A query theory account of the attraction effect

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ABSTRACT

We provide novel support for Query Theory, a reason-based decision framework, extending it to multialternative choices and applying it to the classic phenomenon known as the attraction effect. In Experiment 1 ($N = 261$), we generalised the two key metrics used in Query Theory from binary to multialternative choices and found that reasons supporting the target option were generated earlier and in greater quantity than those supporting the competitor, as predicted by the theory. In Experiment 2 ($N = 703$), we investigated the causal relationships between reasoning and choices by exogenously manipulating the order in which participants generated their reasons. As predicted, the size of the attraction effect was a function of this query order manipulation. We also introduced a bidirectional reason coding protocol to measure the valence of reasons, which confirmed support for Query Theory. We suggest the Query Theory framework can be useful for studying the high-level deliberation processes behind multialternative choices.

1. Introduction

Most of our daily choices involve a multiplicity of alternatives often defined over a variety of different attributes. A large body of experimental evidence suggests that such multialternative, multiattribute decisions may be systematically affected by contextual features (Huber, Payne, & Puto, 1982; Simonson, 1989; Tversky, 1972).

A classic context effect of this kind is the *attraction effect* (Huber & Puto, 1983), also known as the 'asymmetric dominance effect' or the 'decoy effect'. This effect, which has been studied extensively (see Marini, Ansani, & Paglieri, 2020, for a summary of empirical studies), shows that one option in a choice set — often referred to as the *target* — can gain in choice share over its *competitor* when an asymmetrically dominated *decoy* option — i.e., an option that is unambiguously worse than the target but not the competitor — is added to the set. The attraction effect is usually demonstrated when the target, the competitor, and the decoy are defined over two common attributes associated with numeric values (Bhatia & Stewart, 2018; Frederick, Lee, & Baskin, 2014). For example, consider a consumer choosing between two smartphones that differ in terms of storage capacity and malfunctioning rate. Smartphone A has a storage capacity of 16 gigabytes (GB) and a 3% probability of malfunctioning in the first two years. Smartphone B has a

32 GB storage capacity and a 5% malfunctioning rate. The attraction effect arises when the relative choice share between phones A and B is influenced by the presence of a third, asymmetrically dominated smartphone. So, adding smartphone D_A, with a 12 GB storage capacity and a 3.5% malfunctioning rate, is expected to promote phone A. Conversely, adding smartphone D_B, with a 28 GB storage capacity and a 5.5% malfunctioning rate, is expected to promote B. Equivalently, A can be expected to be chosen more frequently in the choice set {A, B, D_A} than in the set {A, B, D_B}.

The attraction effect is of particular interest in behavioural science for several reasons. First, it violates Luce's axiom of rational choice theory and the related principle of independence of irrelevant alternatives (Luce, 1959, 1977). The axiom states that the probability of choosing one option over another should not be affected by adding or removing irrelevant options. The violation is obvious in the case of the attraction effect, as adding an irrelevant, transparently dominated option that no one is expected to choose increases the probability of people choosing the dominating option. Second, due to its potential to influence choices in a predictable direction, the effect is often viewed as a marketing tool, and hence is one of the most widely studied phenomena in consumer behaviour (Frederick et al., 2014). Third, as the attraction effect cannot be explained by models which compute the subjective

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value of each option based only on its own attribute values (Turner, Schley, Muller, & Tsetsos, 2018; Tversky, 1972), it has led to the development of a number of process models that aim to explain multi-alternative choices with cognitive mechanisms such as attentional weights or loss aversion (Bhatia, 2013; Trueblood, Brown, & Heathcote, 2014; Usher & McClelland, 2004).

Most recent cognitive models proposed to explain multialternative choices typically consider momentary shifts in attention, which are assumed to reflect information processing and result in changes in the options' subjective values at small time intervals. These are then propagated through to an evidence accumulation or drift diffusion framework to predict preference and reaction time. For example, the multialternative decision by sampling model (Noguchi & Stewart, 2018) assumes that people make attribute-wise comparisons between options, with more frequent comparisons of options which are similar to each other. Since the target option is both similar to the decoy and dominates it on one or more attributes, it is evaluated frequently and positively. Alternatively, the multialternative version of the decision field theory (Roe, Busemeyer, & Townsend, 2001) assumes that evidence accumulation is characterised by a lateral inhibition mechanism according to which similar options tend to suppress each other. However, since the decoy is asymmetrically dominated, the net amount of evidence accumulated for it tends to be negative, resulting in a negative 'inhibition' that effectively promotes the target (for a thorough review of evidence accumulation models used to explain context effects see Noguchi & Stewart, 2018, and Turner et al., 2018).

While these models share a focus on attentional processes in an evidence accumulation framework, a variety of different mechanisms have been proposed to account for choice context effects. For instance, the associative accumulation model (Bhatia, 2013) assumes that, when the different attributes are on similar numeric scales or transformed as such, individuals pay more attention to an attribute when its sum of values across the available options is high. Because the target and decoy have similar values on both attributes, the sum of values will be higher for the attribute that favours the target (with both high decoy and target values) than the attribute that favours the competitor (with only high competitor values). Consequently, more attention is given to the target-favouring attribute and comparisons that favour the target, resulting in the attraction effect.

The link between attention and choices is clearly evident when participants' information gathering processes are studied via process-tracing methods such as eye tracking (Noguchi & Stewart, 2014; Shimojo, Simion, Shimojo, & Scheier, 2003). However, it is crucial to understand how signals captured by such *low-level* attentional processes are integrated in *high-level* deliberation, and how individuals produce reasons by making comparisons based on contextual information. The low-level elements that drive the attraction effect in the models described above are not consciously accessible by decision makers, nor are elements such as attentional shifts under strict conscious or deliberative control. They could be conceived as simple building blocks that must somehow still be combined by the individual into a subjectively coherent preference or a consciously available justification. For this, and for anything open to introspection, we suggest that a higher-level model is required. That is, a paradigm that explains how these smaller low-level building blocks become a more coherent whole, in terms of a preference and the decision maker's own understanding of their reasoning, or their ability to justify their choices to other individuals. For the attraction effect, the importance of reasons was prominently noted by Simonson (1989), who showed that the dominance relationship between the target and a decoy could serve as a powerful motivation to choose the target. Simonson (1989) also showed that the strength of the attraction effect increased when participants were expected to justify their choices to others, a finding which cannot be explained by low-level processes alone.

A candidate framework through which low-level cognitive processes can be linked to higher-level deliberation is Query Theory (Johnson, Häubl, & Keinan, 2007; Weber et al., 2007). Query Theory proposes that, during decision making, individuals decompose a task into queries that are executed sequentially. Each query involves the evaluation of possible decision outcomes and is resolved by distinct reasons generated by the decision maker. For instance, for a consumer considering a choice between smartphones, examples of queries include 'why should I buy smartphone A?' and 'why should I buy smartphone B?'. Examples of reasons associated with these queries are 'I would choose this smartphone because it has enough storage for my photos' or 'I don't replace my phone very often, so a low malfunctioning rate is important'.

Based on the notion of output interference, Query Theory suggests that the processing of one piece of information can suppress the subsequent processing of other information. Specifically, output interference implies that earlier queries have greater weights than later ones, and that the execution of each query inhibits further information processing and can terminate deliberation. This leads to the general prediction that reasons favouring the chosen option are generated earlier and in greater quantity than reasons favouring other options.

In the Query Theory framework, the context of a decision task may be expected to influence query order, leading to the earlier processing of salient and accessible information (Spälti, Brandt, & Zeelenberg, 2017). Although queries cannot be directly observed (though measurements such as eye tracking can provide potential insights), the resulting reasons can be traced in experiments. Studies are typically conducted using a methodology known as *aspects listing*, which requires participants to list the reasons that come to their mind as they are evaluating the available options. This methodology allows researchers to test the general prediction of Query Theory by investigating whether the quantity and positions of the generated reasons favour the chosen option, and whether different contexts systematically affect reason generation. It has been found that, for instance, designating one of the options as the default (Dinner, Johnson, Goldstein, & Liu, 2011) or framing attributes differently (Hardisty, Johnson, & Weber, 2010) affects query order and, consequently, decision outcomes. Because the range of available options is, like default settings and attribute framing, an important contextual feature, and because comparisons between options are key to reason generation, this suggests that the attraction effect could also arise as a result of the order and quantity of reasons generated as decision makers deliberate.

While Query Theory has been used to explain a range of phenomena observed in binary decision tasks (Dinner et al., 2011; Hardisty et al., 2010; Johnson et al., 2007; Spälti et al., 2017; Weber et al., 2007), it is largely unknown whether it is applicable to multialternative choices with more than two options. In this paper, we report two preregistered experiments based on the aspect listing methodology that investigate whether Query Theory can be used to explain the attraction effect. Using stimuli adapted from previous research (Noguchi & Stewart, 2014; Zhou, Kim, & Laroche, 1996), in Experiment 1 we considered whether the general prediction of Query Theory — that choice is predicted by the quantity and order of reasons generated during deliberation — applies to three-option choice sets made of a target, a competitor and a decoy defined over two common attributes. Asking participants to classify their reasons based on which option they supported, we generalised the Content and Order scores used in tests of Query Theory to the case of multiple options. We expected the presence of a decoy to increase the number of reasons favouring the target option and, due to output interference, for those reasons to appear earlier in the deliberation process. Both predictions were supported.

In Experiment 2, we focused on establishing causality by manipulating the order in which participants generated their reasons and examining whether that had a systematic impact on choices. Correspondingly, the attraction effect was greatly reduced when participants were asked to start their deliberation by generating reasons in favour of the competitor. Again, choice was systematically correlated with the number of reasons generated by the participants. Thanks to a new bidirectional coding protocol that allowed participants to express the

positive or negative valence of their reasons by classifying them as either favouring or opposing any of the available options, we were also able to explore how the presence of a decoy affected deliberation, in particular the role of negative reasons involving the decoy.

By showing that the mechanisms of reason generation and output interference posited by Query Theory matter for the attraction effect, we went beyond earlier studies on the role of reason-based decision making for context effects (Simonson, 1989) and presented high-level deliberation as a sequential process to gather evidence in multialternative choice tasks. We hence demonstrated that Query Theory is a viable decision framework for multialternative choices, and provided preliminary evidence that it could serve as a useful bridge to understand the important link between high- and low-level decision-making processes.

2. Experiment 1

2.1. Method

Participants were asked to make a choice between three different smartphones, and list the reasons they considered during their deliberation.

To test for the attraction effect, we used two main options (A and B) and two decoys, one dominated by option A (denoted D_A) and one by option B (denoted D_B). These are shown in Table 1.

In each condition, the choice set included both main options (A and B) and one of the decoys (D_A or D_B), which designated one of the main options as the target and the other as the competitor. For each of A and B, the attraction effect could be detected by testing whether its choice share was higher when it was the target than when it was the competitor, irrespective of whether the target was the majority choice. This is a well-established design in the multialternative choice literature (e.g., Trueblood, Brown, Heathcote, & Busemeyer, 2013). We chose this ternary design instead of one that compares a binary choice with a ternary choice in which a decoy is added to the initial binary set because of our interest in participants' reasons. The number of reasons is likely to be affected by the number of available options, an issue that does not arise in a design in which the number of options is held constant.

Experiment 1 used a 2 Target (A vs B) × 2 Sequence (Choice-first vs Reason-first) design and involved four main stages.[1]

- **Choice**: Participants were asked to make one ternary choice. As shown in Table 1, the attribute values of two main options (i.e., A and B) remained the same across Target conditions, while the third option functioned as a decoy and its attribute values varied to designate either main option as the target (i.e., the decoy option was set to either D_A or D_B). The three options were presented in a 3 (options) × 2 (attribute) matrix in which the positions of the options and the attributes were randomised across participants.
- **Aspect Listing**: Participants were asked to list, one at a time, the reasons that came to their minds as they were considering the options, with a minimum of one reason. This aspect listing procedure was either manually terminated when a participant decided that they had already given all the reasons that allowed them to make their

choice, or automatically terminated when they had input ten reasons.
- **Reason Coding**: Participants were asked to use tick boxes to indicate, for each of their reasons, which option(s) it supported. Participants could state that a given reason supported a single option or multiple options. At this stage, the positions of the reasons shown on screen were randomly shuffled, so that they did not necessarily reflect the order in which they were entered. Participants were told that the positions were shuffled.
- **Reason Weighting**: Participants were asked to use a slider to indicate how important each reason was in reaching their decision. The values of the sliders range from −100 to 100, though these numerical values were not shown to participants. The positions of the reasons shown on screen were the same as in the previous reason coding stage.

The standard methodology places aspect listing before choice (Johnson et al., 2007; Weber et al., 2007). We included a Sequence manipulation, which varied whether aspect listing took place before or after the choice stage. This manipulation was included to verify that prior reason listing has no systematic effects on choice (Adjerid, Samat, & Acquisti, 2016). In both cases, reason coding and reason weighting took place after the completion of both the aspect listing and choice stages.

The stimuli were adapted from earlier studies (Zhou et al., 1996). We conducted a pretest and found that, in line with the attraction effect, the target was chosen in 70% of the cases. With this effect size, simulations show that a significant attraction effect (at $\alpha = 0.05$) can be found in 98% of 1000 iterations with a sample size of 70 participants per condition.

Participants were recruited from Prolific. Since we required participants to provide written reasons, we aimed to recruit only English speakers. We excluded mobile users due to the difference in input methods and its potential impact on aspect listing. To check that participants were paying attention, at the end of the experiment they were asked to identify which type of product their choice was about.

The experiment was approved by the Humanities and Social Sciences Research Ethics Committee of the University of Warwick (UK).

2.1.1. Predictions

All predictions were preregistered.[2]

For the attraction effect, we predicted that the decoy option would not be chosen, since it was transparently dominated by the target. Additionally, we predicted that the choice share of an option would be higher when it was the target than when it was the competitor. From Query Theory, we predicted that reasons supporting the chosen option would be generated in greater quantity and earlier in the deliberation process. Finally, conditional on finding the attraction effect, we predicted that reasons supporting an option would be generated in greater quantity and earlier when it was the target than when it was the competitor.

2.1.2. Indices

To analyse the quantity and positions of reasons generated by the participants (hereafter called *reason structure*), we used two types of indices known as *Content* and *Order* scores.

A Content score represents the extent to which reasons supporting one of the options are generated in greater quantity by a participant. We define the Content score for option *i* as:

$$Content_i = \frac{n_i}{N}$$

where $Content_i$ is the proportion of reasons supporting *i* generated by a

Table 1
Choice options used in Experiment 1.

Smartphone	Storage Capacity	Malfunctioning Rate
A	16 GB	3%
B	32 GB	5%
D_A	12 GB	3.5%
D_B	28 GB	5.5%

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[1] See Supplementary Materials for screenshots of Experiment 1.

[2] The preregistration can be found on OSF Registries: https://osf.io/b9pz8

participant (n_i is the number of reasons supporting option i of that participant and N is their total number of reasons). Given the two main options in our experiment (i.e., options A and B), we can use the proportions of reasons favouring each option to define $Content_A$ and $Content_B$. Furthermore, Content scores can be defined with respect to the target manipulation, hence $Content_{Target}$, $Content_{Competitor}$, and $Content_{Decoy}$ represent the proportion of reasons favouring the target, competitor, and decoy respectively.

Similarly, an order score represents the extent to which reasons supporting an option are generated earlier by a participant. The Order score for option i is defined as[3]:

$$Order_i = \begin{cases} 1 - \left(\dfrac{MR_i}{N+1}\right), & n_i > 0 \\ 1 - \left(\dfrac{N+1}{N+1}\right) = 0, & n_i = 0 \end{cases}$$

where MR_i is the median rank of the participant's reasons that support i (the first reason having rank 1, the second 2, etc.), n_i and N are defined as above. Thus, $Order_i$ reflects the median position of reasons supporting option i generated by a participant, transformed so that scores are between 0 and 1, with higher scores indicating that reasons supporting i are generated earlier. For the two main options, we can define $Order_A$ and $Order_B$. Similarly to Content scores, Order scores can also be defined with respect to the target manipulation, resulting in $Order_{Target}$, $Order_{Competitor}$, and $Order_{Decoy}$.

Given the definition of Content and Order scores, when a participant generates more (respectively, fewer) reasons supporting option A than supporting option B, the difference between the Content scores of options A and B (i.e., $ContentDifference_{AB} = Content_A - Content_B$) will be positive (negative). Similarly, when reasons supporting option A are generated earlier (respectively, later) than those supporting option B, the difference between the Order scores of options A and B (i.e., $OrderDifference_{AB} = Order_A - Order_B$) will be positive (negative). Similarly, when a participant generates more (fewer) reasons for the target than the competitor, $ContentDifference_{TC} = Content_{Target} - Content_{Decoy}$ will be positive (negative), with $OrderDifference_{TC}$ defined analogously to $OrderDifference_{AB}$.

2.2. Results

We recruited 283 UK residents whose first language is English (53% female, 47% male, mean age = 37). Of these, 20 participants were flagged as mobile users and excluded from the analysis. Two further participants were excluded as they explicitly expressed confusion about the experiment during the reason listing procedure.[4] No participants failed the attention check. Hence, the data of 261 participants entered the analysis stage.

2.2.1. Main analysis

Very few participants chose the decoy (no more than 6% in any condition), which was as expected since the decoy was dominated by the target on both attributes. As specified in the preregistration, those who chose the decoy were removed from the analysis, allowing us to treat choice as a binary outcome. Our analysis will be based on the remaining 253 participants.

The attraction effect

Fig. 1 shows the proportion of participants choosing the target, as a function of whether it was A or B, and of whether reasons were elicited before or after choices were made. It is clear that the attraction effect was found in both the Reason-first and Choice-first conditions: while participants were slightly more likely to choose the target when it was B than when it was A, overall they chose it more frequently than the competitor (65.6% of the time in both the Choice-first and Reason-first conditions, as shown by the black diamonds in Fig. 1).

A logistic regression shows that, in line with the attraction effect, the target was significantly more likely to be chosen than the competitor ($b = 0.68$, $z = 4.95$, $p < .001$, 95% CI [0.41, 0.95]). Participants were also more likely to choose the target when it was option B than when it was A ($b = -0.45$, $z = -3.32$, $p < .001$, 95% CI [−0.73, −0.19]), suggesting B may have generally been considered a more attractive smartphone.[5] The sequence manipulation had no effect; that is, there is no evidence that the aspect listing procedure itself affected choice ($b = -0.02$, $z = -0.14$, $p = .885$, 95% CI [−0.29, 0.25]).[6]

Reason structure

Participants provided a total of 527 reasons, 2.1 on average. No participants reached the limit of ten reasons. The average number of reasons was not affected by whether the target was A or B, or whether aspect listing preceded or followed choice.[7]

Based on the participants'"" own coding, the majority of reasons (86.91%) supported only one option: 33.59% supported option A, 50.85% supported B, and 2.47% supported one of the decoys. Furthermore, 2.85% of reasons supported both option A and D_A, while another 2.85% supported both B and D_B. When considering the reasons with regard to the Target manipulation, 51.80% supported the target and 32.64% supported the competitor. Table 2 shows examples of typical reasons elicited via aspect listing, and reports the coding provided by the participant.

We also manually checked the coding of all reasons, and found that 91.65% were coded in a way that matched experimenter judgement. Our analysis will follow the preregistered plan of using the participants' coding.[8]

Reason structure and choices

As predicted by Query Theory, option A was more likely to be chosen by participants who generated more reasons in its favour (as captured by the $ContentDifference_{AB}$ variable), and those who generated reasons in its favour earlier (as captured by $OrderDifference_{AB}$). Both effects were statistically significant, as shown by the regression results below.

Numbers of Reasons: A logistic regression shows that $ContentDifference_{AB}$ is a significant predictor of choosing phone A ($b = 4.92$, $z = 6.19$, $p < .001$, 95% CI [3.68, 7.12]). The sequence manipulation had no effect on choices ($b = -0.20$, $z = -0.54$, $p = .589$, 95% CI [−1.02, 0.52]), and did not interact with $ContentDifference_{AB}$ ($b = 0.74$, $z = 0.93$, $p = .350$, 95% CI [−0.65, 2.92]).[9]

Positions of Reasons: A logistic regression shows that $OrderDifference_{AB}$ is a significant predictor of choosing A ($b = 6.60$, $z = 8.48$, $p < .001$, 95% CI [5.25, 8.36]). The sequence manipulation had no effect ($b = -0.35$, $z = -1.14$, $p = .255$, 95% CI [−1.03, 0.21]), nor did it interact with $OrderDifference_{AB}$ ($b = 1.00$, $z = 1.28$, $p = .199$, 95% CI

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[3] Subtracting the transformed median rank from 1, which departs slightly from the definition used in the preregistration, eases the interpretation of our regressions with no material effect on the results.

[4] This exclusion criterion was not preregistered. Including these two participants does not alter any of our conclusions.

[5] Note that this strength of preference is not so large as to cause concerns of the degree noted in Huber, Payne, and Puto (2014). In fact, such an effect would reduce the power in detecting an attraction effect, but the relative preference found for the target is robust.

[6] See Table S1 in the Supplementary Materials.

[7] See Supplementary Materials.

[8] We repeated all main analyses reported in the paper excluding participants who failed our check on the coding of any reason. This did not qualitatively change any of our conclusions. See Supplementary Materials for details.

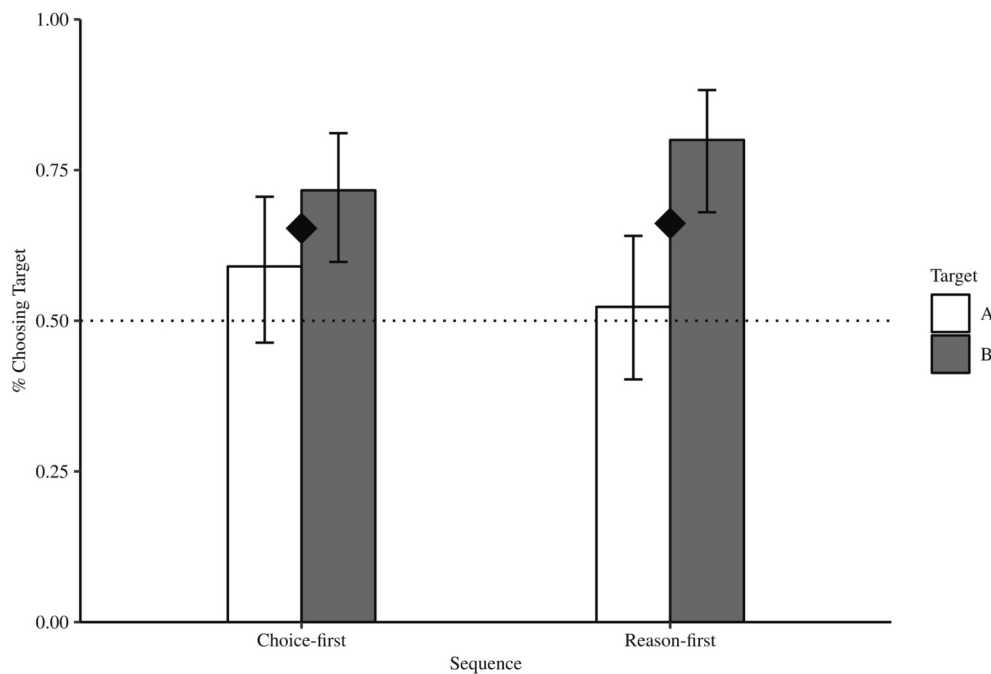[9] See Model 1 of Table S2 in the Supplementary Materials.

Fig. 1. Proportion of participants choosing the target option by conditions in Experiment 1 (error bars are confidence intervals of a logistic regression model, black diamonds are the mean proportion in each Sequence condition).

Table 2
Examples of reasons in Experiment 1.

Reason	Participant Coding
'Smartphone A has the least chance of malfunctioning.'	Supports A
'Smartphone B has double the storage capacity than smartphone A.'	Supports B
'Capacity (i.e., strong attribute of smartphone B) is not so important.'	Supports A & D_A
'Smartphone A doesn't have enough storage.'	Supports B & D_B

[−0.43, 2.73]).[10]

To our knowledge this is the first evidence that Query Theory can be used to predict multialternative choices.

Reason structure and the attraction effect

Thus far, we have shown that we successfully replicated the attraction effect, and that the patterns of reasons generated by participants were consistent with the general predictions of Query Theory: participants generated reasons in favour of the chosen option earlier and in greater quantity. To directly test whether the reason-based mechanism embedded in Query Theory is a possible mechanism behind the attraction effect, we use the $Content_{Target}$ and $Order_{Target}$ scores to look at the likelihood that the target was chosen as a function of whether reasons in its favour were generated in greater number and earlier than reasons supporting the competitor.

To visualise our data, we split our participants between (i) those who provided more reasons supporting the target (i.e., they had a positive $ContentDifference_{TC}$), (ii) those who reported an equal number of reasons supporting the target and the competitor (with a $ContentDifference_{TC}$ equal to zero), and (iii) those who reported more reasons in favour of the competitor (with a negative $ContentDifference_{TC}$). For each of these subsamples, the left panel of Fig. 2 shows the proportion of participants choosing the target, separately for the Choice-first and Reason-first

conditions. The percentages at the top of each bar indicate how many participants fell in each category. The pattern is very clear. In both cases, a sizeable majority of participants (between 54.40 and 60.94%) produced more reasons in favour of the target. Those who did, chose the target in virtually all cases. Of those who generated more reasons in favour of the competitor (between 30.40 and 34.38%), a tiny minority chose the target. Equal numbers of reasons were much less common, and were more often associated with target rather than competitor choices.

The right panel of Fig. 2 presents an analogous analysis based on the order of reasons. Here, because a null $OrderDifference_{TC}$ is hard to interpret, we only look at participants who reported reasons for the target earlier or later on average (i.e., they had, respectively, positive or negative $OrderDifference_{TC}$). Of the majority of participants who produced reasons in favour of the target earlier (which happened to be the exact same participants who reported more reasons in favour of the target), virtually everybody chose the target. Among the minority (between 35.94 and 36.80%) who reported reasons for the competitor earlier, target choices were much less common.[11]

As shown in the following analyses, the effects of both Content and Order are statistically significant in the direction predicted by Query Theory. In these analyses, we also wanted to see whether generating reasons supporting the decoy had any effect on choice. For this reason, rather than using $ContentDifference_{TC}$ as the predictor, we included $Content_{Target}$ and $Content_{Decoy}$ as separate predictors. We did not include $Content_{Competitor}$, as the three measures are not independent. Similarly, we included $Order_{Target}$ and $Order_{Decoy}$ in another model to test the potential effects of the positions of reasons supporting the target and the decoy.

Numbers of Reasons: A logistic regression shows that $Content_{Target}$ is a significant predictor of the likelihood of choosing the target ($b = 7.45$, $z = 7.64$, $p < .001$, 95% CI [5.80, 9.72]), and that this effect does not differ depending on whether the target was A or B ($b = -0.45$, $z = -0.49$, $p = .625$, 95% CI [−2.44, 1.32]). The proportion of reasons supporting the

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[10] See Model 2 of Table S2 in the Supplementary Materials.

[11] In the Supplementary Materials, we report the equivalent of Figure 2 excluding participants who produced exactly one reason. The patterns remain unchanged.
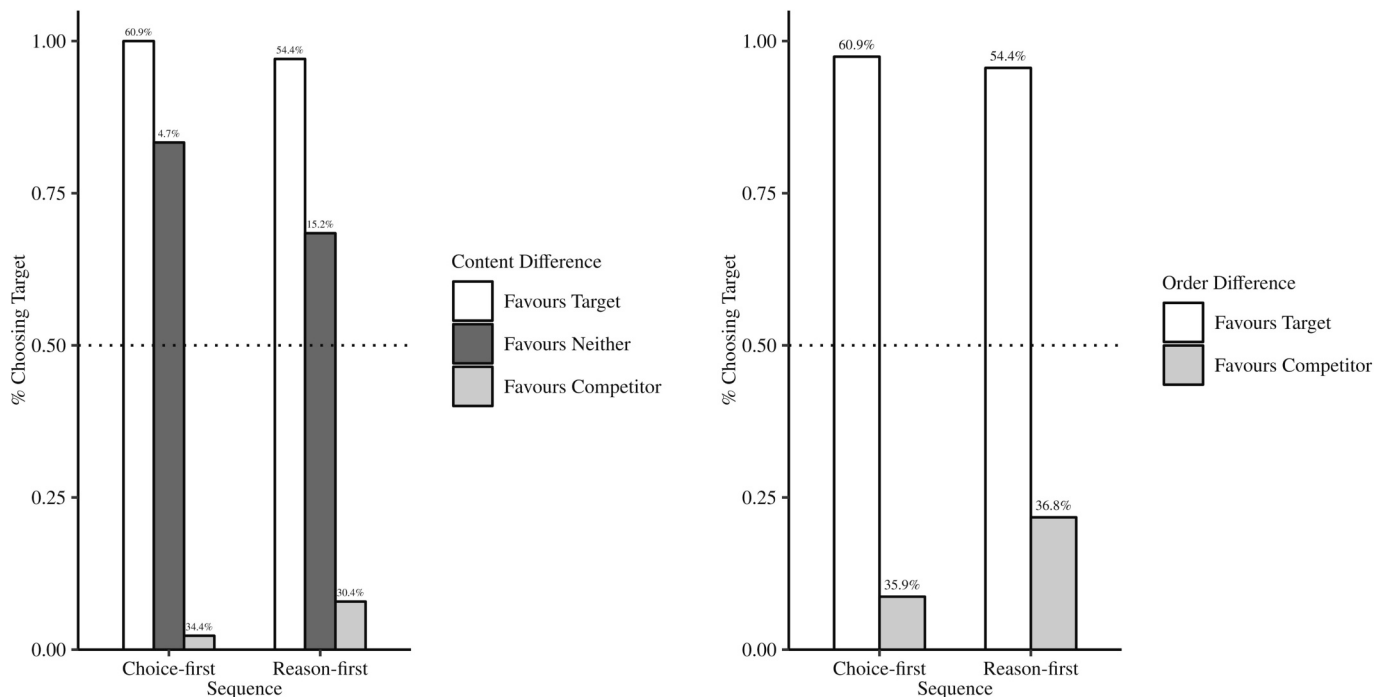
Fig. 2. (Left) Proportion of participants choosing the target option by Sequence and Content Difference in Experiment 1. (Right) Proportion of participants choosing the target option by Sequence and Order Difference in Experiment 1.

decoy ($Content_{Decoy}$) did not affect choice ($b = 0.39$, $z = 0.36$, $p = .715$, 95% CI [−1.79, 2.52]), nor did it interact with the Target variable ($b = −1.20$, $z = −1.11$, $p = .266$, 95% CI [−3.33, 0.98]). Neither the Target ($b = −0.14$, $z = −0.29$, $p = .776$, 95% CI [−1.08, 0.88]) nor the Sequence manipulation ($b = 0.29$, $z = 0.92$, $p = .357$, 95% CI [−0.30, 0.94]) had a significant effect on choices.[12]

Positions of Reasons: A logistic regression shows that $Order_{Target}$ is a significant predictor of the likelihood of choosing the target ($b = 11.01$, $z = 8.81$, $p < .001$, 95% CI [8.78, 13.74]), and that this effect does not differ depending on whether the target was A or B ($b = −1.57$, $z = −1.31$, $p = .189$, 95% CI [−4.08, 0.73]). $Order_{Decoy}$ did not influence choice ($b = −0.40$, $z = −0.32$, $p = .750$, 95% CI [−2.76, 2.18]), nor did it interact with which option was the target ($b = −0.69$, $z = −0.55$, $p = .584$, 95% CI [−3.21, 1.74]). The target manipulation did not affect choices ($b = 0.04$, $z = 0.10$, $p = .924$, 95% CI [−0.87, 1.05]), nor did Sequence ($b = 0.42$, $z = 1.64$, $p = .100$, 95% CI [−0.06, 0.94]).[13]

These results show that the structure of reasons underlying the attraction effect is compatible with the general prediction of Query Theory: when participants deliberate their choice between a target and a competitor, the presence of a decoy leads them to generate more reasons in support of the target, and to do so earlier in the deliberation process. That is, the exogenous change in the decision context created by the presence of an asymmetrically dominated decoy shapes peoples' reasoning and is systematically related to their choices.

2.2.2. Exploratory analysis

The effect of target on reasons. In addition to the above preregistered analyses, we tested whether, independently of which option was chosen, participants generated more reasons supporting the target, and did so earlier in their deliberation. We found evidence for both effects, supporting Query Theory's notion of output interference.

Numbers of Reasons: A linear regression model on

$ContentDifference_{AB}$ shows that reasons supporting option A were generated in greater quantity when option A was the target ($b = 0.24$, $t = 4.44$, $p < .001$, 95% CI [0.13, 0.34]).

Positions of Reasons: A linear regression model on $OrderDifference_{AB}$ shows that reasons supporting option A were generated earlier when option A was the target ($b = 0.11$, $t = 3.89$, $p < .001$, 95% CI [0.05, 0.16]).

Weights of reasons. As a further test for the notion of output interference, we investigated whether early reasons were rated as more important than later ones. As the majority of participants generated between one and three reasons, we ran two separate linear regressions for those who submitted either two or three reasons. The first model shows that, for participants who provided exactly two reasons (41.50% of participants), their second reason was rated as significantly less important than their first reason ($b = −43.70$, $t = −6.70$, $p < .001$, 95% CI [−56.56, −30.83]). For those who provided exactly three reasons (22.13%), the second model shows that later reasons were rated as less important than earlier ones ($b = −7.92$, $t = −2.06$, $p = .041$, 95% CI [−15.51, −0.33]).

2.3. Discussion

In Experiment 1, we found the attraction effect, as expected. In line with Query Theory, the number and order of distinct reasons produced by participants during their deliberation were correlated with multi-alternative choices, such that reasons supporting the chosen option, as well as the target option, were generated earlier and in greater numbers. Consistently with the notion of output interference, participants rated the earlier reasons as more important for their choice than later ones.

However, while these results are indicative that a reason-generation mechanism like the one posited by Query Theory may be among the drivers of the attraction effect, they do not establish a causal link between reason generation and choice. This is the main objective of Experiment 2.

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[12] See Model 1 of Table S3 in the Supplementary Materials.
[13] See Model 2 of Table S3 in the Supplementary Materials.

3. Experiment 2

Adapting the methodologies of Johnson et al. (2007) and Dinner et al. (2011) from binary to multialternative choices, in Experiment 2 we exogenously manipulated the order of decision queries in a way that, if the Query Theory mechanism is at work, there should be systematic consequences on the prevalence of the attraction effect. This provides a fundamental test of Query Theory.

We also extended our reason coding protocol to allow participants to distinguish between positive and negative reasons. This is a non-trivial task in multialternative choices. Unlike in binary choices, where queries that positively evaluate an option can be reasonably assumed to be against the other option, in multialternative choices each reason can support or oppose one or multiple options, and the extent to which this happens can vary between individuals. Thus, comparing our original unidirectional coding with this new bidirectional coding provides an extra robustness check on our results. Additionally, we can use the bidirectional coding to conduct exploratory analyses of the effects of reasons driven by comparisons that involve the decoy to shed further light on how the Query Theory mechanism applies to the attraction effect.

3.1. Method

As in the 'Reason-first' design of Experiment 1, participants were asked to list the reasons they considered before making a choice between three smartphones. To ease comparability, the option set was the same as in Experiment 1 (see Table 1). In each condition, the three smartphones differed in storage capacity and malfunctioning rate. One of the smartphones was a decoy.

Experiment 2 used a 2 Target (A vs B) × 2 Query Order (Target-first vs Competitor-first) design and involved five main stages, which appeared in the sequence outlined below.[14]

- Aspect Listing: The three options were presented in a 3 (options) × 2 (attribute) matrix, as in Experiment 1. In the Target-first (respectively, Competitor-first) condition, the target (respectively, competitor) was placed in the first row of the matrix. The placement of the two other options was randomised across participants. The order of the two attributes (i.e., the column in which they appeared) was also randomised. The aspect listing procedure consisted of two phases. In the first phase, participants were invited to provide reasons supporting the first smartphone, one at a time. So, in the Target-first (Competitor-first) condition, they started with reasons in favour of the target (competitor). Participants were instructed to provide at least one reason supporting the first smartphone, and could continue until they had listed all their reasons for that option. In the second phase, they were given the opportunity to submit reasons supporting the other two smartphones, if they had any. They could skip this phase if they did not have any reason. Each phase would also be terminated if a participant had input ten reasons.
- Choice. The participant chose one of the three options. The interface was identical to that used in Experiment 1.
- Reason Coding (Unidirectional): As in Experiment 1, participants were asked to indicate, for each of their reasons, which option(s) it supported. They could select a single option or multiple options for each reason. The positions of the reasons were randomly shuffled, as in Experiment 1.
- Reason Coding (Bidirectional): In this newly added reason coding stage, participants were told that the researchers were interested in knowing both positive and negative aspects of their reasons. For each of their reasons, they were instructed to indicate which option(s) it was in favour of or against. Participants could select a single

classification or multiple classifications for each reason, mixing positive and negative codings if they so wished. The positions of the reasons were the same as in the unidirectional coding stage.
- Reason Weighting: As in Experiment 1, participants were asked to indicate how important each reason was in reaching their decision. The positions of the reasons were the same as in the two previous stages.

Participants were recruited from Prolific. We ran simulations to estimate the required sample size for this experiment. Results showed that, with the assumption of a small-to-moderate Query Order effect,[15] a significant result (at $\alpha = 0.05$) could be found in 91% of all iterations when the total sample size was 600. Assuming a pilot study of 30 participants[16] and allowing for the exclusion of 10% of participants for failure in the attention check (the same check as in Experiment 1), we preregistered a total sample size of 696 participants. As in Experiment 1, we recruited only English speakers and excluded mobile users.

3.1.1. Predictions

All predictions were preregistered.[17]

As a validity check of our Query Order manipulation, we expected participants to generate reasons supporting the target earlier in the Target-first conditions than in the Competitor-first conditions.

For the attraction effect, we predicted that, in the Target-first conditions, the choice share of an option would be higher when it was the target than when it was the competitor. We further predicted that this effect would be larger than in the Competitor-first conditions. Since the experiment was the first to adopt the Query Order manipulation in ternary choice tasks, we predicted only the direction of the effect, not specifying whether we expected the attraction effect to be smaller, completely eliminated, or reversed in the Competitor-first conditions.

Applying the logic of Query Theory and the suppression mechanism of output interference, we predicted that the number of reasons supporting the target would be higher in the Target-first conditions than in the Competitor-first conditions. We did not have predictions on whether an overall effect with respect to the number of reasons could be found in the Competitor-first conditions and also when averaging across all conditions.

3.1.2. Indices

Content and Order scores were used to analyse the structure of reasons submitted by participants. $Content_i$ and $Order_i$ are defined as in Experiment 1 for each option i. These were computed considering reasons supporting option i as coded under the unidirectional protocol.

As Experiment 2 introduced a new bidirectional reason coding protocol, we defined an additional type of Content scores:

$$Content_i^{'} = \frac{(n_i^+ - n_i^-)}{N}$$

where n_i^+ is the number of reasons in favour of option i generated by a participant, n_i^- is the number of reasons against i, and N is their total number of reasons. Hence, $Content_i^{'}$ is the net proportion of reasons

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[14] See Supplementary Materials for screenshots of Experiment 2.

supporting *i* according to the bidirectional protocol.

With the above indices, the variables *ContentDifference$_{TC}$* and *OrderDifference$_{TC}$* needed for our analysis of the reason structure can be defined based on the unidirectional coding, and the former also on the bidirectional coding.

3.2. Results

713 UK residents whose first language is English completed the study on Prolific (52% female, 48% male, mean age = 41). 10 participants were flagged as mobile users and excluded from the analysis. No participant failed the attention check. Therefore, the data from 703 participants entered the analysis stage.

3.2.1. Main analysis

Very few participants chose the decoy (no more than 3% in any condition). Following the same exclusion criteria as in Experiment 1, participants who chose the decoy option were removed and the following analyses were based on the remaining 692 participants.

The attraction effect

Fig. 3 shows the proportions of participants choosing the target option as a function of whether the target was A or B, and whether participants were instructed to provide reasons supporting the target or the competitor first. Choice shares in the Target-first conditions demonstrated an attraction effect consistent with the results of Experiment 1: while participants were more likely to choose the target when it was option B than when it was option A, they chose the target more frequently than the competitor on average (71.10% of the time, represented by the black diamond on the left). Importantly, and in line with our predictions, the proportion of participants choosing the target was higher in the Target-first conditions than in the Competitor-first conditions (i.e., the differences between the two black diamonds). The average choice share in the Competitor-first conditions (i.e., the black diamond on the right) was also noticeably closer to 50%.

A logistic regression shows that the target was significantly more likely to be chosen than the competitor, demonstrating an overall attraction effect ($b = 0.71$, $z = 7.44$, $p < .001$, 95% CI [0.52, 0.90]). Furthermore, participants were more likely to choose the target when they were instructed to submit reasons in its favour first ($b = 0.45$, $z = 4.94$, $p < .001$, 95% CI [0.27, 0.63]). This effect reflects the differences between the two black diamonds in Fig. 3, supporting our prediction that the Query Order manipulation could influence choice shares and the size of the attraction effect. Finally, as in Experiment 1, the target was more likely to be chosen when it was B than A ($b = -1.08$, $z = -11.21$, $p < .001$, 95% CI [−1.27, −0.89]).

Since our main prediction for the attraction effect was specifically made for the Target-first conditions, we further divided participants based on the Query Order manipulation and performed analyses separately. For the Target-first conditions, a logistic regression shows that the target option was more likely to be chosen than the competitor ($b = 1.08$, $z = 7.75$, $p < .001$, 95% CI [0.81, 1.36]), replicating the attraction effect from Experiment 1. The target was also chosen more frequently when it was option B than when it was A ($b = -0.89$, $z = -6.43$, $p < .001$, 95% CI [−1.18, −0.63]). For the Competitor-first conditions, a separate logistic regression shows that the target was still more likely to be chosen than the competitor on average ($b = 0.28$, $z = 2.18$, $p = .029$, 95% CI [0.03, 0.54]), but the effect was much smaller than in the Target-first conditions. Thus, while the attraction effect was clearly reduced by our Query Order manipulation, this suggests either that the effect does not only operate through query order, or that the decoy still influences query generation even when the order is directly manipulated. Again, the target was more likely to be chosen when it was option B than when

it was A ($b = -1.22$, $z = -9.35$, $p < .001$, 95% CI [−1.48, −0.97]).[18]

Overall, this analysis shows that our Query Order manipulation did influence the extent to which participants chose the target option, in line with the predictions of Query Theory.

Reason structure

Participants provided 3.15 reasons on average, submitting an average of 1.71 reasons in the first phase of aspect listing (i.e., when they were instructed to provide reasons in favour of the target option in the Target-first conditions or the competitor option in the Competitor-first conditions), and an average of 1.44 reasons in the second phase (when they were asked to provide reasons for the other two options, if they had any). As in Experiment 1, we checked the participants' coding of their reasons and found that it matched the experimenter's judgement in 95.08% of the cases.[19]

Table 3 shows some of the typical reasons generated by participants in Experiment 2.

Under the unidirectional coding protocol, the majority of reasons (85.89%) supported only one option: 36.53% supported option A, 41.41% supported B, and 7.95% supported one of the decoyss.

Among reasons that supported option A under the unidirectional coding protocol, 33.96% were coded as favouring only option A under the bidirectional protocol, while 57.61% were in favour of A and against one or two of the other options. As for reasons that supported option B under the unidirectional coding protocol, 33.74% were in favour of only option B under the bidirectional protocol, while 54.71% were in favour of B and against at least one of the two other options.

Overall, the vast majority of reasons were coded consistently under the two coding protocols.

Reason structure and the query order manipulation

Positions of Reasons: As a manipulation check, we examined compliance with our request to submit a first reason supporting the target option in the Target-first conditions and supporting the competitor in the Competitor-first condition, as coded under the unidirectional protocol. Overall, our request was followed by 94.65% of participants.[20] When the target option was B, compliance was higher in the Target-first condition (97.09%) than in the Competitor-first condition (92.12%). When the target option was A, compliance was equally high in the Target-first condition (94.83%) and in the Competitor-first condition (94.48%).

Averaging over all conditions, a linear regression on *OrderDifference$_{TC}$* shows that reasons in favour of the target option were generated earlier in the Target-first conditions ($b = 0.33$, $t = 49.20$, $p < .001$, 95% CI [0.31, 0.34]), confirming the effectiveness of our Query Order manipulation. Which option was the target did not have a significant effect on the order of reasons ($b = -0.01$, $t = -1.87$, $p = .062$, 95% CI [−0.03, 0.00063]).

Number of Reasons: As in Experiment 1, our analysis of the numbers of reasons will be based on the Content scores computed using the unidirectional coding. Since the scores obtained using the unidirectional and bidirectional coding were highly correlated,[21] we report the equivalent analysis for the bidirectional coding in the Supplementary Materials (Table S6).

A linear regression on *ContentDifference$_{TC}$* shows that, in line with the

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[18] See Table S4 in the Supplementary Materials.

[19] As in Experiment 1, we repeated all main analyses reported in the paper excluding participants who failed our check on the coding of any reason. This did not qualitatively change any of our conclusions. See Supplementary Materials for details.

[20] We did not exclude participants based on compliance with our query order manipulation, in line with our preregistration.

[21] Content$_{Target}$ and Content$'_{Target}$ had a correlation of $r = 0.52$, while the two types of *ContentDifference$_{TC}$* had a correlation of $r = 0.76$
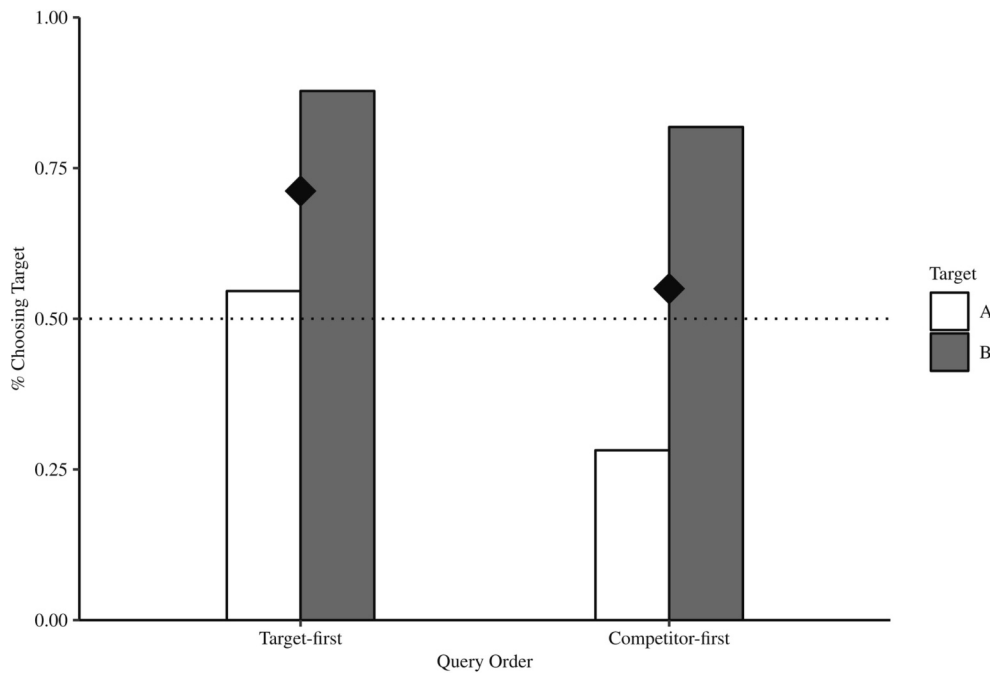
Fig. 3. Proportion of participants choosing the target option by conditions in Experiment 2.

Table 3
Examples of reasons in Experiment 2.

Reason	Unidirectional Coding	Bidirectional Coding
'Low malfunction rate.'	Supports A	Favours A
'The reliability of A is better than B and C.'	Supports A	Favours A, Opposes B & D_B
'Phone A has a higher storage capacity than phone C.'	Supports A	Favours A, Opposes D_A
'Phone B has the highest malfunctioning rate.'	Supports A	Favours A & D_A, Opposes B
'Phones B and C have a relatively high malfunctioning rate which would put me off buying them.'	Supports A	Opposes B & D_B
'Highest storage capacity.'	Supports B	Favours B
'Phone B has a much larger capacity than the other two phones.'	Supports B	Favours B, Opposes A & D_A
'Smartphone B has a greater storage capacity than C, whilst also sustaining a lower malfunctioning rate.'	Supports B	Favours B, Opposes D_B
'Higher storage capacity than smartphone A.'	Supports B	Favours B & D_B, Opposes A
'Phone A doesn't have enough storage and Phone C is worse.'	Supports B	Opposes A & D_A

predictions of Query Theory, participants submitted more reasons in favour of the target than the competitor when prompted to generate reasons for the target first ($b = 0.11, t = 8.33, p < .001$, 95% CI [0.09, 0.14]). Participants also generated more reasons in favour of the target than the competitor on average ($b = 0.09, t = 6.85, p < .001$, 95% CI [0.07, 0.12]), and when the target was B than when it was A ($b = -0.05, t = -3.56, p < .001$, 95% CI [−0.08, −0.02]).[22]

We repeated this analysis separately for the Target-first conditions and the Competitor-first conditions. In the Target-first conditions, participants submitted more reasons in favour of the target than the competitor on average ($b = 0.21, t = 11.37, p < .001$, 95% CI [0.17, 0.24]), and when the target was option B than when it was A ($b = -0.04, t = -2.39, p = .017$, 95% CI [−0.08, −0.0078]). On the contrary, in the

Competitor-first conditions, participants generated a similar number of reasons for the target and the competitor overall ($b = -0.02, t = -0.98, p = .328$, 95% CI [−0.06, 0.02]), but produced more reasons in favour of the target than the competitor when the target was B than when it was A ($b = -0.05, t = -2.63, p = .009$, 95% CI [−0.09, −0.01]). Comparing the two models, our findings suggest that the Query Order manipulation weakened the attraction effect by influencing the number of reasons generated by participants in the direction predicted by Query Theory.

These findings provide support for Query Theory, especially its notion of output interference: a manipulation of reason order can suppress positive reasons for some options, as related queries are evaluated later in the deliberation process.

Reason structure and the attraction effect

As in Experiment 1, we investigate the relationships between choice, the Query Order manipulation, and reason structure.

Fig. 4 shows the likelihood of participants choosing the target option as a function of whether they submitted more reasons, an equal number o re, or fewer reasons in favour of the target than the competitor. In the left panel, the sample is split based on $ContentDifference_{TC}$ computed using the unidirectional coding and the right panel based on the bidirectional coding. As in Experiment 1, participants who provided more reasons in favour of the target were more likely to choose it compared to participants who reported an equal number of reasons for the target and the competitor and participants who gave more reasons for the competitor. However, the pattern is less extreme. This is likely the result of the Query Order manipulation, which instructed participants to submit at least one reason in favour of the target or the competitor, regardless of whether they had a strong preference for the other option. Nevertheless, the relationship between the numbers of reasons supporting the two main options and the likelihood of choosing the target is still very evident, and statistically significant.

A logistic regression shows that, based on the unidirectional coding, participants who submitted more reasons supporting the target were more likely to choose it ($ContentDifference_{TC}$: $b = 3.18, z = 8.43, p < .001$, 95% CI [2.47, 3.95]), in line with the prediction of Query Theory. Once $ContentDifference_{TC}$ is controlled for, the Query Order manipulation is no longer significant ($b = 0.19, z = 1.90, p = .057$, 95% CI [−0.0057, 0.39]). This suggests that the manipulation influenced
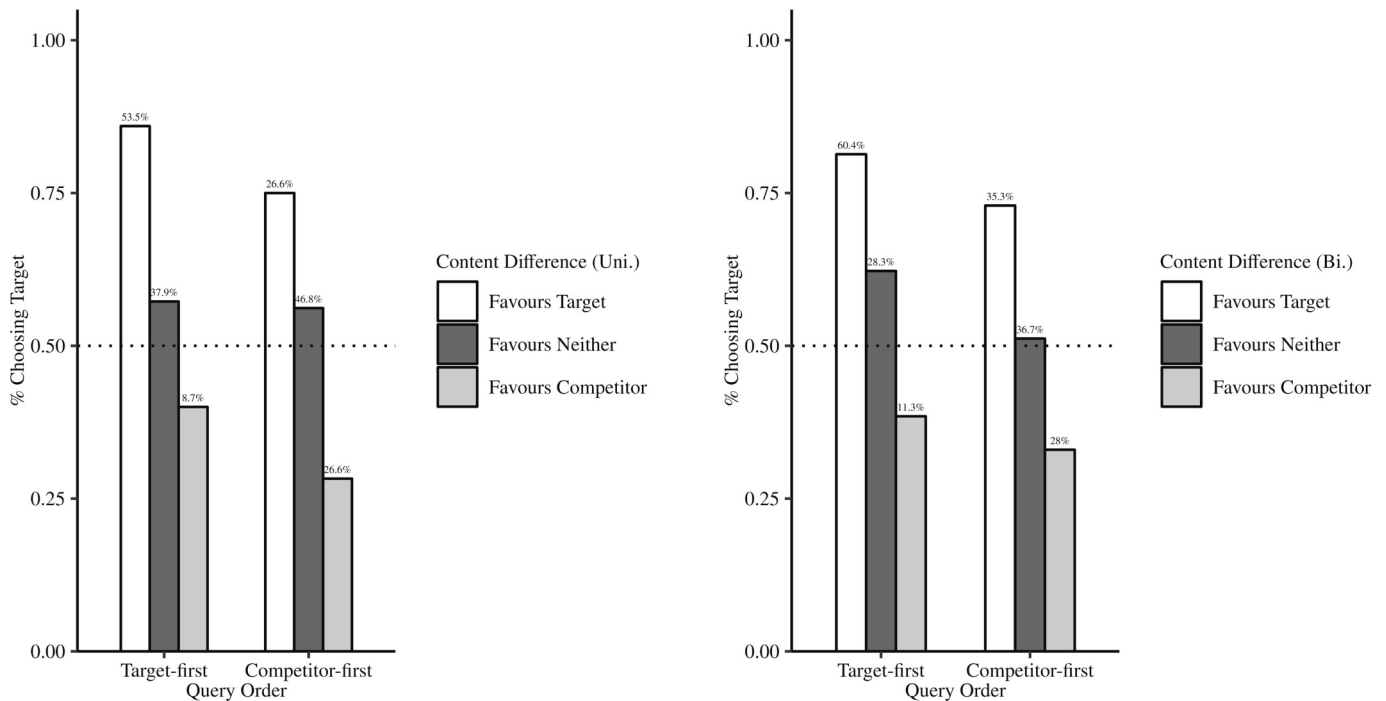
Fig. 4. (Left) Proportion of participants choosing the target option by Query Order and Content Difference (Unidirectional) in Experiment 2. (Right) Proportion of participants choosing the target option by Query Order and Content Difference (Bidirectional) in Experiment 2.

choices through the process of reason generation, in accordance with the mechanism described by Query Theory. Participants were more likely to choose the target on average ($b = 0.52$, $z = 5.04$, $p < .001$, 95% CI [0.32, 0.73]) and when it was B ($b = -1.14$, $z = -10.68$, $p < .001$, 95% CI [-1.35, -0.93]).[23]

We repeated the above analyses with $ContentDifference_{TC}$ computed using the number of reasons coded under the bidirectional protocol. Participants were more likely to choose the target when they generated more reason supporting it ($ContentDifference_{TC}$: $b = 1.79$, $z = 7.88$, $p < .001$, 95% CI [1.36, 2.25]). Controlling for $ContentDifference_{TC}$, the Query Order manipulation still had a significant effect ($b = 0.24$, $z = 2.36$, $p = .018$, 95% CI [0.04, 0.43]), but the effect of the Query Order manipulation was weaker. Participants were more likely to choose the target on average ($b = 0.49$, $z = 4.71$, $p < .001$, 95% CI [0.29, 0.69]), and when it was B ($b = -1.13$, $z = -10.82$, $p < .001$, 95% CI [-1.34, -0.93]).[24]

Exploratory analysis

Mediation analysis. We further investigated whether the effect of the Query Order manipulation on choice was mediated by the number of reasons supporting the two main options. In the analyses above, we already demonstrated that the Query Order manipulation had a significant effect on $ContentDifference_{TC}$ (computed under the unidirectional protocol) and that the Query Order manipulation no longer had a significant effect on choice once the unidirectional $ContentDifference_{TC}$ was controlled for. Combined, these results suggest a full mediation. To quantitatively test the indirect effect (path *ab* in Fig. 5), we adopted the classic approach proposed by Baron and Kenny (1986) and performed a
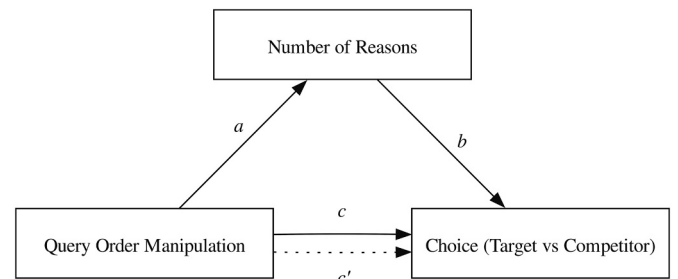

Fig. 5. Paths of mediation. Direct effect (c) of Query Order on choice and indirect effect (ab) mediated by ContentDifference_{TC}.

Sobel-Aroian test (Sobel, 1982).[25] The results show a significant mediation ($z = 5.91$, $p < .001$).

For the bidirectional coding protocol, the Query Order manipulation also had a significant effect on $ContentDifference_{TC}$ (as shown in Table S6 of Supplementary Materials). The Query Order manipulation still had a significant effect on choice when the bidirectional $ContentDifference_{TC}$ was controlled for, but the effect was weaker, which suggests a potential partial mediation. A Sobel-Aroian test on the indirect effect shows that the mediation is significant ($z = 5.53$, $p < .001$).

Weights of reasons

As in Experiment 1, we examined whether early reasons were rated as more important than later ones as a further test for output interference. In Experiment 2, the majority of participants submitted between two and four reasons, hence we ran three separate linear regressions. For participants who generated exactly two reasons (31.07% of all

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[23] See Model 1 of Table S7 in the Supplementary Materials.
[24] See Model 2 of Table S7 in the Supplementary Materials.

[25] There is no consensus on how to calculate indirect effects for dichotomous outcome variables, but it has been suggested that the classic approach is applicable and actually results in low bias (Rijnhart, Twisk, Eekhout, & Heymans, 2019).

participants), the second reason was rated as significantly less important than the first ($b = -15.52$, $t = -3.19$, $p = .002$, 95% CI [−25.09, −5.96]). Participants who submitted exactly three reasons (35.55%) rated later reasons as less important than the first ($b = -11.53$, $t = -5.00$, $p < .001$, 95% CI [−16.05, −7.01]). The same holds for those who provided exactly four reasons (20.23% of all participants; $b = -9.94$, $t = -5.77$, $p < .001$, 95% CI [−13.32, −6.55]).

Types of reasons

While the Content scores above show an overall increase in target-supporting reasons, they do not show how people compared the options, including the decoy, in coming up with those reasons. As an exploratory analysis to investigate how the decoy and order manipulations differently impacted reasons for the target and competitor, Fig. 6 shows the subset of bidirectionally coded reasons which favoured exactly one of the two main alternatives (target or competitor) as a function of whether they also favoured the decoy, opposed it, or neither favoured it nor opposed it. The resulting twelve codings include the most common codings used by participants, and account for 76.79% of all reasons generated. The top panel of Fig. 6 shows the proportion of all reasons in the Target-first conditions given each coding (78.11% combined), while the bottom panel does the same for the Competitor-first conditions (75.40% combined). In line with the results above, there

were more reasons that favoured the target (white bars) in the Target-first conditions and more that favoured the competitor (grey bars) in the Competitor-first conditions. This occurred both for reasons that were not coded as related to the decoy (middle cluster) and for those that were coded as providing evidence against the decoy (right cluster). Reasons that were coded as favouring the decoy (left cluster) were relatively rare, with unsurprisingly almost no reasons generated that favoured both the decoy and the competitor. For reasons that did not mention the decoy, it was more common to generate reasons that purely favoured one of the main alternatives (solid bars) without being explicitly against the other alternative (striped bars). For reasons that were explicitly against the decoy, the opposite occurred, with reasons mentioning all three options (i.e., explicitly against the other main alternative) both more common and more affected by the order manipulation.

This pattern of differing proportions matches what one would expect from Query Theory. In the case of the competitor, there is one salient reason for preferring it: the one attribute on which it scores well, where it is better than both the target and the decoy. This is represented in the Competitor-first condition by the large proportions of reasons that solely favour the competitor and reasons that favour the competitor while being against both target and decoy. For the target, there are a wider range of relative comparisons on which it is favoured: on one attribute being better than both the competitor and the decoy, and on the other
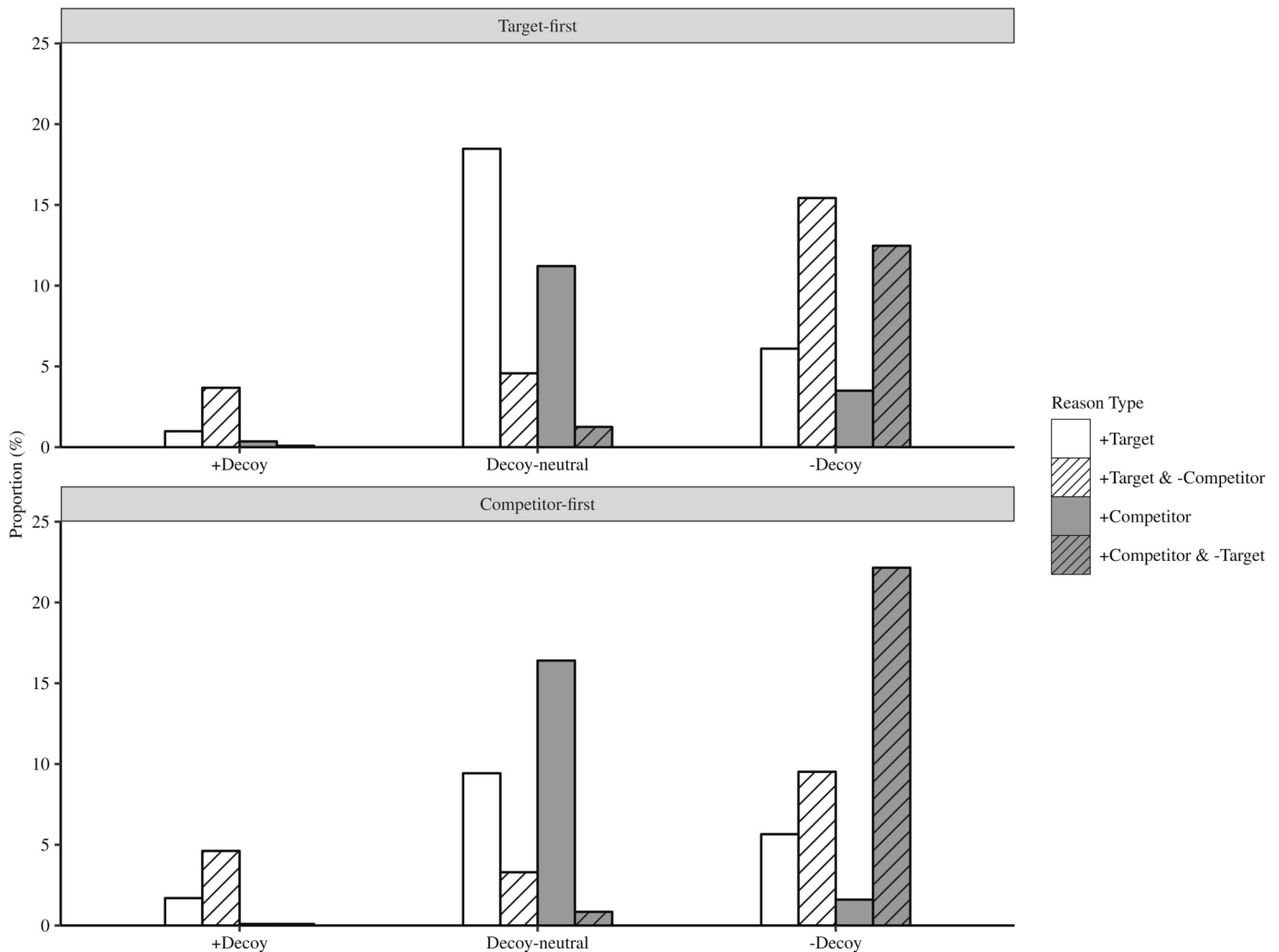

Fig. 6. All reasons (bidirectionally) coded as favouring only the target or competitor provided by participants in Experiment 2 and their proportions among all reasons, by Query Order conditions. White bars represent reasons in favour of the target (+Target) and grey bars represent those in favour of the competitor (+Competitor). Striped bars represent reasons that were additionally coded as against either the target (-Target) or competitor (-Competitor). The clusters of bars are grouped by whether reasons were in favour of the decoy (+Decoy), against it (-Decoy), or neither (Decoy-neutral).

attribute being better than the decoy. This is represented generally, and particularly in the Target-first condition, by the more equal proportions of reasons supporting just the target, supporting the target but opposing the competitor, supporting the target but opposing the decoy, and supporting the target and opposing both competitor and decoy.

In the Supplementary Materials, we present an analogous analysis on the types of reasons provided by participants, conditioning on whether they chose the target or the decoy (see Fig. S5). The observed patterns are analogous to those in Fig. 6 and support the notion that the presence of a decoy affects reason generation in line with a Query Theory account of the attraction effect.

3.3. Discussion

Experiment 2 provides further evidence that the reason-generation mechanism assumed by Query Theory can be used to explain multialternative choice phenomena like the attraction effect. By exogenously manipulating the order in which participants generated their reasons, we were able to systematically affect the prevalence of the effect, hence providing causal evidence in favour of that mechanism. Correspondingly, the effect of our manipulation was mediated by its impact on participants' reasoning process: when participants were asked to start their deliberation by considering reasons in favour of the target, they produced more reasons in its favour and were more likely to choose it than when they started with reasons supporting the competitor; this effect percolated through to participants' choices.

Our new bidirectional coding protocol offers additional insights into how reasoning is related to the specific features of the attraction effect. Due to the asymmetric dominance relationship between the target and the decoy, reasons favouring the decoy were extremely rare. The unfavourable comparisons between the decoy and the target, as well as those between the decoy and the competitor, were clearly evident in the deliberation process and responded consistently to our Query Order manipulation.

4. General discussion

This paper is the first application of Query Theory to multialternative choices. By focusing on the well-known attraction effect, we have provided evidence that context effects can be understood through the lens of reason-based deliberation processes. In line with the general prediction of Query Theory, Experiment 1 found that reasons in support of the chosen option were generated earlier and in greater quantity than reasons supporting the other options. When one option was promoted as the target by the presence of an asymmetrically dominated decoy, that option was both chosen more frequently than its competitor and supported by more reasons, which were generated by participants earlier during their deliberation. By exogenously manipulating query order, Experiment 2 provided causal evidence that reasoning affects choices in multialternative settings and that query order can influence the likelihood of the target option being chosen. Our mediation analysis shows that the effect of the exogenous manipulation on choice was mediated by its impact on reason structure.

As mentioned in the Introduction, high-level reason-based processes like those accessible through the aspect listing methodology are likely to be inextricably linked to low-level, information-gathering and attentional processes often studied with eye-tracking methods. Previous eye-tracking studies have demonstrated a link between choice and low-level attentional processes. For instance, Noguchi and Stewart (2014) found that within-attribute transitions in visual fixations were more frequent than within-option ones, which suggests that information sampling in multialternative choices involves comparing the options one attribute at a time. They also found that, in the attraction effect, the most common comparisons prior to choice were between the target and the decoy, and that the target was more likely to be chosen in trials in which more of these target-decoy comparisons were made. This can be seen as low-level process evidence for a reason-based mechanism, since these attention patterns can facilitate or represent reason identification such as 'the target is better than the decoy on attribute j'. This is supported by the findings of Marini et al. (2020) and Król and Król (2019), which demonstrated that the target option was attended to more often when the attraction effect was found.

Our results are consistent with these findings: we found that the choice of the target option was predicted by a higher number of reasons supporting it, which is an expected correlate of the target option drawing more attention during the information sampling process. Additionally, many — but not all — of the reasons submitted by participants involved comparisons of two options, typically on a single attribute (e.g., 'phone A has almost twice the storage of phone B'), which was in line with the conclusions of Noguchi and Stewart (2014). However, some reasons did involve the evaluations of all three options on an attribute (e.g., 'phone C has the lowest malfunctioning rate out of the three phones'), which illustrates the complexity of high-level deliberation processes, with reason generation going beyond the lower-level attentional mechanisms that to date have only provided reliable insight into binary comparisons. That the properties of the generated reasons were then found to fully mediate the effect of order manipulation upon choice shows that it is important to understand the relationships between lower-level process information and higher-level reason generation. Thus, a methodology focused on high-level reasoning can usefully complement lower-level process data and provide additional insights.

Our results also demonstrate the complexity of trying to categorise people's decision process as either a purely within-attribute or within-option information sampling process. While both the two- and three-option reasons can be viewed as consistent with cognitive models that explicitly assume a relativistic, within-attribute comparison of options (Bhatia, 2013; Noguchi & Stewart, 2018; Roe et al., 2001), it was also common for participants to generate reasons that they believed related to only a single option (see, e.g., the solid Decoy-neutral bars in Fig. 6). These are the kinds of reasons we might expect to be produced by models that assume people process information primarily within options. Furthermore, it was common for reasons to relate to more than two options, demonstrating a richer and more complex comparison strategy than can be captured by many process models, particularly those that incorporate only binary comparisons. This heterogeneity in the type of processing implied by different reasons matches the heterogeneity observed in studies of attentional processes in other areas of multiattribute choice, such as risky or intertemporal choice (Amasino, Sullivan, Kranton, & Huettel, 2019; Reeck, Wall, & Johnson, 2017; Stewart, Hermens, & Matthews, 2016; Su et al., 2013).

The explanations for the attraction effect provided by the cognitive models discussed above primarily focus on how adding the decoy changes the information available to the participant, such as by providing contextual information on the weighting of attributes or providing relatively more favourable comparisons for the target (Turner et al., 2018). In Experiment 2, where we substantially reduced the attraction effect by requesting people generate reasons supporting the competitor first, we demonstrated the attraction effect is influenced not just by the availability of extra reasons or comparisons, but also by the order in which they are considered. Consistent with Query Theory, we find strong evidence for the importance of an inhibitory effect of early reasons on the generation of subsequent reasons (Johnson et al., 2007; Weber et al., 2007). In the Competitor-first condition, despite there being more attributes that favoured the target over the decoy than the competitor over the decoy, we found reasons comparing the competitor favourably to the decoy were more common. This suggests a mechanism through which these extra available comparisons influence choice, which is largely absent from existing evidence accumulation models of the attraction effect (Turner et al., 2018, although see Usher & McClelland, 2004). Namely, these additional comparisons increase the likelihood of a reason supporting the target being generated first, which

then suppresses the generation of subsequent reasons or comparisons that support the competitor. While evidence accumulation models do naturally consider the order in which information is sampled, our results suggest that including a more explicit order constraint, such as an inhibitory process, could increase their ability to capture the attraction effect.

Our methodology and findings open new avenues for future research on the psychological processes behind both the attraction effect and other phenomena in behavioural science. For instance, to examine how low-level information is integrated into high-level reasoning processes and perform related computational work to evaluate cognitive models, a useful path forward could be to combine aspect listing with attentional tracing methods. By measuring fixations (e.g., visual fixations or hovers in mouse tracking) on options and attribute dimensions prior to the submission of each reason, as well as transitions between them, future studies can investigate important questions such as whether explicit reasons are a direct reflection of evidence accumulation or whether high- and low-level processes are to some degree complementary. Naturally, another direction would be to explore whether the reasoning mechanisms characterised by Query Theory can explain other context effects such as the compromise and the similarity effects, or multi-alternative choices with more dimensions in the attribute space.

4.1. Conclusions

The notion that preference is constructed during decision making is a primary concern in the cognitive sciences. This work brings together two key aspects of the discipline, namely preference construction in multi-alternative choices and high-level psychological mechanisms, and presents evidence that the classic attraction effect can be explained by a reason generation process as depicted by Query Theory. Consistent with the literature, our findings show that choices are driven by reasons produced as individuals gather evidence in a decision context. The structure of this reasoning process is shaped by the presence of irrelevant and asymmetrically dominated options. Furthermore, experimentally manipulating the order in which options are considered can systematically influence choice outcomes. These results also accord with earlier studies on low-level cognitive mechanisms, adding to the growing consensus that preference construction is manifested through stepwise comparisons, and shedding some preliminary light on how evidence gathered from such comparisons is combined and processed through higher-level deliberation. This stresses the importance of investigating psychological processes at multiple levels to develop a more comprehensive view of human cognition in complex choice environments.

Credit author statement

Neo Poon developed the initial concepts and the study designs, with contributions from Andrea Isoni, Timothy L. Mullett, and Ashley Luckman who were PhD supervisors of Neo Poon. Neo Poon completed all data collections and performed all described data analyses.

Data availability

The data sets are available on OSF and this is noted in the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi. org/10.1016/j.cognition.2023.105495.

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