Goals shape dynamics of attention and selection for value-based decision-making

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Abstract

Humans can flexibly adjust how they make decisions to arbitrary goals. However, most theories in decision-making focus on predicting one specific choice type (i.e., choosing the best option). Here, we link decision-making and cognitive-control research to test a theory that accounts for flexible adjustments of choice mechanisms to different goals and demands. Our biologically inspired model specifies how different features translate into evidence for the current goal, and how evidence is mapped onto different output structures. We tested the model in an eye-tracking study in which participants were asked to choose one out of four consumer products or to appraise the entire set, each with respect to positive or negative value. The results confirmed our preregistered hypotheses that response time (RT) should decrease with the overall value of a set of options in choose-best but increase in choose-worst trials. As predicted, this interaction was absent in appraisal RT, which instead exhibited an inverted-U-shaped pattern. Furthermore, the amount of attention devoted to an option was positively related to its value in choose-best, negatively related in choose-worst trials, and unrelated when participants appraised entire sets of products. Time-resolved analyses of eye movements revealed strategic goal-dependent search processes, as attention is increasingly focused on goal-congruent options in choice but remains more uniformly distributed in appraisal. Our findings suggest that cognitive control shapes choice and search dynamics by flexibly adjusting them to current goals and demands.

Humans are remarkably flexible decision-makers. When presented with a given set of options – say, for clothing in a given store – they can pick the outfit that makes them look smart, the one that is most comfortable, or the one that works best at a “bad taste”-themed party. They can also integrate over all options to evaluate how much they like or dislike them overall, for instance, to evaluate whether the store is probably too expensive or suitable to shop for that bad taste party. How such different goals shape the unfolding of a decision has received little attention in research on value-based decision-making, primarily because this research has predominantly investigated choices that maximize subjective value. Here, we shed light on the ways different goals shape decision-making dynamics.

Previous research has successfully formalized how people compute values for options in order to compare between them and choose the best one (Collins & Shenhav, 2021; Rangel & Clithero, 2014). This work shows that decision-making can be modeled as a sequential sampling process where value-based evidence in favor of options is sampled repeatedly and accumulated over time until a desired level of evidence is reached and the winning option is chosen (Busemeyer et al., 2019; Colas, 2017; Leng et al., 2025). Sequential sampling models reproduce key features of value-based choice such as faster and more consistent choices with larger difference in options values (Value Difference), and faster responses the more valuable the options are on average (Pirrone et al., 2022; Overall Value; Smith & Krajbich, 2019; Ting & Gluth, 2025; Usher & McClelland, 2001; Wang, 2012).

Recent work has challenged some of the interpretations of these canonical findings and revealed novel mechanisms that guide decision-making. For instance, people might choose faster among higher value options because they are motivated or invigorated by the expected reward that these options offer (Niv et al., 2006). Alternatively, these options may provide stronger evidence in favor of being chosen which in turn leads to a faster decision (Hunt et al., 2012). In a previous study, we tested these competing reward-based and evidence-based hypotheses by asking participants to choose the option they prefer the least rather than the most (Frömer et al., 2019). We found that the typical overall value speeding effect flipped in this condition, such that people were now *slower* to choose for higher value options. To account for these findings computationally, we modified an evidence accumulation model called the leaky competing accumulator model (LCA) (Usher & McClelland, 2001). In the LCA, evidence accumulates separately for each option and accumulators compete via mutual inhibition. The higher the options’ values, the faster activity in the accumulators rises, which in turn increases the speed at which either of them reaches a bound. Importantly, in such a framework, decisions and their dynamics are not ultimately guided by how rewarding the options are per se, but rather how congruent that reward is with one's choice goal. This goal-alignment of inputs can be implemented by endowing the LCA with a *transformation goal* that specifies how subjective values need to be mapped onto choice-relevant evidence. With this flexible input coding, the LCA predicts that RT decreases as the goal-congruent overall value increases, exactly as found empirically.

Extending our behavioral results, Sepulveda et al. (2020) showed that the goal congruency effect extends to perceptual decisions, overall value-related increases in choice confidence, and, critically, how people allocate their attention to the choice options. Whereas previous work had shown that people are more likely to choose options they look at more, suggesting that gaze amplifies reward value (Smith & Krajbich, 2019), Sepulveda and colleagues showed that gaze instead depends on one’s choice goal. Rather than finding that gaze and choice are negatively coupled when choosing the worst item and uncoupled in perceptual choice (as predicted by reward amplification), they found that these were positively coupled across all choice conditions. Instead, gaze itself favored goal-congruent options. More broadly, the eye-tracking results of Sepulveda et al., (2020) are consistent with the view that people do not distribute their attention randomly but in a strategic and goal-congruent manner to identify and increasingly focus on the most likely choice candidates (Callaway et al., 2021; Gluth et al., 2024; Gluth et al., 2020; Jang et al., 2021).

Broadening the types of decisions under consideration further suggests that the relationship between overall value and choice may depend on additional control mechanisms. Previous work has found that when appraising options as a set, that is, integrating over their values, the relationship between overall value and RT takes yet another form (Shenhav & Karmarkar, 2019). Here, RT showed an inverse U-shaped relationship with overall value: participants were fastest to evaluate how much they liked the options when values were overall very low or very high, and slowest when the options were valued in the average range. Thus, the relationship between value and RT appears to vary with one's *integration goals*, such as the goal to appraise a set of options as a whole vs. the goal to choose only one from the set. However, given that previous work only studied positive appraisal and did not characterize eye movements, it remains open how transformation goals (e.g., goodness vs badness) and integration goals (e.g., choose vs appraise) jointly shape attentional and decision dynamics under these different goals. To address these questions, here we recorded eye-movements from participants and systematically varied their choice goals to test predictions about transformation and integration goals' impact on gaze allocation and decision-making involving value-based options.

Results

Transformation and integration goals shape behavioral correlates of value

To test how transformation goals and integration goals jointly shape decisions, we had 44 participants choose or appraise option sets under different transformation goals while recording their eye movements. Across four separate blocks, participants performed choose best, choose worst, appraise liking and appraise disliking decisions in counterbalanced order (Fig. 1 A). Their responses demonstrate the expected patterns for each type of decision: The probability of choosing the most goal-congruent options increased with the difference between the most congruent option's value and the average remaining option values (value difference, $b = 0.33$, $p < .001$), and participants were similarly accurate across 'choose best' and 'choose worst', and across the range of overall value (ps > .1). Appraisal ratings were positively correlated with overall value when appraising liking ($b = 0.26$, $p < .001$), and negatively correlated with overall value when appraising disliking ($b = -0.26$, $p < .001$, for full results, see Supplement, Table 1).

Having validated their responses, we tested pre-registered response time predictions (https://osf.io/jbphq) from a computational model of flexible decision making (Frömer et al., 2022). The model extends the modified LCA that we previously used to capture goal-congruency effects on choice (Frömer et al., 2019; cf., Usher & McClelland, 2001). Like its predecessor, the model features a transformation goal mechanism that transforms sampled values into goal-congruent evidence and predicts a goal-congruency effect in choice, which we replicate empirically (Fig. 1 B). As in our previous studies, participants' responses sped up with increasing overall value when choosing the best option, and slowed down when choosing the worst options, with a significant interaction of goal and overall value ($b = -0.08$, $p < .001$, for full results, see Supplement, Table 2).

The critical novel predictions arise from an additional flexible integration-goal mechanism that shapes how evidence is integrated to form a decision (Frömer et al., 2022): When appraising options (rather than choosing among them), the model predicts an inverse U-shaped relationship between RT and overall value, accounting for previous findings under these conditions (Shenhav & Karmarkar, 2019). The model also generates the novel prediction that this inverse U-shaped relationship should be invariant across appraisals of liking and disliking (Fig. 1 B) (Frömer et al., 2022). These predictions arise because during appraisal, rather than integrating evidence in favor of each choice stimulus, the model needs to integrate evidence *across* consumer products in favor of each potential rating response. Unlike in choice, these potential responses are ordered, so that ratings closer together are more similar than ratings further apart. We incorporate this structure into the model by changing how evidence being accumulated is distributed across response options, and how these options mutually inhibit each other (cf. Ratcliff, 2018). The intuition is that appraising a set as very good implies that is unlikely that you will appraise the set as very bad, whereas appraising it as somewhat good can be consistent with it being either very good or neutral. Consistent with our model predictions, appraisal RT showed a quadratic effect of overall value on RT ($b = -0.01$, $p < .001$), that did not significantly vary by condition ($b = -0.00$, $p = .172$).

We also found a significant interaction of the *linear* overall value effect with transformation goal ($b = 0.01$, $p = .004$), reflecting opposite linear trends in liking (*faster* for higher overall value) and disliking (*slower* for higher overall value), although these individual trends themselves did not reach significance (ps > .125). We also found that participants were significantly slower when either choosing ($b = -0.05$, $p = .003$) or appraising ($b = -0.06$, $p = .011$) under a negative frame (worst, disliking). This finding, which is not currently accounted for by our model, could reflect additional inputs on action selection, for instance from a Pavlovian system that facilitates approach towards rewards (Fontanesi et al., 2019; Guitart-Masip et al., 2012), or a cost on value transformation. All of our behavioral findings replicated in a separate online study (see Supplement Fig. S1, Table 3,4).

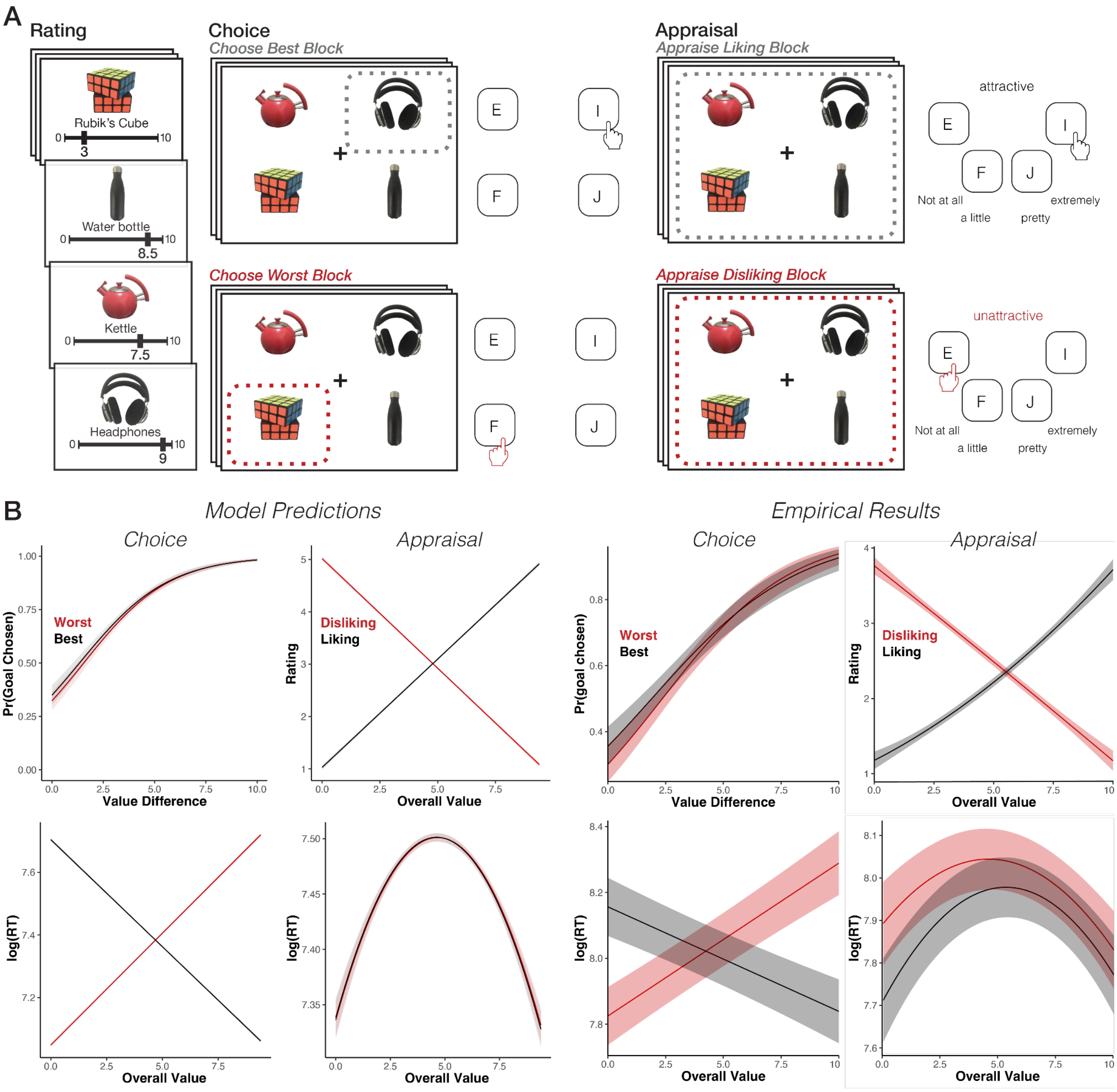

Figure 1. Transformation and Integration goals shape behavioral correlates of value. A Trial schematic**.** Participants rated consumer products in isolation and subsequently performed four blocks of decisions about sets of four products varying independently in value difference and overall value. The four decision blocks orthogonally manipulated transformation and integration goals. Integration goals: In the Choose blocks, participants chose one of the four options, in Appraisal blocks, they rated the four options as a set. Transformation goals: In the Best/Liking blocks, participants evaluated how good the options are, in the worst/disliking blocks, they evaluated how bad the options are. The same four response keys were used in all blocks, either representing the location of the options (Choice) or the levels of the rating scale (Appraisal). **B** Model predictions. Our computational model predicts that relationships between overall value and RT vary linearly in Choice and show an inverse U-shaped pattern in Appraisal. During Choice, but not Appraisal, the model predicts that the relationship reverses. **C** Empirical results. Participants' behavior confirms these model predictions. Lines show predicted effects from linear mixed effects models. Shaded areas represent 95% confidence intervals.

Value-based attention prioritization in Choice but not Appraisal

Previous work has shown that people should and do prioritize goal-congruent options during choice, becoming increasingly more likely to de-prioritize options they are unlikely to choose and to focus on options they are likely to choose (Callaway et al., 2021; Gluth et al., 2024; Gluth et al., 2020; Jang et al., 2021; Westbrook et al., 2020). Critically, this behavior is normative only in choice. Extending the optimality logic to appraisal, we predicted that when appraising options people should not prioritize but rather allocate gaze evenly across options. To test these predictions, we determined dwell times for each item and regressed each option's value, integration goal (Appraisal vs Choice) and transformation goal (Good: Best, Like vs Bad: Worst, Dislike) onto these dwell times. Based on previous work (Kovach et al., 2014; Sepulveda et al., 2020), we predicted that when seeking to choose the best option, participants would be more likely to fixate on items with higher values, whereas when seeking to to choose the worst item, participants should be more likely to look at items with lower values. For appraisal, we reasoned that since all items are equally relevant to determining how much participants like or dislike the options overall, we should not see any such prioritization effects, but participants should allocate gaze equally across all items regardless of their values or the the frame. Consistent with these predictions (Fig. 2), we found a 3-way interaction of integration goal, transformation goals and value ($b = 0.04$, $p < .001$). Nested models showed that during choice, people prioritized high-value options when choosing the best option ($b = 0.02$, $p < .001$), and low value options when choosing the worst option ($b = -0.02$, $p < .001$). In contrast, there were no value effects during appraisal ($p > .933$), consistent with equal sampling of all options for the purpose of value integration (for full results, see Supplement, Table 5).

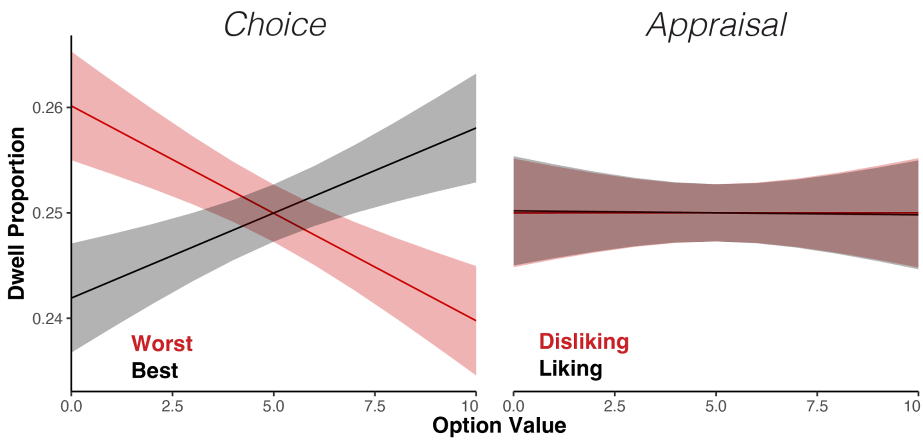

Figure 2. Goals modulate value-based attention prioritization during choice but not appraisal. The dwell proportion of an option varied with its value in choice but not appraisal. In the choose-best condition dwell proportion increased with value, and in the choose-worst condition it decreased. There was no relationship between value and dwell proportion in either appraisal condition. Lines show predicted effects from linear mixed effects models. Error bars represent 95% confidence intervals.

To further test how goals shape the distribution of attention across options, we quantified gaze entropy for each trial. Gaze entropy indexes the degree to which all options are looked at versus individual options being prioritized (Fig. 3 B) – entropy is zero if participants look at only one option and maximal (i.e., 2) when gaze is evenly distributed across all four options. To identify how goals shape gaze, we tested the degree to which gaze entropy was influenced by value difference and overall value under the different goals. We found that gaze entropy decreased when value difference was higher ($b = -0.01$, $p < .001$), suggesting that people focused on fewer options when some of them stood out as more goal-congruent (Fig. 3 C top). This value difference effect was significantly larger in choice than in appraisal, as indicated by a significant interaction between integration goal and value difference (b = -0.01, p = .003). Matching our earlier results, we found that in choice, entropy decreases with the overall goal-congruency of options, that is, it is higher for low value options when choosing the best (b = -0.02, p <.001) and higher for high value options when choosing the worst (b = 0.02, p<.001, Fig. 3 C bottom). When no goal-congruent items are available, people continue to search all options rather than prioritizing one or a few. Importantly, we found no such indications of prioritization in Appraisal (p > .113). Not only were the goal-dependent overall value effects not significant in appraisal, we also observed a significant 3-way interaction of integration goal, transformation goal and overall value (b = -0.03, p<.001), showing that the goal-congruency effect was significantly larger in choice than in appraisal (for full results, see Supplement, Table 6).

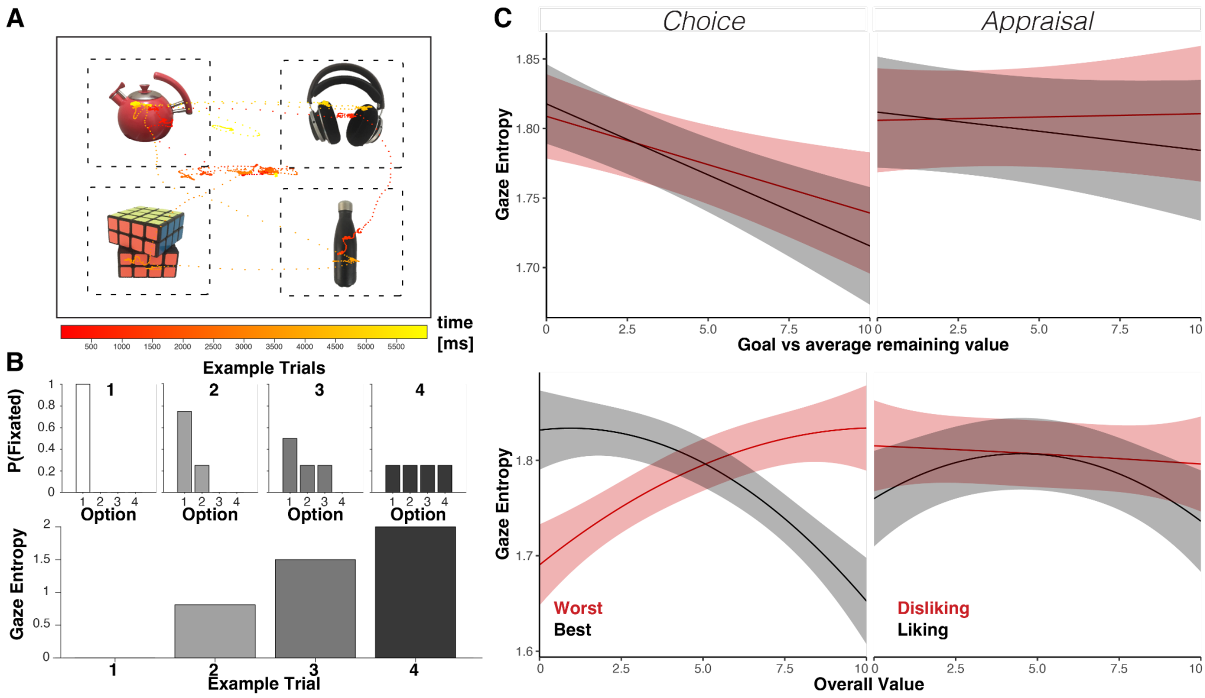

Figure 3. Gaze distribution varies with option values in Choice but not Appraisal. A Gaze path illustration. A single trial's gaze path over time is shown superimposed on example choice options. We extracted fixations within areas of interest in the form of equal sized boxes around each option (shown as dashed boxes for illustration only). For each option, the fixation proportion relative to the total fixation time on all options was computed. **B** Relationship between gaze distribution and gaze entropy. Illustrated are 4 exemplary trials with varying gaze distributions across four options (top) and the corresponding gaze entropy (bottom). The more even the gaze distribution, the higher the gaze entropy. **C** Gaze entropy for Choice and Appraisal as a function of value difference (top) and overall value (bottom). During Choice people prioritize/deprioritize goal-congruent options as their value difference to other options increases and when overall values are more congruent with their choice goals. These effects are not observed during Appraisal. Lines show predicted effects from linear mixed effects models. Shaded areas represent 95% confidence intervals.

Early option exploration is modulated by goal value during Choice but not Appraisal

We next tested how attention is allocated over time. To test whether participants already exhibited goal-dependent prioritization during early option exploration and whether option exploration differed between appraisal and choice, we first focused on the first four fixations (excluding trials with fewer than four fixations total, Choice: 6%; Appraisal: 8%). We predicted that participants should distribute these first four fixations across all four options. Indeed, we found that, in about three quarters of trials, participants used the initial four fixations to evaluate all four options. Although this equal distribution of attention is sensible in both appraisal and choice (to identify all options;Russo & Leclerc, 1994), participants can sometimes speed up the choice process by focusing their attention on (highly) goal-congruent options (Gluth et al., 2020). In line with this intuition, an ANOVA revealed that participants were more likely to look at all four options during the initial four fixations when appraising the options than when choosing among them (Fig. 4). We found no significant difference between transformation goals nor an interaction (ps > .5668). Thus, participants explored options more evenly in appraisal than in choice, but there were no differences between the types of choices or appraisals on average. In line with the idea that people can focus on highly goal-congruent options in choice, we expected that any attention prioritization would vary with the overall value of the options and the transformation goal. Indeed, participants were less likely to look at all options first when choosing the best among good value options, and when choosing the worst among bad options, whereas they were equally likely to look at all options during appraisal. These patterns underpinned a significant interaction between overall value and transformation goal in the Choice condition ($t = -5.41$, $p < .001$) but not the Appraisal condition ($t = -0.56$, $p = .5707$). Thus, participants were less likely to look at all four options first when choosing among more goal-congruent options, indicating that goals already shaped early option exploration.

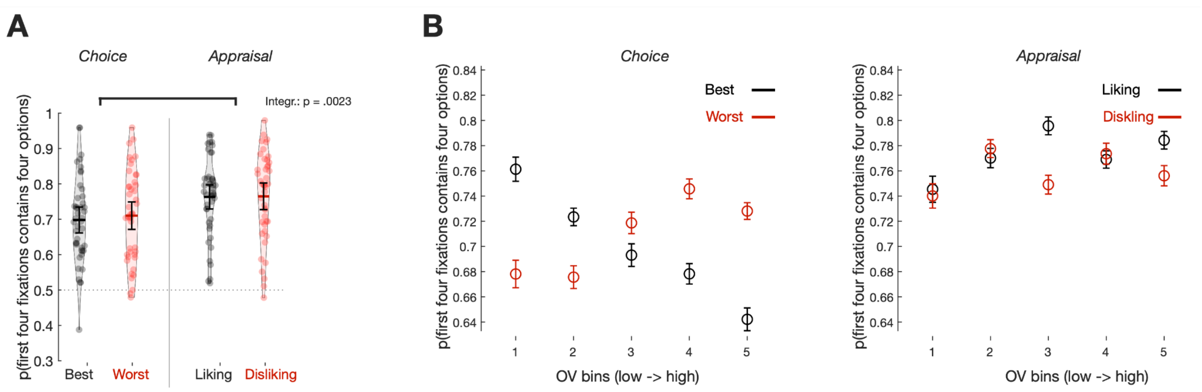

Figure 4: The probability of looking at all four options within the first four fixations varies by goal. A Distribution of early fixations in choice and appraisal. The violin plot illustrates probabilities for each condition, showing a tendency among participants to view all four options within the initial four fixations more frequently in the Appraisal condition compared to the Choice condition. Each filled circle represents an average probability from an individual participant. **B** Dependency of early fixations on overall value. *Left panel*: As overall value increases the probability of fixating all four options first decreases in the Choose Best condition but increases in the Choose Worst condition; *Right panel*: The probability of looking at all four options with the initial four fixations is not modulated by overall value, transformation goal nor by their interaction (ps > .2046). OV bins are calculated on an individual level. Error bars indicate the mean ± 95% confidence interval.

Dissociable goal-dependent gaze dynamics in Appraisal vs Choice

To better characterize attention allocation over the entire course of a decision, we next investigated how fixation patterns varied over time as a function of goals and their interaction with option values. It is possible that people exhibit goal-dependent prioritization in both choice and appraisal, but that these have a different time-course and dynamic in appraisal. For instance, it could be that over the course of an appraisal people attend to all options equally, but that they systematically start with more goal-congruent options and then shift to less goal-congruent options. To test this, we calculated the probability of fixating on the highest-value (Rank1) and lowest-value (Rank4) options within 10-millisecond bins, and conducted a regression analysis using rank, transformation goal, and their interaction as predictors for each integration goal manipulation (see Methods for details). Goal-dependent attention prioritization would be evident in an interaction between rank and transformation goal. We found such a positive interaction between Rank and Transformation goal between 1700 ms and 2860 ms following stimulus onset in choice, and between ~230 ms and 410 ms, and from 990 to 1550 ms in appraisal, indicating that people prioritized goal-congruent options over goal incongruent options during those windows (Fig. 5A). Post-hoc analyses indicated that this interaction was not solely attributed to any specific transformation goal. Descriptively, participants tended to fixate on the Rank1 option more than the Rank4 option in the Liking condition (Appraisal: $t = 1.47$, $p = .3430$), but less often in the Disliking condition (Appraisal: $t = -0.35$, $p = .7272$). In the later time windows (i.e., last positive interaction), we found positive rank effects in best/liking (Choice: 3.17, $p = .0028$; Appraisal: $t = 1.21$, $p = .2308$) and negative rank effects in worst/disliking conditions (Choice: -2.96, $p = .0050$; Appraisal: $t = -0.81$, $p = .4200$), but these contrasts were only significant in choice.

These results suggest that goal-driven attention prioritization may emerge as a decision unfolds. To test whether attention prioritization emerges towards the response, we applied the same analysis to response-locked eye movement data (see Fig. 5B). This analysis revealed a single cluster of positive interaction between Rank and Transformation goal in the Choice condition from -1400 ms to -170ms prior to a response. Post-hoc tests showed that rank effects were significant in the choose best condition ($t = 3.37$, $p = .0016$) and the choose worst condition ($t = -3.20$, $p = .0026$). This indicates that participants increasingly focused and then maintained their visual attention on the goal-congruent option prior to making a decision. In contrast, during the Appraisal condition, the interaction between Rank and Transformation fluctuated several times, and we identified three significant clusters, two positive between -2870 and -2380 ms and between -880 and -670 ms, and one negative cluster between -2000 and -1550 ms. Thus, across stimulus and response-locked analyses of appraisal, our findings indicate that participants alternated between windows of prioritization of the most and the least goal-congruent options that balanced each other out in the trial-level measures of attention prioritization.

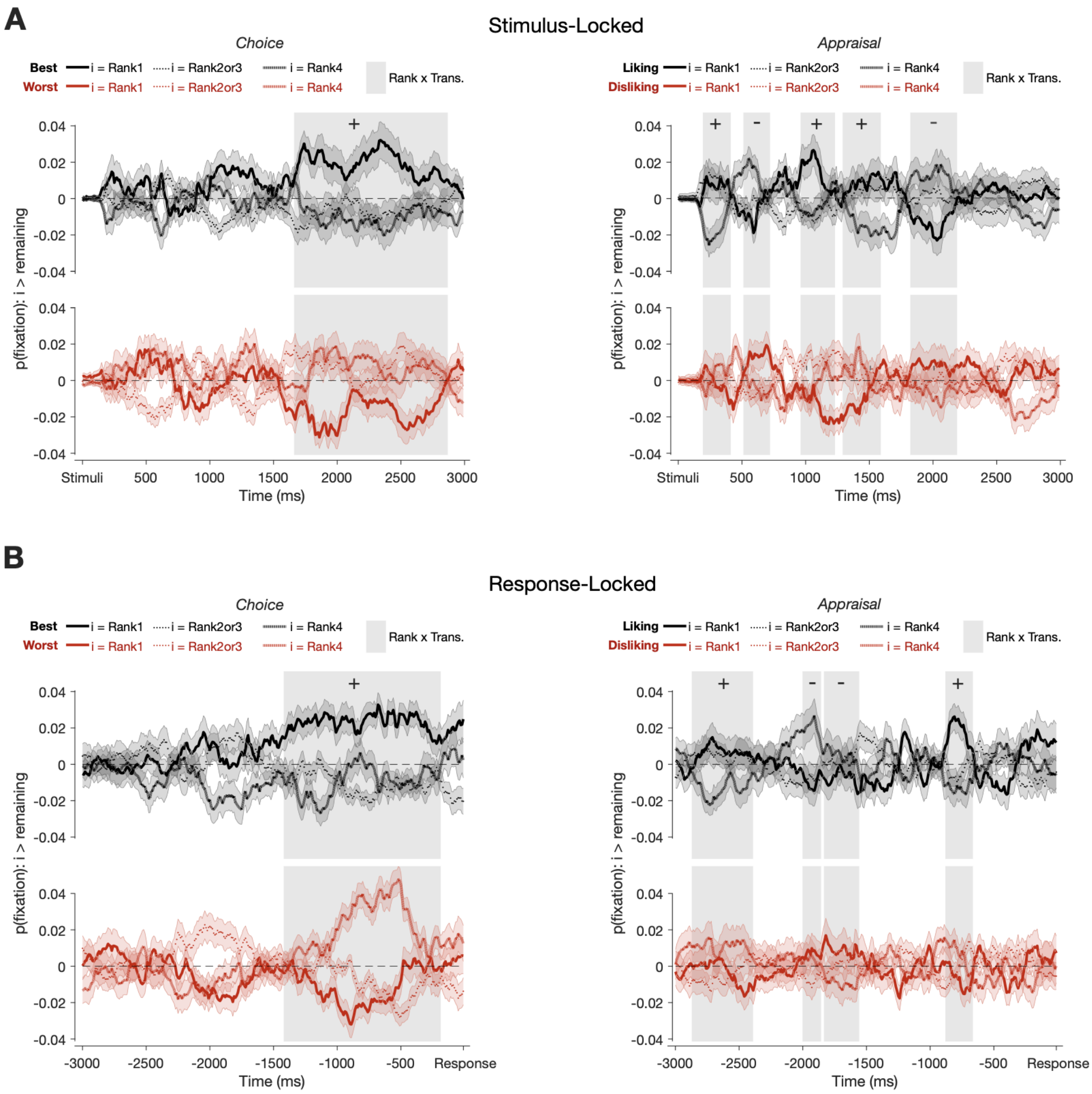

Figure 5. Time-resolved analysis of fixation probability A Stimulus-locked analysis. **B** Response-locked analysis. *Left panels*: Choice conditions; *Right panels*: Appraisal conditions. Lines are computed as the differences in fixation probability between goal-value ranks. Gray boxes indicate significant interaction between Transformation goal and Rank. Shaded areas represent confidence intervals.

Discussion

To make good decisions, we need to gather information about our options and integrate that information over time. Most of our understanding of how these processes unfold and vary with our options' values are grounded in research on decisions that aim to choose the best option. Recent work suggests that this focus on choices of the best option may have obscured additional sources of flexibility in decision-making, such as aligning value representations with what is being accumulated (e.g., goodness vs badness, liking vs disliking; transformation goals), and aligning response representations with how this information is being accumulated (e.g., appraisal vs choice; integration goals) and hampered our interpretations of behavioral and neural correlates of choice value (Frömer et al., 2019; Frömer & Shenhav, 2022; Leng et al., 2024; Sepulveda et al., 2020). Here, we investigated how integration goals and transformation goals shape behavioral and attentional correlates of choice value.

Our behavioral results match predictions of a computational model of flexible value-based decision-making and show that the relationship between RT and overall value is approximately linear in choice and follows an inverse U-shape in appraisal. Furthermore, the direction of this relationship depends on the transformation goal in choice, with faster responses for higher value options when choosing the best option, but slower responses when choosing the worst one. In appraisal, however, this relationship was independent of whether participants appraised how much they liked the items overall or how much they disliked them. We find similar patterns when examining people's gaze during these choices. During choice, but not appraisal, we found goal-dependent attention prioritization, starting as early as during the first four fixations and persisting throughout the time leading up to the response. In appraisal, we instead found no goal-dependent value-prioritization overall, and instead found a close to equal distribution of gaze across all options. Moreover, when examining gaze allocation over time, we found that people are more likely to explore all options first (Fig. 4), and differences in attention allocation between transformation goals at certain timepoints are compensated by opposing effects at other timepoints (Fig. 5).

Our choice behavior results replicate previous findings that the canonical overall value effect on response time, with faster responses when choosing among higher value options (Gluth et al., 2018; Hunt et al., 2012; Shenhav & Buckner, 2014; Ting & Gluth, 2025), flips when people are instructed to choose the worst option (Frömer et al., 2019; Frömer & Shenhav, 2022). This effect can be accounted for by endowing the LCA with goal-dependent value representations that serve as inputs to accumulation (Frömer et al., 2019) or by an alternative sequential sampling model where attention modulates evidence accumulation (Smith & Krajbich, 2019; Ting & Gluth, 2025). In each case the core computation driving the effect is the alignment of value inputs with one's choice goal (Sepulveda et al., 2020). Alongside imaging evidence (Castegnetti et al., 2021; Frömer et al., 2019), these modeling results converge in supporting the hypothesis that option values are represented in a goal-dependent way that allows for efficient decision-making.

Our choice gaze results further replicate the finding that people prioritize goal-congruent options when choosing among them (Gluth et al., 2020; Sepulveda et al., 2020). These results revise previous interpretations of gaze-value coupling during choice (Pearson et al., 2022; Ting & Gluth, 2024). Rather than value capturing attention (Shimojo et al., 2003), a growing body of work suggests that people actively direct attention in a goal-directed fashion, near optimally (Callaway et al., 2021; Jang et al., 2021) or at least highly efficiently (Gluth et al., 2024). In the simplest version, attention could be allocated proportional to the current evidence for each option (Gluth et al., 2020), giving rise to the emerging gaze-choice coupling typically observed in value-based choice. Sepulveda et al. found goal-dependent prioritization after about 800ms and interpreted this delay as evidence for an initial random exploration of options with goal-dependent prioritization only occurring thereafter. Our time-resolved analyses are consistent with this interpretation, showing goal-dependent prioritization only around 1600ms, roughly double the time in Sepulveda et al. who used only two options whereas we had four in the present study. However, these results are qualified by our complementary data which strongly suggest that goal-dependent prioritization was already evident within the first four fixations. One possible explanation for this discrepancy is that Sepulveda et al displayed options in a gaze-contingent manner, which prevents parafoveal option processing and has been shown to alter choice processes (Eum et al., 2023). However, our own time-resolved analysis also failed to reveal significant early goal-dependent prioritization effects. Thus, these early effects, even when present, are probably not sufficiently temporally synchronized across trials and too fleeting to detect with this analysis. They are certainly dwarfed by the emerging, temporally extended prioritization of the ultimately chosen option leading up to the choice.

The patterns observed during appraisal were markedly distinct from those observed during choice. As predicted by our model (Frömer et al., 2022) and shown in previous work (Froemer et al., 2024; Shenhav & Karmarkar, 2019), participants were fastest when appraising more extreme options (either high or low in value). Importantly, unlike during choice, in both the model and empirical data, this pattern was invariant to the transformation goal (i.e., whether participants were rating their liking or disliking of the set as a whole). The model predicts these dissociable effects of transformation goals across conditions, due to the differences in how the transformation affects the magnitude of the evidence that is accumulated. In choosing the best option, the magnitude of the evidence scales with value and in choosing the worst option it scales inversely with value. The evidence being accumulated in appraisal is not dependent on option values per se, but on the consistency and similarity of option values across options. Stated differently, it is easier to rate a set of low-value options as bad and a set of high-value options as good than to rate a set of partially low- and partially high-value options. Inverting the value scale does not change this consistency and therefore decision dynamics remain the same for liking and disliking appraisals. This is, however, not true for all types of appraisals (Frömer et al., 2022). For instance, our model predicts that appraising the extremity versus mediocrity of options requires value transformations that change the input distribution, and should lead to changes in the relationship between overall value and RT. These results reinforce the overarching idea that relationships between value and behavior are not about value per se but rather depend on the function that value serves in guiding the current action.

The principles governing differences between choice and appraisal are also evident in gaze patterns. Recent research on gaze allocation during choice has highlighted that people allocate gaze near optimally (Callaway et al., 2021; Jang et al., 2021), increasingly prioritizing promising candidates when choosing among more than two options, an adaptive strategy that is perhaps generalized to two-option choices when it is not normative (Sepulveda et al., 2020). From first principles, when all options are equally relevant, as during appraisal, people should instead allocate gaze evenly across all options, regardless of their values. We see that this is indeed the case: during appraisal, people allocate their gaze evenly, independently of value and of transformation goals. While we still see differences in gaze allocation between transformation goals, these are transient and rather follow an oscillatory pattern of prioritization and anti-prioritization that evens out over the entirety of the decision process. The distinct gaze patterns between appraisal and choice support the theory that gaze is allocated adaptively in service of the current goal. These findings further bridge mechanisms of value-based choice with mechanisms of perceptual choice (Grueschow et al., 2015; Sepulveda et al., 2020; Ting & Gluth, 2025), where goal-directed attention is well established and studied (Gottlieb & Oudeyer, 2018; Moneta et al., 2023; Ritz & Shenhav, 2022; Wolfe et al., 1989).

Taken together, this emerging body of work suggests that values serve as an input signal to decision-making just as other (e.g., perceptual) information do, and are similarly subject to control mechanisms that flexibly adapt information processing to a variety of goals. Extreme values draw attention and shape choices even when value is not relevant, but rather than assuming that this makes value special (Pearson et al., 2022), we need to be aware that other salient features do the same (Dai et al., 2020). Our results have implications for the interpretation of neural correlates of choice value and outline control processes that shape and may be mistaken for core decision-making processes like valuation and value comparison (Froemer et al., 2024; Frömer & Shenhav, 2022). In broadening our understanding of these processes lies an opportunity to also better understand the many ways in which decision-making can be challenging and go awry.

Method

Participants

44 participants (37 female, age: M= 24, SD = 4) took part in the study. They gave written informed consent and received 12€/h for their participation. The study was approved by the Local Ethics Committee of the Faculty of Psychology and Human Movement Sciences at the University of Hamburg (approval no. AZ_2022_04).

Procedure and Design

Participants were familiarized with ~250 consumer products, each shown individually with a short label describing the product. Participants clicked through the products at their own pace. In a second round of familiarization, items were shown without the labels and participants were asked to indicate any items they could not identify. Items indicated as not identified were removed from the list for this participant. The remaining items were subsequently shown a third time and participants were asked to rate how much they would want to have that item on a scale from 0 to 10 and following that rating to indicate how confident they are that this is how much they wanted the item on a scale from 1 to 5. Based on the value ratings, we generated custom tailored four-option choice sets that varied in overall value and value difference (for details see Shenhav & Buckner, 2014). The same option sets were shown twice, once in a choice condition, once in an appraisal condition. Participants used E, F, J, and I keys on a standard keyboard to either choose the option on the screen (positions were matched to key locations) or rate the options on the relevant scale using the keys from left to right (cf. Fig. 1). We varied participants' choice goals at a block level with integration goals (appraisal vs. choice) and transformation goals (best/liking vs. worst/disliking) fully crossed. The 4 blocks (choose best, choose worst, appraise liking, appraise disliking) were counterbalanced across participants, and participants practiced the respective button mapping before each block. Due to a coding error, counterbalancing was not implemented as desired and no participants performed the appraise liking block first. Instead about two thirds of participants performed the choose-best block first. In a follow-up online study (see Supplement) we verified that this error did not impact the results. Participants performed up to 60 trials per block, depending on how many choice sets could be generated based on their ratings ($\text{min}_{\text{total trials}}$ = 120, $\text{median}_{\text{total trials}}$ = 208, $\text{SD}_{\text{total trials}}$=24). The study was pre-registered on the open science framework (https://osf.io/jbphq).

Eye movement recordings and preprocessing

Eye-movements during choice and appraisal were recorded using an EyeLink 1000 Plus (SR Research Ltd.) at a sampling rate of 1000Hz. Participants sat at a 93 cm distance from the screen with 1920x1080 pixel resolution, their heads supported by a chin rest. At the start of each trial, we required that participants fixate on a central fixation cross and extracted gaze data from a 150 pixel area of interest around the fixation cross. Only if a fixation was reliably detected for one second, would the trial start. To ensure measurement quality, we performed calibrations prior to the task and every 30 trials or if a fixation could not be detected to start the trial within 5 s from fixation cross onset. Fixations between stimuli onsets and responses were extracted from four 231 x 231 pixel areas of interest in the top-left, bottom-left, top-right and bottom-right of the screen, in which the four images were displayed. Data were preprocessed in four steps using custom matlab scripts (Ting & Gluth, 2025): 1) for each trial we extracted eye-gaze position (left eye only) from option presentation to response onset (as x-y coordinates); 2) we labeled data as 1-4 if the position fell within the area of interest for one of the four options as 'blank' if fixations were detected outside of these areas, and as 'missing' if no fixation was detected; 3) individual 'blank' fixations between fixations on the same option were relabeled as fixations on that option (e.g., 1>>'blank' >> 1 was recoded as 1>>1>>1); 4) trials with more that 30% missing data were discarded. Labeled data were used to compute fixations, fixation durations and proportions (by normalizing total fixation time for each option by total fixation time across all options) and gaze entropy.
Gaze entropy was computed as:

$$Entropy = -\sum_{i=1}^{4} \quad log(P(fixated_i) * P(fixated_i)$$

Analyses

Behavioral analyses

Responses and RT were analyzed using generalized linear mixed effects models and linear mixed effects models respectively. We modeled random intercepts for participants and random slopes for conditions that explained variance in the data (Bates et al., 2015; Matuschek et al., 2017). Responses and RT were analyzed separately for Appraisal and Choice conditions with predictors for value difference (goal value minus average remaining values), linear and Overall Value (quadratic) (average rating of options). For choice we modeled the probability that the goal congruent option was chosen as follows, excluding trials in which more than one option had the most goal-congruent value:

isGoalChosen ~ Good-Bad*(Value Difference+ Overall Value) + (1 | SubNum)

RT across all choice trials was modeled as:

log(RT*1000) ~ Good-Bad*(Value Difference+ Overall Value) + (Overall Value | SubNum)

For appraisal we modeled the response as follows:

Response ~ Good-Bad*(Value Difference + Overall Value + I(Overall Value*Overall Value)) + (Overall Value|SubNum)

Appraisal RTs were modeled as:

log(RT*1000) ~ Good-Bad*(Value Difference + I(Overall Value*Overall Value)) + (1 | SubNum)

Trial-level gaze measures

For each item on each trial we modeled the probability of it being fixated as:

DwellProp ~ Choice-Appraisal*(Good-Bad*(Value + I(Value*Value))) + (1|SubNum)

Gaze entropy for each trial was modeled as:

GazeEntropy ~ Choice-Appraisal*Good-Bad*(Value Difference + Overall Value + I(Overall Value*Overall Value)) + (Choice-Appraisal*Good-Bad|SubNum)

To test the effect of transformation goals (Good-Bad) and integration goals (Choice-Appraisal) as well as their interaction on how participants evaluated options, we computed the probability that the initial four fixations were used to view all options for each participant and for each condition. This analysis comprised only trials with more than four fixations. Average probabilities to fixate all four options were fed into a two-way repeated-measured ANOVA. We also used a logistic regression model to predict whether the initial four fixations were used to evaluate all options:

$$\text{All options viewed in first 4 fixations} \sim \beta 0 + \beta 1 \text{ Value Difference} + \beta 2 \text{ Overall Value} + \beta 3 \text{ Good-Bad} + \beta 4 \text{ Overall Value* Good-Bad} + (1|\text{SubNum})$$

We conducted this regression model separately for the Choice and Appraisal conditions.

Time-resolved gaze analysis

We calculated the probability of fixating on the best (Rank1) to worst (Rank4) options every 10 ms for each trial. These probabilities at each time bin served as the dependent variables in a generalized linear mixed-effects model (GLMM), which included an intercept and two categorical predictors: Rank (three levels: Rank1, Rank2&3, Rank4) and Transformation goal (two levels: Best/Liking, Worst/Disliking), as well as their interaction. We performed GLMMs for Choice and Appraisal conditions, separately. The intercept corresponded to the reference condition: Rank2&3 in the Worst/Disliking condition. The remaining coefficients were estimated relative to this reference condition. The interaction between Rank and Transformation goal was tested using a contrast matrix. Specifically, we examined whether the difference in coefficients between Rank1 and Rank4 was significantly different between the Best/Liking and Worst/Disliking conditions.

In addition to these fixed-effects predictors, we included participant as a random effect to account for individual variability. The analysis was conducted separately for the Choice and

Appraisal conditions with the same significance level of 0.001. Since the average response time across the four conditions was about 3000 ms (Choice: 3463 ms; Appraisal: 3130 ms), we conducted a time-resolved analysis using a time window of 3000 ms following stimulus onset (Figure 5A) or preceding the response (Fig. 5B).

A significant interaction effect at a single time point could occur by chance, particularly when conducting multiple tests over 300 time bins (10ms/bin). To address this, we applied a cluster-based multiple comparison correction procedure with the following steps. First, we identified time points with significant interaction effects ($p<.001$) and grouped neighboring significant time points into clusters. Second, we randomly selected a subset of time points and flipped the sign of interaction effects on those points. We then clustered time points using the method described in the first step. The second step was 1000 times and the maximum sum of t-values for the clusters was recorded in each repetition. Finally, we identified clusters with a sum of t-values exceeding the 97.5th percentile of the randomized distribution of maximum sum of t-values. To enhance our understanding of fixation allocation within each trial, we only included trials with more than two fixations. We repeated these three steps separately for each specific context: (1) positive and negative interactions, (2) stimulus-locked and response-locked fixation data, and (3) Choice and Appraisal conditions.

We then aimed to identify which option drove the interaction. For each time window showing a significant interaction between Rank and Transformation goal, we compared the relative fixation probability (p(fixation): i > rest; see Fig.5 and Fig. S2) to zero using one-tailed t-tests for Rank1 ($i = 1$) and Rank4 ($i = 4$) separately within each condition.

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