Movement planning is not quite optimal

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# Abstract

# Introduction

Humans often make sub-optimal cognitive decisions. Cognitive biases and heuristics describe the systematic ways in which our decisions deviate from optimality (Tversky & Khaneman, 1974). One well known cognitive bias is loss aversion, the tendency to prefer avoiding losses to acquiring gains of equivalent magnitude (Kahneman et al., 1991). Attributing outsized weight to losses in this way limits the extent to which a person can maximize their expected gain.

While cognitive decisions regularly deviate from optimality, perhaps motor decisions do not (Wolpert et al., 1995). The framework of statistical decision theory naturally applies to motor control because it involves the selection of movements whose outcomes are probabilistic, due to noise in the nervous system, and value-laden, because they may be good or bad to varying degrees (Trommershäuser et al., 2008). This has inspired the development of motor tasks which are isomorphic to classic economic choice tasks and which serve as tests of whether human movement decisions maximize expected value (Trommershäuser et al., 2008).

A critical line of research on this topic used an incentivized reaching task to test the optimality of movement decisions (Trommershäuser et al., 2003b, 2003a, 2005; Trommershäuser, Landy, et al., 2006). Participants made rapid pointing movements to small ‘gain’ circles on a screen while avoiding overlapping ‘loss’ circles and the experimenters manipulated the monetary values associated with the two circles. Data from multiple experiments using this task showed that most people aim within a few millimeters of the optimal aimpoint in most conditions. These results suggest that movement decisions may be optimal and unaffected by cognitive biases.

Follow up studies were conducted to probe the limits of the optimality of movement planning using carefully designed variants of the reaching task. One study found that people deviated from optimality when a gain circle was presented with two loss circles associated with different values, since this leads to an asymmetrical value landscape in which the optimal choice is “unintuitive”(Wu et al., 2006). Another study found that people deviated from optimality when the loss circle was presented 400 ms after the gain circle (300 ms prior to the response deadline) (Trommershäuser, Mattis, et al., 2006). These studies suggest that optimality in movement planning is bounded, but that within these bounds, movement planning maximizes expected gain, such as in the original studies on the topic.

However, movement decisions should be considered optimal only if alternative sub-optimal models do not provide a better explanation of observed behavior. No study to our knowledge has specifically investigated whether behavior in the reaching task is shaped by cognitive biases or heuristics, so we conducted two experiments to address this possibility. In an initial experiment, we focused on the possible impact of loss aversion on movement planning but found little supporting evidence. However, we found strong evidence that participants used a sub-optimal strategy. In a second experiment, we replicated our initial findings in a new experiment designed to closely match the original experiment from Trommershauser et al. 2003. These findings suggest that human movement decisions may generally be guided by satisfactory but sub-optimal strategies.

# Experiment 1

## Methods

### Ethics Statement

All procedures were approved by the University of Michigan Institutional Review Board of Health Sciences and Behavioral Sciences and the experiment was carried out in accordance with the guidelines of this review board.

### Participants

32 students from the University of Michigan participated in Experiment 1. All participants gave written informed consent to participate in the study. All participants were right-handed, free of neurological disorders, and had normal or corrected-to-normal vision. At the end of the experiment, participants were compensated at a rate of $10/hour plus bonuses. A participant’s base hourly compensation was not affected by their performance in any task.

### Apparatus

Participants sat in an immobile chair in a small room in front of a 23” touchscreen computer monitor, and a keyboard positioned such that the spacebar was 21.5 cm away from bottom of the monitor. We programmed the reaching task using PsychoPy (Peirce, 2007) and the loss aversion task using PyGame (Shinners, 2011).

### Reaching Task

Participants performed an incentivized reaching task designed to study the optimality of movement planning (Trommershäuser et al., 2003b). A trial of the reaching task began with a 1.5s payoff cue indicating the potential gains and losses for the trial. This was followed by a white fixation cross that remained until the participant presses the space bar. After the space bar was pressed, the cross turned blue and blue box was presented for 400 to 600 ms to indicate where the stimuli might appear. Next, overlapping circles (radii of 8.5mm) appeared at a random location and the participant released the space bar, reached out, and touched the screen. The circles’ centers were 1 radius or 1.4 radii apart and the loss circle could appear to the left or the right of the gain circle; the A close up of a map

Description automatically generatedvertical position of the two circles was always the same.

Figure 1 Example trial and expected value surface. (a) Participants are first presented with information about the potential payoffs. Next, they initiate the trial by pressing and holding down the spacebar. A fixation cross is presented for a variable delay interval. Next, the stimuli are presented, and the participant releases the spacebar and reaches out to touch the stimulus. They are shown feedback at the end of each trial indicating the location they touched and the payoff they received. (b) Estimated expected earnings associated with aimpoints over a range of x-coordinates and participants (i.e., training variances).

After completing a movement, they received feedback about where they touched and the gain or loss they acquired. However, if the movement was completed too quickly (t < 50ms after stimulus onset) the trial was aborted, and they received feedback stating, “Too soon”. And if the movement was completed too slowly (t > 1s after stimulus onset), they received feedback stating, “Too slow” and incurred a loss of -$5.

Participants trained on the task in three phases. In Phase 1, they simply reached to a yellow dot on the screen. Phase 1 consisted of twelve blocks of thirty-six trials. We use endpoint data from Phase 1 of training to obtain a prior estimate of participants movement variability. In Phase 2 of training, participants were introduced to the incentivized reaching task. This task requires rapid reaching to small ‘gain’ circles while avoiding overlapping ‘loss’ circles. Phase 2 included possible payoffs of -$5+$1, $-1+$1, and -$0+1 and consisted of six blocks of thirty-six trials. In Phase 3 of training, additional ‘high stakes’ payoff conditions were included: -$15+$3, -$3+$3. Phase 3 consisted of two blocks of thirty-six trials. Stimulus locations and payoff conditions varied randomly from trial to trial.

A day later, participants returned to perform the incentivized reaching task for actual cash bonuses. Before beginning the test, session participants completed a “pre-test” to ensure they understood how much money they would win or lose depending on the outcome of their movement. Once they completed the pre-test with 100% accuracy, the participant began the test session, which consisted of ten blocks of sixty trials. During the test session, the following conditions varied randomly from trial to trial: stimulus location, loss circle side (left or right), distance between circles (1-radius, 1.4 radii), loss-to-gain ratio (-5/1, -1/1), and order of magnitude (1x, 3x). After the test session, there was a raffle in which one trial was randomly selected from each block (ten trials total) and the participant gained or lost money (from an endowment of $30) based on their performance on the randomly selected trials. The raffle procedure was explained to participants at the start of the experiment. After the raffle, participants performed the loss aversion task.

### Loss Aversion Task

Finally, participants completed a gambling task to measure their individual loss-aversion (Tom et al., 2007). In this task, participants were presented with a randomized series of 50/50 gambles. Potential gains ranged from +$10 to +$30, while potential losses ranged from -$5 to -$15. Participants were instructed to evaluate each gamble independently and to accept or reject each of these gambles and to avoid simple decision-making rules. After the completion, a raffle occurred in which a trial was randomly selected, and the participant gained, or lost money based on the values of the selected gamble and the outcome of a virtual coin flip. The raffle procedure was explained to participants before they began the task.

We measure loss aversion by fitting logistic regression models to gamble acceptance with gain and loss magnitude as predictors, separately for each participant. Loss aversion is computed simply as the ratio of loss sensitivity and gain sensitivity: . For subjects whose lambda were missing or implausible , we let lambda equal 1.5, which represented our prior belief that people have a small amount of loss aversion. This correction applied to fifteen subjects, eleven of whom were pilot subjects who did not complete the loss aversion task.

### Data Pre-processing

First, we filtered out all trials in which responses occurred more than one second after stimulus onset. Next, we centered the endpoints around the center of the reward circle and scaled the endpoints by the radius of the reward circle. On half the trials, the loss circle was actually to the right of the gain circle. Thus, the mean horizontal endpoint at this stage of preprocessing represents horizontal bias. We computed this bias for each participant and subtracted it from each endpoint. Next, we reflected all points from the right-side-loss trials over the y-axis. Finally, we excluded all endpoints outside of +/- 2 radii from origin in the horizontal or vertical directions.

### Sensitivity analysis

We quantified the sensitivity of movement planning to variables including loss-to-gain ratio (5:1, 1:1), distance between circles (1R, 1.4R), order of magnitude (1x, 3x), loss aversion (), and training variance (). The dichotomous predictors were coded as [-0.5, 0.5], the continuous predictors were ranked and standardized, and the outcome, horizontal endpoint, was standardized.

A Bayesian hierarchical regression model was used to estimate the effects of the predictors on the outcome. This model assumed that endpoints were normally distributed. The intercepts on the mean were allowed to vary by subject around a group mean. The error-variance was also allowed to vary by subject around a group mean, since each subject has unique motor variability. We assigned weakly informative priors to all parameters, N(1,1) for the error-variance and N(0,1) for all other parameters. The model was implemented using the R package {brms} (Bürkner, 2017, 2018) and the probabilistic programming language Stan (Carpenter et al., 2017). Posterior parameter estimates were obtained using Markov Chain Monte Carlo sampling with four chains and 10000 iterations (7500 warmup, 2500 post-warmup) per chain.

For regression results, we report the median posterior estimates, credible intervals, and probabilities of direction; these statistics convey an effect’s size, uncertainty, and existence, respectively (Kruschke, 2014; Makowski et al., 2019).

### Zero-loss analysis

To check whether people aimed at the origin on zero-loss trials, we fit an intercept-only Bayesian hierarchical regression model to data from trials in which the loss value was zero. This model allowed intercepts and error-variance to vary by subject. For this model, we did not standardize the horizontal endpoint data, so that the posterior estimate for the intercept could be easily used to test the hypothesis that the mean endpoint was zero.

### Noise-reduction analysis

We tested the hypothesis that incentives reduced motor noise by fitting two hierarchical regression models. In the first model, M, loss-ratio was included as a predictor for endpoint mean but not endpoint variance. In the second model, MV, loss-ratio was included as a predictor for endpoint mean and endpoint variance. We coded loss-ratio using the linear contrast [-0.5, 0, 0.5] and the endpoint outcome was again standardized. Intercepts on the mean and variance were allowed to vary by subject in both models.

### Computational Modeling

We evaluate four computational models against observed endpoint data to investigate the strategies that participants used to plan their movements. The first model, MEV, states that people select aimpoints that maximize expected value:

The model assumes that participants use an estimate of their motor variance () to anticipate the probabilistic consequences of possible movements (we’ll refer to this as a forward model).

To estimate a forward model for each subject, we considered a 1D grid of possible aimpoints from x = 0 to x = 1 by 0.01 (in radius units). Next, we calculated an endpoint covariance matrix for each subject using their training data (Phase 1 for Experiment 1) and used these covariance matrices to simulate 100k endpoints from a bivariate normal distribution around each possible aimpoint. We then used these simulated data to estimate the probabilities of different outcomes (loss, gain, loss+gain, miss) conditional on each aimpoint.

The product of the forward model and the values associated with different outcomes yields a landscape of expected gain over a range of possible aimpoints. The aimpoint that is ultimately selected is the aimpoint that maximizes this landscape of expected gain (for a given condition and subject).

The second model that we considered, MELV, was the same as the first, except that the loss values were multiplied by a measure of the individual’s loss aversion prior to computing the landscape of expected gain. When loss aversion is greater than one, the model predicts greater shifts away from origin compared to MEV in response to increases in the ratio of loss to gain.

The third model that we considered, MSWU, was similar to the first two, except that both the forward model (probabilities) and the values were subject to non-linear transformations. In particular, negative values were transformed using the utility function (Wu et al., 2009):

And probabilities were transformed using the weighting function (Prelec, 1998):

This model predicts larger shifts compared to MEV in response to increasing loss-ratio when and , but smaller shifts when and . Point estimates of and for each subject were obtained using maximum likelihood estimation with the gradient-free constrained optimizer BOBYQA (Powell, 2009) via the R package {optimx}. The ML estimates were then used to compute predicted mean endpoints for each subject and condition.

The fourth model that we considered, H, was quite different from the other models. According to this model, participants aim at the center of the gain circle when the loss is zero and at the midpoint of the gain-only region at y = 0 when the loss is greater than zero. This model represents the null hypothesis that participants follow a simple heuristic rather than maximizing a value landscape.

### Bayesian Model Evaluation

The computational models above predict aimpoints (i.e. endpoint means) for each subject and condition. We perform an initial assessment of model fitness by comparing the predicted aimpoints to observed aimpoints (Fig. 2B & 3B). However, we assume that endpoints are normally distributed around these means, with variances that vary across individuals around a population mean variance. We therefore implement each model as a Bayesian normal-distribution model with a hierarchical variance and with means determined by the predictions of the computational model. The distributional model was as follows:

where is an individual id, is a condition id, is the group mean variance, is the variance of across individuals, is the model-predicted aimpoint and are observed (horizontal) endpoints.

A benefit of Bayesian modeling is that it affords an estimate of a posterior distribution from which hypothetical replication datasets can be drawn. This is called the posterior predictive distribution and its relation to the observed data allows for flexible evaluations of the absolute and relative goodness of fit of models. We assess the overall predictive accuracy of the models using Bayesian leave-one-out (LOO) cross-validation estimates of the expected pointwise log predictive density for new data (Vehtari et al., 2017). This estimate of out-of-sample predictive fit is defined as:

where,is the predictive density given the data minus the point. We use this Bayesian LOO estimate to compute an information criterion deviance score () and to compare models in terms of the mean and standard error of their pairwise differences in LOO (LOOdiff). We assessed the condition-specific predictive accuracy of our models using the mean predictive error . Posterior predictive checks were done using the R packages {loo} and {bayesplot} (Gabry et al., 2019).

## Results

### Sub-optimal sensitivity to payoffs and probabilities

We first asked whether reaching behavior was sensitive to three variables needed to compute the optimal aim point: the loss to gain ratio, the distance between loss and gain circles, and the participant’s movement variance. The optimal strategy predicts a positive effect of increased loss ratio, a negative effect of increased space, and a positive effect of movement variance. We fit a hierarchical regression model to examine these effects (See Sensitivity Analysis in Methods).

Movement decisions were sensitive to the ratio of loss to gain, as evidenced by a positive effect of loss ratio (5:1 – 1:1 – 0:1) on mean endpoint . Our participants were sensitive to the spatial information, since there was a large negative effect of circle distance (1R - 1.4R) on mean endpoint . However, movement planning did not appear to be tailored to an individual’s estimate of their own movement variability, since there was little evidence of an effect of ranked training variance on mean endpoint . These findings suggest that movement planning is related to expected gain, but probably not in an optimal way, given the decoupling of mean endpoint from prior endpoint variance.

### No obvious effect of loss aversion on behavior

The optimal model also predicts that performance will *not* be affected by extraneous factors such as the order of magnitude of the payoffs (1x, 3x) or an individual’s loss aversion bias. We tested these predictions by including additional predictors in the regression model described above. We found little evidence for an effect of payoff multiplier or ranked loss aversion . These findings suggest that movement planning is not straightforwardly related to loss aversion.

### Sub-optimal behavior in the absence of loss

A clear prediction of the optimal model is that people will aim at the center of the reward circle (at origin) when there is zero potential loss, since this aimpoint maximizes the probability of touching the target. We tested this hypothesis by modeling data from the zero-loss-condition using a hierarchical regression model with a single intercept predictor that varied across subjects. We found that the estimated mean endpoint was credibly greater than zero , suggesting that participants did not aim at origin in the zero-loss condition. This finding contradicts the hypothesis that movement planning maximizes expected gain, since aiming away from origin in the zero-loss condition generally lowers one’s expected gain.

### Decision models

Next we fit computational models to endpoint data to infer which decision strategies were most likely used. The first model, MEV, selects aimpoints that maximize expected value, and thus represents the hypothesis that movement planning is optimal.

The second model, MELV, selects aimpoints that maximize expected loss-averse value. This represents the hypothesis that movement planning maximizes expected value, where the value being maximized is itself biased by the individual’s loss aversion (measured in a separate task).

The third model, MSWU, selects aimpoints that maximize subjective weighted utility. This represents the hypothesis that movement planning maximizes a subjective utility function in which values and probabilities are non-linearly modified (a la Prospect Theory). This model allows for the possibility that participants assign diminishing marginal disutility to losses and that they assign too much or too little weight to low or high probability events.

The fourth model, H, is a simple heuristic: when there is a potential loss, aim at the midpoint of the gain-only region at y = 0, otherwise, aim at the origin. This represents the (null) hypothesis that people rely on a cognitively inexpensive heuristic that leads to satisfactory outcomes.

### Model comparison

We found that the MSWU model outperformed the H model , the MEV model and the MELV model . Comparing the model-predicted aimpoints to observed aimpoints (mean endpoints) revealed that the MEV and MELV models overestimated the extent to which people shift away from origin when potential losses outweigh potential gains (Fig. 3A). This was corroborated by posterior predictive checks on the models which showed that the means of endpoint data simulated from MEV and MELV were greater than the mean of observed data for conditions in which losses outweighed gains (Fig. 3B). These findings suggest that participants deviated significantly from the optimal strategy when losses outweighed gains.



Figure 2. (A) Illustrations of the utility and probability weighting functions used in the MSWU model. (B)Estimates for parameters in the MSWU model. Column heights represent median estimates and points represent individual subjects’ estimates. was the sample

### Distortions of probability and value

The best-fitting model, MSWU, involved the maximization of a non-linear utility function. The curvature arose in two ways: first, from a parameter governing the diminishing marginal utility of losses, and second from a parameter governing the weighting of outcome probabilities. Individual parameter estimates were obtained using maximum likelihood estimation prior to fitting the full Bayesian group model. The distributions of the maximum likelihood estimates for and give insight about how our participants processed value and probability information in this task. The distribution of most likely estimates suggested that most participants assigned linear utility to losses, but some assigned diminishing marginal (dis)utility . The distribution of estimates suggested that our participants tended to underweight low probabilities and overweight large probabilities .

### Incentive-motivated noise-reduction

Lastly, we considered the possibility that participants increased their expected gain not only by shifting their aimpoints but also by decreasing their movement variance. Decreasing one’s movement variability leads to a decrease in the conditional probability of touching the loss region for any aimpoint to the right of origin. We tested whether participants decreased their variance by comparing the relative fit of two hierarchical regression models: one model, M, in which loss ratio affected endpoint mean and another model, MV, in which loss ratio affected endpoint mean and endpoint variance. We found that the MV model fit better than the M model . In the MV model, there was a negative effect of ratio on endpoint variance and a positive effect of ratio on endpoint mean .These findings indicate a motivational benefit of incentives on the precision of movement, suggesting an alternative mechanism by which people may increase expected gain in movement planning.

# Experiment 2

## Methods

### Ethics Statement

All procedures were approved by the University of Michigan Institutional Review Board of Health Sciences and Behavioral Sciences and the experiment was carried out in accordance with the guidelines of this review board.

### Participants

15 students from the University of Michigan participated in Experiment 2. All participants gave written informed consent to participate in the study. All participants were right-handed and had normal or corrected-to-normal vision. At the end of the experiment, participants were compensated at a rate of $10/hour plus performance bonuses and their outcome from the loss aversion task described below, if applicable. A participant’s base hourly compensation was not affected by their performance in any task.

### Apparatus

Participants sat in an immobile chair in a small room in front of a 23” touchscreen computer monitor, and a keyboard positioned such that the spacebar was 21.5 cm away from the bottom of the screen. We programmed the reaching task using OpenSesame (Mathôt et al., 2012) and the loss aversion task using the PyGame (www.pygame.org)

### Reaching Task

Participants performed a task similar to the task from Experiment 1, with modifications to make it more similar to the original experiments in this area of research (Trommershäuser et al., 2003b, 2003a). Here the training session consisted of ten blocks of thirty trials where they reached to green circles while avoiding overlapping red circles. The movement time limit was infinite in block one, 850 ms in blocks two through four, and 700 ms in blocks five through ten. Participants accumulated gains by touching the green circles (+100 points) and incurred losses by moving too slowly (-700 points). The test session occurred a day later and consisted of twelve blocks of thirty trials. The loss value varied randomly across blocks between -0, -100, and -500 points. The movement time limit during the test was 700ms and was associated with a -700-point loss. The distance separating the gain and loss circles was always one radius, which always equaled 8.5mm. Accumulated points were converted to a cash bonus at a rate of 25 cents per 1000 points.

### Loss Aversion Task

After the reaching test, participants completed the same loss aversion task used in Experiment 1. Five participants had implausible loss aversion estimates, which were revised to 1.5 to represent a moderate level of loss aversion.

### Data Analysis

All analyses were almost identical to those used in Experiment except that multiplier variable and spatial distance variable were absent since these did not vary in Experiment 2.

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Figure 3. (A) Observed vs model-predicted mean endpoints. (B) Mean posterior predictive error computed using 10k posterior draws.

## Results

We conducted a second experiment to test the robustness of our initial results. This second experiment was designed to closely match the experiments used in the seminal papers in this area of research (Trommershäuser et al., 2003b, 2003a).

We replicated the findings of a positive effect of loss ratio on mean endpoint and no effect of ranked training variance . We did find some evidence for an effect of loss aversion however And we found that mean endpoints were different from origin in the zero-loss condition . These results corroborate our initial conclusion that movement planning adapts to changing payoffs, but probably not in an optimal way.

We next replicated the finding that the MSWU model outperformed the H model the MEV model and the MELV model . Comparing predicted aimpoints to observed aimpoints revealed the same overestimation of aimpoints by MEV and MELV for conditions in which the loss outweighed the gain (Fig. 3B). And this finding was again supported by posterior predictive checks showing that the means of posterior-predicted endpoints greatly exceeded the mean of observed endpoints when the loss outweighed the gain (Fig. 3C). The distributions of ML parameter estimate for the MSWU model again suggested that our participants treated losses as having diminishing marginal disutility , as well as over-weighted low probabilities and under-weighted high probabilities .

Finally, we found additional support for the hypothesis that incentives decrease motor noise. Again, we found that the MV model fit better than the M model . In the MV model, there was a negative effect of ratio on endpoint variance and a positive effect of ratio on endpoint mean .

# Discussion

We assessed the optimality of movement planning using a visually guided reaching task with outcome-contingent gains and losses. The optimal solution to this task is the aimpoint that maximizes expected value given an individual’s movement variability. We tested the hypothesis that people make optimal movement decisions by comparing their behavior in two experiments to qualitative and quantitative predictions of optimal and suboptimal computational models. Across both experiments, we found compelling evidence that human behavior deviated systematically from the optimal strategy. People deviated from optimal in two clear ways: first, they aimed too close to the loss region when potential losses outweighed potential gains and second, they aimed too far from the loss region when potential gains outweighed potential losses. In both experiments, we found that behavior was best captured by a suboptimal decision strategy whereby participants maximize a subjective weighted utility measure with distorted information about probability and value. Furthermore, we found strong evidence that subjects also reduced their movement precision when losses outweighed gains, suggesting a mechanism by which people may increase the expected value of their reaching movements beyond adjusting their aimpoints.

*According to the optimal model of incentivized reaching behavior, participants’ use a memory of their endpoint variance in training and an observation of the current potential losses and gains to estimate the expected gain associated with different reach aimpoints. Thus, if participants follow this strategy they will aim further from the loss region when the loss-to-gain ratio is large (-5:1) compared to when it is small (-1:1), and participants with large endpoint variance will aim further from the loss region than participants with small endpoint variance. Across two experiments, Bayesian regression analyses showed that endpoint variance had minimal influence horizontal reach endpoint. This finding was inconsistent with the optimal model of human performance in this task. We therefore formulated a heuristic model of task performance that does not depend directly on endpoint variance. Follow-up model-comparison analyses revealed that reach endpoint data were significantly more likely under the heuristic model compared to the optimal model. Importantly, this advantage was driven by behavior in the large loss ratio condition, where nearly all participants were fit significantly better by the heuristic model compared to the optimal. When the loss ratio was -1:1, the models had similar fits to the data, but the optimal model had a small advantage overall. These results suggest that participants deviated from the optimal strategy as the loss ratio increased from -1:1 to -5:1.*

*Prior work has similarly shown that human visuomotor decision making under risk is suboptimal in some variants of the incentivized reaching task. For example, human performance has been shown to be suboptimal with rapidly varying payoff conditions (Neyedli & Welsh, 2014), complex expected value landscapes (Wu et al., 2006), and delayed onset of payoff-information (Trommershauser 2006b). However, much of this prior work assumes that the seminal work using this task provides strong evidence for near-optimal visuomotor decision making under risk. We show that this assumption may be unfounded and that even the original paradigm elicits behavior that deviates from optimal when the potential for financial loss was large. Sensorimotor behavior may be closer to optimal when potential losses are smaller because the person does not exert much attention or effort to the task, thus allowing the behavior to unfold in an automatic manner. However, when potential losses are large, the behavior may be influenced more by top-down cognitive control processes (Botvinick & Braver, 2014; Yee & Braver, 2018). While heightened investments of attention and effort are may enhance performance in some ways, this cognitive dependence may also render the behavior vulnerable to cognitive biases and heuristics. While we found no evidence that people followed the loss-averse strategy, we obtained strong evidence supporting the hypothesis that people followed a simple heuristic strategy when the potential losses were large.*

*A key computational difference between the heuristic and optimal strategies is that the heuristic does not depend on recomputing aim points as a function of varying payoffs. If the relative costs of relying on the optimal strategy outweigh its relative benefits for performance, then people may not rely on it. Thus, participants in our experiments may have deviated from the optimal strategy when the loss ratio was large because in that condition the costs of the optimal strategy outweighed its benefits. We confirmed using simulations that the extrinsic benefits of the optimal strategy over the heuristic strategy were smaller when the loss ratio was large (≈+0.15 expected gain, assuming a reward of 1) compared to when the loss ratio was small (≈+0.5 expected gain). Therefore, our participants probably had less incentive to rely on the more costly on-line optimization strategy when the loss ratio was large. This alone may be sufficient to explain why participants used the inexpensive heuristic when the loss ratio was large.*

*We find that participants do not shift their aimpoints in response to payoff information to the extent that is predicted by the optimal model. The optimal strategy incorporates an estimate of the participant’s endpoint variance and assumes that their variance does not change in response to payoff information. But there is evidence that motivation facilitates the reduction of neuronal noise in the motor system (Manohar et al., 2015). Thus, it was plausible that our participants had smaller endpoint variance when the loss ratio was large, enabling them to aim closer to the loss region without increasing their risk of loss. Follow-up Bayesian analyses revealed that the variance of participants’ endpoints decreased as the loss ratio increased. The optimal model explored in our analyses makes the dubious assumption that endpoint variance is constant, whereas our data show that endpoint variance varies systematically with payoff information and may indeed be a means by which people adaptively enhance the expected value of their sensorimotor behaviors. Nonetheless, when we examined an alternative version of the optimal model with condition-specific variances estimated from the test session, the model still provided a worse overall fit participants’ data compared to the heuristic model.*

*There are several questions unanswered by the present study that could be addressed by future work. Data from conditions with small potential losses were fit best by the optimal model but data from conditions with large potential losses were fit best by the heuristic model. However, it remains unknown whether this is because people are switching between the optimal and heuristic strategies, or because people are following some other unknown strategy that would generate the pattern of data observed here. Another unanswered question is whether Another issue with this work is that several theoretically distinct models make very similar predictions (typically within a few pixels) and are associated with similar expected gains in the present task. Therefore, it may be inherently difficult to empirically distinguish between plausible alternative models of behavior in this task and future work should explore alternative tasks that are designed specifically to distinguish optimal and plausible alternative suboptimal models.*

*In sum, we provide evidence across two incentivized reaching experiments that humans do not make perfectly rational decisions about where to aim their movements when there are large potential losses at stake. An optimal agent would integrate an estimate of its own endpoint variance with payoff information and perceptual information to find an aimpoint with maximal utility. The optimal agent therefore aims further from the loss region when its variance estimate increases or when the potential loss-to-gain ratio increases. However, our participants did not display these behavioral patterns to the extent that was predicted by the optimal model. Instead, our data suggest that participants may follow an alternative heuristic strategy when the potential losses are large. According to this model, the agent solves a simplified version of the decision problem, one in which the solution is more or less invariant to endpoint variance and loss-to-gain ratio. Our participants unequivocally deviated from the objectively rational strategy. However, they also did not behave in a manner fit to be described as irrational. Regarding the question of human rationality, our work provides support for a more moderate position according to which people, with their limited computational resources (time, memory, attention, etc.), tend to solve simplified versions of difficult problems, leading to behavior that is satisfactory, but not optimal.*

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