps > .682$. The main effect suggests that attention bias is not a significant predictor of choice: $\beta = 0.00$ (95% CI [−0.01, 0.02]), $\chi^2(1) = 0.05, p = .821$ for the counts and $\beta = 0.00$ (95% CI [−0.00, 0.00]), $\chi^2(1) = 2.02, p = .155$ for the duration. Thus, the prediction from the attribute-wise comparison models is not supported.

Alternative-wise comparison. In the alternative-wise comparison models, a bias in attention towards one pair of alternatives negatively correlates with probability of the remaining alternative being chosen, as in the simulation described above. To examine this prediction, we counted the number of transitions between each pair of alternatives within each trial. First we describe how, over the time course of a trial, some transitions come to be more frequent than others. Then we test whether the transition frequencies on a trial can be used to predict the choice on that trial in the way alternative-wise comparison models predict.

The transitions are displayed in Fig. 8 which shows that the differences between the transitions emerge over a trial. Transitions were transformed by adding 1 and logging before being entered into a mixed-effect linear regression in which the effects of block were examined. Fixed factors are block (1, 2, or 3), participant group (engaged or less-engaged), choice-type (attraction, compromise, or similarity), and transition (between A and B, between B and the third alternative, or between A and the third alternative), and the random factor was by-participant intercepts. Random factors do not include by-participant slopes, to keep the model complexity manageable. The four-way and three-way interaction effects indicate that the interaction effects do not depend on participant group ($ps > .308$), but that block has different effect depending on choice-type and transition ($\chi^2(8) = 385.89, p < .001$). Thus, the mixed-effect model is fit to each choice-type separately.

The model fits suggest that the effect of block depends on transition for all the choice-types (the attraction choices: $\chi^2(4) = 135.90, p < .001$; the compromise choices: $\chi^2(4) = 101.16, p < .001$; the similarity choices: $\chi^2(4) = 170.04, p < .001$). When the mixed-effect models were fit separately to each block, the model fits indicate that in the attraction and compromise choices, the transitions differ from each other non-significantly in Block 1 ($ps > .147$), but significantly in Blocks 2 and 3 (the attraction choices: $\chi^2(2) = 48.04, p < .001$ and $\chi^2(2) = 111.68, p < .001$, respectively; the compromise choices: $\chi^2(2) = 35.60, p < .001$ and $\chi^2(2) = 87.38, p < .001$) In the similarity choices, the transitions differ in all the blocks (Block 1: $\chi^2(2) = 9.08$, $p = .011$; Block 2: $\chi^2(2) = 65.98, p < .001$; Block 3: $\chi^2(2) = 100.71, p < .001$).

Although the significance of the differences in the transitions differs between blocks, the direction of the differences is consistent across the blocks. In short, we see that, as the choice unfolds, differences in the frequencies of each transition type emerge. Before the attribute values have been read, there can be no bias to make some transitions more frequently than others. So gradually emerging differences in the transitions are entirely expected. The consistent directions of the differences imply that the process of decision making is not qualitatively different between the blocks.

The second state of our analysis is to see whether transition frequencies can be used to predict choices as the alternative-wise comparison models predict. We summed the transitions across the blocks and displayed the summed transitions in Fig. 9. The transitions are largely consistent with the predictions for the alternative-wise comparison models for all three choice types. For example, the transition between Alternatives A and B is more frequent before A or B is chosen, and also the transition between Alternatives A and the third alternative is more frequent before A or the third alternative is chosen.

These transitions were entered into a mixed-effect logistic regression to predict the choice of Alternative A. The fixed effects include participant group and choice type, and the random effects are by-participant slopes and intercept. The interaction effects indicate that the effect of transitions does not significantly depend on the participant group ($ps > .567$), but that the effect depends on the choice-type: $\chi^2(2) = 82.53, p < .001$.

Consistent with the prediction, the transition between Alternatives B and D is a significant, negative predictor of choice A in the attraction choices: $\beta = -0.18$ (95% CI [−0.27, −0.09]), $\chi^2(1) = 16.11, p < .001$. Also the transition between B and S is a significant negative predictor in the similarity choices: $\beta = -0.39$ (95% CI [−0.48, −0.31]), $\chi^2(1) = 92.13, p < .001$. However, the effect of the transition between B and C is not significant in the compromise choices: $\beta = -0.02$ (95% CI [−0.10, 0.06]), $\chi^2(1) = 0.24$, $p = .626$.

In addition, some of the transitions, which involve Alternative A, significantly predict the choice of A. In the attraction choices, the transition between Alternatives A and D predicts the choice of A: $\beta = 0.27$ (95% CI [0.19, 0.35]), $\chi^2(1) = 49.37, p < .001$. This effect further implicates the alternative-wise comparison in the attraction choices, as the comparison between A and D always favours A.

Also in the compromise choices, the transition between Alternatives A and B and also between A and C predict the choice of A: $\beta = 0.09$ (95% CI [0.02, 0.25]), $\chi^2(1) = 6.63$, $p = .010$; and $\beta = 0.13$ (95% CI [0.06, 0.20]), $\chi^2(1) = 12.11$, $p < .001$. In the similarity choices, the transition between Alternatives A and S predicts the choice of A: $\beta = 0.12$ (95% CI [0.04, 0.20]), $\chi^2(1) = 7.78, p = .005$.

The other significant predictor is not readily explained by the alternative-wise comparison. In the attraction choice, the transition between A and B negatively predict the choice of A: $\beta = -0.08$ (95% CI [−0.15, −0.01]), $\chi^2(1) = 4.69, p = .030$.

Thus, the effects of the transitions on choice are generally consistent with the predictions from the alternative-wise comparison, though some additional effects are not readily explained.

Attribute-and-alternative-wise comparison. According to the attribute-and-alternative-wise comparison, an

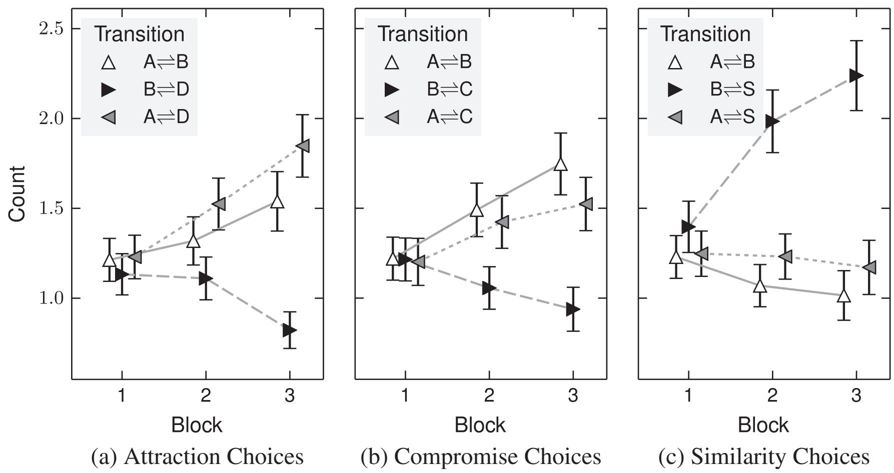
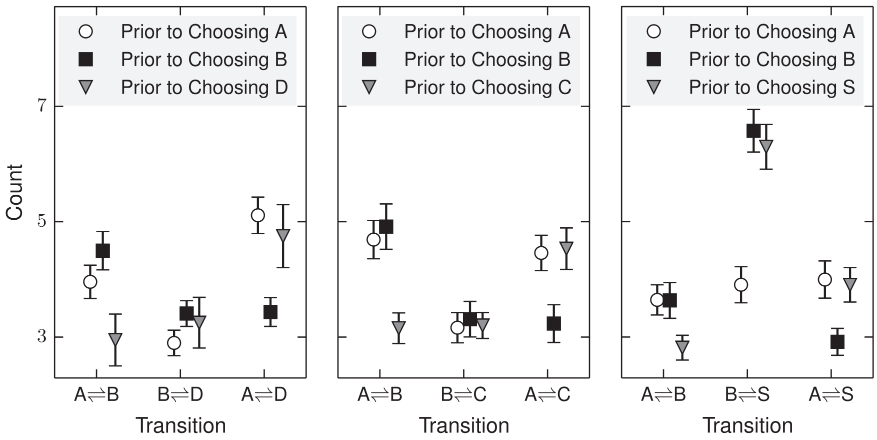


Fig. 8. Number of transitions prior to making a choice. Error bars are standard errors of the mean.



(a) Attraction Choices (b) Compromise Choices (c) Similarity Choices

Fig. 9. Number of transitions prior to making a choice. Error bars are standard errors of the mean.

attention bias towards one pair of alternatives predicts the choice of the alternative better on the attended attribute dimension, as described above. As the transitions are correlated between the attribute dimensions, we summed the numbers of fixation transitions favourable for each alternative, so that the larger count indicates more comparisons favourable to an alternative. For example, in an attraction choice, the transitions favourable for Alternative A is the sum of the transitions between Alternative A and B on the quality dimension and between A and D on both quality and economy dimensions. Our analysis here follows the same procedure as the analysis for attribute-wise comparisons and for alternative-wise comparisons above: First we explore how the counts of favourable transitions unfold over the time course of a trial and then we explore whether these counts predict choice as the attribute-and-alternative-wise comparison models predict.

The favourable transitions are summarised in Fig. 10. In the attraction choices, the transitions favourable to Alternative A increase with block, because the transition between Alternatives A and D, which favours A, becomes more frequent with block (see Fig. 8). Likewise in the compromise choices, as the transition between Alternatives A and B and between Alternatives A and C becomes more frequent, the transitions favourable to A increase. Also in the similarity choices, as the transition between Alternatives B and S becomes more frequent, the transitions favourable to B and S increase.

These transitions are transformed by adding 1 and logging, and then entered into a mixed-effect linear regression. Fixed effects are block (1, 2, or 3), participant group (engaged or less-engaged), choice-type (attraction, compromise, or similarity), and favoured alternative (A, B, or the third alternative). By-subject intercepts but not slopes are included in the random effects. The interaction and main effects indicate that the transitions do not differ significantly between participant groups (*ps* > .430), but that the effect of block differs between the choice-types and alternatives ($\chi^2(8) = 167.29$, $p < .001$). Thus, we fit the mixed-effect model to each choice-type separately.

In all three choice-types, the interaction and main effects indicate that the count does not differ between the participant groups (*ps* > .097), but that the effect of favoured alternative depends on the block (the attraction choices: $\chi^2(4) = 107.95$, $p < .001$; the compromise choices: $\chi^2(4) = 37.30$, $p < .001$; the similarity choices: $\chi^2(4) = 55.36$, $p < .001$).

Again, although the significance of the difference differs between the blocks, the directions of the differences are consistent across the blocks. Thus, we summed the transitions across the blocks and displayed the transitions as a function of the chosen alternative in Fig. 11.

Consistent with the prediction from the attribute-and-alternative wise comparison, the transition is generally higher for the alternative to be chosen. Before Alternative A is chosen (the empty circles), for example, the transition favouring A (the left column in each plot) is higher than the other transitions across the three choice-types.

These transitions were then entered into a mixed-effect logistic regression to predict the choice of Alternative A. The fixed effects include participant group and choice-type, and the random effects are by-participant slopes and intercept. The interaction effects indicate that the effect of transitions does not depend on the participant group (*ps* > .28), and that the effect depends on the choice-type: $\chi^2(6) = 39.25$, $p < .001$.

Consistent with the prediction, the transition, which indicates more frequent comparison favourable to Alternative A, is a significant predictor of choice A in the attraction, compromise, similarity choices: respectively, $\beta = 0.17$ (95% CI [0.11, 0.24]), $\chi^2(1) = 26.76$, $p < .001$; $\beta = 0.17$ (95% CI [0.07, 0.26]), $\chi^2(1) = 11.77$, $p < .001$; and $\beta = 0.24$ (95% CI [0.14, 0.34]), $\chi^2(1) = 20.69$, $p < .001$.

In addition, the transition, which indicates more frequent comparison favourable to other alternatives than A, is a significant, negative predictor of choice A in the attraction and similarity choices. In the attraction choices, the transition favourable to Alternative B shows $\beta = -0.19$ (95% CI [−0.29, −0.10]), $\chi^2(1) = 15.89$, $p < .001$. In the similarity choices, the transition favourable to Alternative B

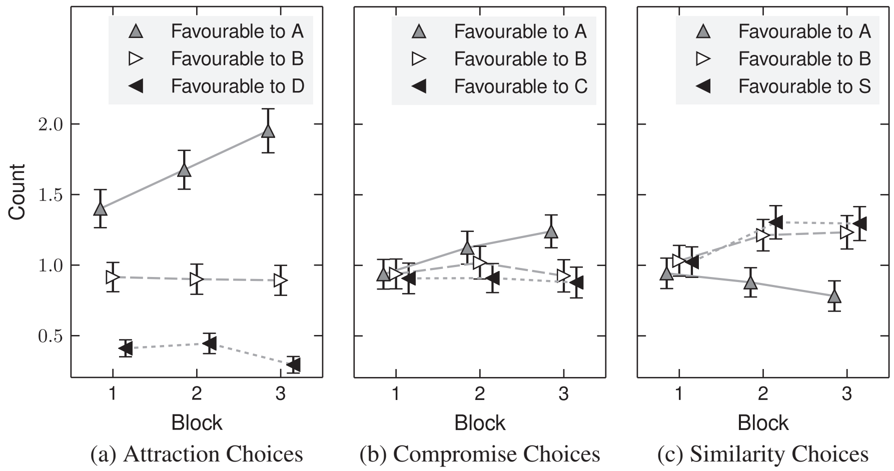


Fig. 10. Number of transitions prior to making a choice. Error bars are standard errors of the mean.

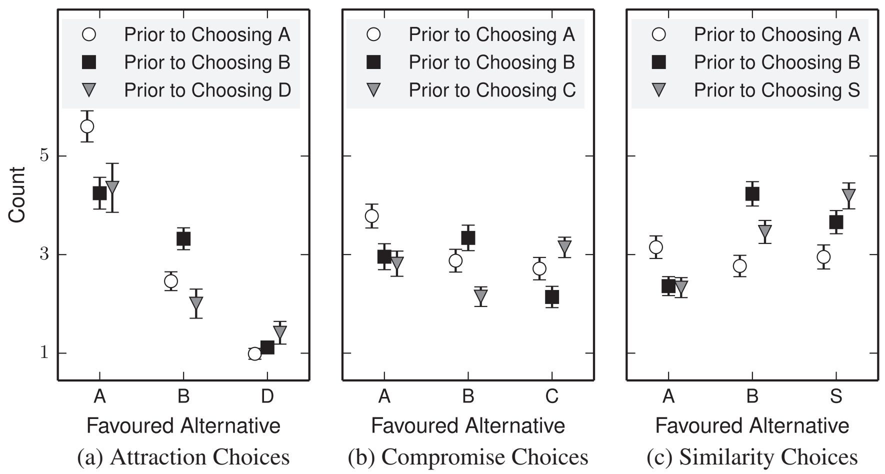


Fig. 11. Number of transitions prior to making a choice. Error bars are standard errors of the mean.

shows $\beta = -0.28$ (95% CI [-0.40, -0.17]), $\chi^2(1) = 25.18$, $p < .001$; and that favourable to S shows $\beta = -0.17$ (95% CI [-0.27, -0.08]), $\chi^2(1) = 12.51$, $p < .001$.

Thus, the results consistently support the prediction from the attribute-and-alternative-wise comparison.

4. Discussion

The present study replicated the attraction, compromise, and similarity effects in a within-participants design using 40 different consumer choice scenarios. This is the second study, following Berkowitsch, Scheibehenne, and Rieskamp (in press), to simultaneously replicate the three effects in consumer choice. This is also the first study to record eye movements in participants showing these effects.

This study investigated the psychological processes of multi-alternative choice, focusing on how alternatives are compared against each other. We examined transitions of attention while a choice was being made. Specifically, the pattern of eye movements was examined to differentiate between three types of comparison model: attribute-wise, alternative-wise, and attribute-and-alternative-wise.

Transitions between alternatives within an attribute dimension were more frequent that transitions within alternatives between attributes, consistent with attribute-wise and attribute-and-alternative-wise models. The attribute-wise comparison models predict that bias towards a dimension should increase the probability that the alternative highest on that dimension should be chosen, but there was no significant effect of attribute-dimension bias. The alternative-wise comparison models predict that bias towards a pair of alternatives should decrease the probability that the third alternative is chosen, and this effect of alternative-pair bias was found. Finally, the attribute-and-alternative-wise comparison models alone predict an interaction between the alternative-pair and the attribute dimension attended. For a given pair and dimension, the alternative higher on the attribute dimension attended should be favoured over the alternative lower on the attribute dimension attended. This interaction was observed. Overall, the eye movement data are most consistent with the attribute-and-alternative-wise comparison models, in which comparisons are between pairs of alternatives on single dimensions.

The finding of more transitions between alternatives within an attribute dimension could be influenced by physical locations of the alternatives within the display. In our experiment, the distance between the alternatives is deliberately very similar to the distance between two attribute values within an alternative. However, if between-alternative distances were minimised compared to within-alternative distances, attention might transition more frequently between alternatives, appearing as if the alternative-wise comparison is supported. Previous research however, has also favoured the attribute-wise comparison over the alternative-wise comparison: When an individual is allowed to choose which information to examine, the individual more often decides to reveal information on one attribute dimension across available alternatives (Payne, 1976). Also, our results conform previous findings, where transition is more frequent between alternatives on a single attribute dimension than within an alternative (Russo & Dosher, 1983).

While attribute-wise comparison models are supported by the attention-transition evidence, these models are not consistent with the null effect of attention bias on choice. This result has implications for computational models beyond the class of comparison-based models described above. For instance, the associative accumulation model (Bhatia, 2013) explains the context effects with attention bias towards one attribute dimension over the other. Also, the range-normalisation model (Soltani, De Martino, & Camerer, 2012) predicts that the attention bias should lead to different choices. These explanations are not consistent with the present results.

These relationships between transition and choices extend previous findings on eye-movement and choice. Krajbich and Rangel (2011) for instance, proposed a drift–diffusion model which incorporated fixations, by assuming that the drift rate was higher for fixated alternatives. This model relates a priori ratings of the attractiveness of alternatives and the fixation times on each alternative during a choice to the final choice of alternative. That is, to predict choice this model requires the pattern of fixations and also attractiveness judgements for each alternative. In contrast, our study focused on predicting choices from the pattern of attention transitions alone.

A second major finding is the gaze cascade effect (Shimojo et al., 2003; Simion & Shimojo, 2007). The gaze cascade effect is a developing bias to direct an eye-fixation toward the alternative ultimately chosen. As a result, choice can be predicted from transitions (Bird et al., 2012). While it is not clear how well this gaze cascade effect correlates with preference development (e.g., Glaholt & Reingold, 2009, 2011), our results confirm the positive relationship between the gaze cascade (measured from transitions) and choice. Also, the results show that even after controlling for this gaze cascade effect, the pattern of transition still predicts choices and reveals details of the comparison process in choice making.

In our analysis we were careful to explore how eye movements changed over the time course of a choice, because changes might indicate different stages of processing (e.g., Glöckner & Herbold, 2011). Although we did find a surprising tendency for early fixations to be longer, we did not find any qualitative shift in the pattern of eye movements. Instead, each of the biases we find emerged gradually within a trial. This is not surprising because, given that the biases are defined only by the relation of the attribute values to one another and not by some more obvious cue like physical location on the screen, these biases cannot emerge until the attribute values have been read and compared. Our data are most consistent with a single continuous cognitive process operating over the whole time course of a choice, unless of course each cognitive process produces the same pattern of eye movements. For example, an individual may make comparisons to make a choice and then make comparisons to justify the choice before declaring the choice (Mercier & Sperber, 2011). Thus some or maybe all eye movements may be the result of a post-choice justification process, though we think it unlikely that none of the eye movements reflects the choice process. If so, the choosing and post-choice justification both rely upon a series of comparisons of pairs of alternatives on a single dimension.

The effects of attention bias on a choice are consistent with the attribute-and-alternative-wise comparison models. Here a choice is reached through a series of comparisons of pairs of attributes on a single dimension, as in the decision by sampling model (Stewart, 2009; Stewart et al., 2006, in press; Stewart & Simpson, 2008), the 2N-ary choice tree model (Wollschläger & Diederich, 2012), and the multi-attribute linear ballistic accumulator model (Trueblood et al., in press).

Acknowledgements

Neil Stewart was supported by Grants from the Economic and Social Research Council ES/K002201/1 and ES/K004948/1, and the Leverhulme Trust RP2012-V-022. We thank Adam Sanborn for his helpful discussion.

Appendix A. Multi-alternative decision field theory

In this appendix, we describe the computation to derive the results in the left panel in Fig. 2. The parameter values and the alternative values are taken from Hotaling, Busemeyer, and Li (2010).

In simulating multi-alternative decision field theory, we label three alternatives as A, B, and T, where T indicates D, C or S depending on the choice set. These alternatives are described with two attributes, E (economy) and Q (quality). The value of Alternative A on the economy dimension is denoted as E_A and that on the quality dimension is Q_A. The values used in the simulation is summarised in Table A1. Preference for the three alternatives is organised in a column vector, P. The first element in this vector corresponds to preference for Alternative A, the second corresponds to preference for B, and the third corresponds to preference for T. This preference is iteratively updated as follows:

$$P(t+1) = SP(t) + V(t+1),$$

where S is a 3×3 feedback matrix and V is a 3×1 momentary valence vector. In the feedback matrix, the influence of Alternative i on j, s_{ij}, is computed as:

$$s_{ij} = 0.99(\delta_{ij} - 0.05exp(-0.022D_{ij}^2)).$$

Here, δ_{ij} is 1 if i equals j, otherwise δ_{ij} is 0. Also, D_{ij} is a distance between Alternatives i and j, which is defined as:

$$D_{ij} = \frac{(\Delta Q_{ij} - \Delta E_{ij})^2}{2} + 12\frac{(\Delta Q_{ij} + \Delta E_{ij})^2}{2},$$

where

$$\Delta Q_{ij} = Q_i - Q_j$$

and

$$\Delta E_{ij} = E_i - E_j.$$

The momentary valence vector is computed with four matrices:

$$V(t) = CMW(t) + C\epsilon(t),$$

where

$$C = \begin{bmatrix} 1 & \frac{-1}{2} & \frac{-1}{2} \\ \frac{-1}{2} & 1 & \frac{-1}{2} \\ \frac{-1}{2} & \frac{-1}{2} & 1 \end{bmatrix},$$

$$M = \begin{bmatrix} E_A & Q_A \\ E_B & Q_B \\ E_T & Q_T \end{bmatrix},$$

and

$$\epsilon(t)N = \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}\right).$$

The attention weight W is a 2×1 vector. When the economy dimension is attended,

$$W(t) = \begin{bmatrix} 1 \\ 0 \end{bmatrix}. \quad (A.1)$$

When the quality dimension is attended,

$$W(t) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}. \quad (A.2)$$

The iterative update starts with zero preference for all the alternatives, and after 1000 iterations, the alternative with the highest preference is chosen. For each specified frequency of (A.1) and (A.2), a choice is simulated 10^6 times to derive the probability of choosing each alternative.

Appendix B. Modified version of the comparison grouping model

In this appendix, we describe the computation to derive the results in the right panel in Fig. 2.

The three alternatives are labelled as A, B, and T, where T indicates D, C or S depending on the choice set. These alternatives are described with two attributes, E (economy) and Q (quality). The value of Alternative A on the economy dimension is denoted as E_A and that on the quality dimension is Q_A. The parameter values and the values for the alternatives (Table B1) are taken from Tsuzuki (2004). In the comparison grouping model, each alternative and each attribute dimension iteratively develops preference. We denote preference for Alternative A as P_A. Then,

$$P_A(t+1) = P_A(t) + \Delta_A(t+1). \quad (B.1)$$

If Alternative A is not attended at time $t+1$, $\Delta_A(t+1)$ is 0, otherwise

$$\Delta_A(t+1) = \begin{cases} \delta_A(1 - P_A(t)) - 0.04P_A(t) if \quad \delta_A > 0 \\ \delta_A P_A(t) - 0.04P_A(t) if\, \delta_A \quad \leqslant 0 \end{cases} \quad (B.2)$$

where

$$\delta_A = W_{E_A}P_E(t) + W_{Q_A}P_Q(t) - 0.60(P_B(t) + P_T(t)), \quad (B.3)$$

and

$$W_{E_A} = \frac{ln(E_A + 31) - 3.35}{0.905}.$$

Preference for the other alternatives is updated in the same manner.

In addition, preference for attribute dimensions is updated at each iteration. Letting P_E preference for the economy dimension, P_E is updated using Eqs. (B.2) and (B.3), but instead of Eq. (B.3), we have

$$\delta_E = W_{E_A}P_A(t) + W_{E_B}P_B(t) + W_{E_T}P_T(t).$$

Preference for the quality dimension is updated in the similar manner.

The iteration is initiated with preference for attribute dimensions being 0.50 each, and preference for alternatives starts with 0, rather than a random sample from the uniform distribution between 0.25 and 0.75 as in the original model. Also, unlike the original model, preference for two attribute dimensions and only two alternatives is updated at one iteration.

Table A1
Values used in the simulation.

Third alternative (T)	EA	EB	ET	QA	QB	QT
D	1.0	3.0	0.5	3.0	1.0	2.5
C	2.0	3.0	1.0	2.0	1.0	3.0
S	1.0	3.0	2.9	3.0	1.0	1.1

Table B1
Values used in the simulation.

Third alternative (T)	EA	EB	ET	QA	QB	QT
D	2.0	8.0	1.5	8.0	2.0	7.5
C	5.0	8.0	2.0	5.0	2.0	8.0
S	2.0	8.0	7.5	8.0	2.0	2.5

After 1000 iterations, the alternative with the highest preference is chosen. For simplicity, frequency of attending a pair of Alternatives A and B is the same as attending a pair of Alternatives A and T. For each frequency of attending a pair of Alternatives B and T, a choice is simulated 10^6 times to derive the choice probability.

References

Berkowitsch, N. A. J., Scheibehenne, B., & Rieskamp, J. (in press). Rigorously testing multialternative decision field theory against random utility models. *Journal of Experimental Psychology: General.*

Bhatia, S. (2013). Associations and the accumulation of preference. *Psychological Review, 120*, 522–543.

Bird, G. D., Lauwereyns, J., & Crawford, M. T. (2012). The role of eye movements in decision making and the prospect of exposure effects. *Vision Research, 60*, 16–21.

Birnbaum, M. H. (2008). New paradoxes of risky decision making. *Psychological Review, 115*, 463–501.

Glaholt, M. G., & Reingold, E. M. (2009). The time course of gaze bias in visual decision tasks. *Visual Cognition, 17*, 1228–1243.

Glaholt, M. G., & Reingold, E. M. (2011). Eye movement monitoring as a process tracing methodology in decision making research. *Journal of Neuroscience, Psychology, and Economics, 4*, 125–146.

Glöckner, A., & Herbold, A.-K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making, 24*, 71–98.

Hotaling, J. M., Busemeyer, J. R., & Li, J. (2010). Theoretical developments in decision field theory: Comment on Tsetsos, Usher, and Chater (2010). *Psychological Review, 117*, 1294–1298.

Huber, J., Payne, J., & Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of Consumer Research, 9*, 90–98.

Krajbich, I. & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. Proceedings of the National Academy of Sciences, 108.

Mercier, H., & Sperber, D. (2011). Why do humans reason? Arguments for an argumentative theory. *Behavioral and Brain Sciences, 34*(57–74), 57–74.

Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Bahvior and Human Performance, 16*, 366–387.

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative decision field theory: A dynamic connectionist model of decision making. *Psychological Review, 108*, 370–392.

Russo, J. E., & Dosher, B. A. (1983). Strategies for multiattribute binary choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9*, 676–696.

Russo, J. E., & Leclerc, F. (1994). An eye-fixation analysis of choice processes for consumer nondurables. *Journal of Consumer Research, 21*, 274–290.

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience, 6*, 1317–1322.

Simion, C., & Shimojo, S. (2007). Interrupting the cascade: Orienting contributes to decision making even in the absence of visual stimulation. *Perception & Psychophysics, 69*, 591–595.

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2012). A 21 word solution. *SSRN*: <http://ssrn.com/abstract=2160588 or http://dx.doi.org/10.2139/ssrn.2160588>.

Simonson, I. (1989). Choice based on reasons: The case of attraction and compromise effects. *Journal of Consumer Research, 16*, 158–174.

Simonson, I., Bettman, J. R., Kramer, T., & Payne, J. W. (2013). Comparison selection: An approach to the study of consumer judgment and choice. *Journal of Consumer Psychology, 23*, 137–149.

Soltani, A., De Martino, B., & Camerer, C. (2012). A range-normalization model of context-dependent choice: A new model and evidence. *PLoS Computational Biology, 8*(7), 1–15.

Stewart, N. (2009). Decision by sampling: The role of the decision environment in risky choice. *Quarterly Journal of Experimental Psychology, 62*, 1041–1062.

Stewart, N., Chater, N., & Brown, G. D. A. (2006). Decision by sampling. *Cognitive Psychology, 53*, 1–26.

Stewart, N., Reimers, S., & Harris, A. J. L. (in press). On the origin of utility, weighting, and discounting functions: how they get their shapes and how to change their shapes. *Management Science*.

Stewart, N., & Simpson, K. (2008). A decision-by-sampling account of decision under risk. In N. Chater & M. Oaksford (Eds.), *The probabilistic mind: Prospects for Bayesian cognitive science* (pp. 261–276). Oxford, England: Oxford University Press.

Trueblood, J. S., Brown, S. D., & Heathcote, A. (in press). The multi-attribute linear ballistic accumulator model of context effects in multi-alternative choice. *Psychological Review.*

Tsuzuki, T. & Guo, F. Y. (2004). A stochastic comparison-grouping model of multialternative choice: explaining decoy effects. In K. Forbus, D. Gentner, & T. Regier (Eds.), *Proceedings of the twenty-sixth annual conference of the cognitive science society* (pp. 1351–1356).

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review, 79*, 281–299.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5*, 297–323.

Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: The leaky, competing accumulator model. *Psychological Review, 108*, 550–592.

Wollschläger, L. M., & Diederich, A. (2012). The 2n-ary choice tree model for n-alternative preferential choice. *Frontiers in Psychology, 3*(189).