Title
People use Newtonian physics in intuitive sensorimotor decisions under risk

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 45(45)

Authors
Tatai, Fabian
Straub, Dominik
Rothkopf, Constantin

Publication Date
2023

Peer reviewed

People use Newtonian physics in intuitive sensorimotor decisions under risk

Fabian Tatai (fabian.tatai@tu-darmstadt.de)
Centre for Cognitive Science, Technical University of Darmstadt
Institute of Psychology, Technical University of Darmstadt

Dominik Straub (dominik.straub@tu-darmstadt.de)
Centre for Cognitive Science, Technical University of Darmstadt
Institute of Psychology, Technical University of Darmstadt

Constantin A. Rothkopf (constantin.rothkopf@tu-darmstadt.de)
Centre for Cognitive Science, Technical University of Darmstadt
Institute of Psychology, Technical University of Darmstadt

Abstract

Decisions under risk have been classically studied with tasks involving lotteries with explicit monetary rewards and uncertain gambles. More recently, sensorimotor decisions, specifically single movements to targets yielding rewards and losses, have been conceptualized as decisions under risk. While human choices between gambles have long been known not to maximize expected gains, sensorimotor decisions have been well described by statistical decision theory in many tasks. However, because many naturalistic scenarios of sensorimotor decisions are inescapably governed by the laws of physics, the question arises, how people act under such circumstances. Here, participants slid pucks to target areas, providing gains and losses in a virtual environment so that the uncertainty inherent in motor control interacts with the physical relationships governing objects' motion. Using model comparison with several generative models of participants' sliding actions, we find evidence that human motor decisions in scenarios with prospective economic outcomes take Newtonian physics into account.

Keywords: intuitive physics; decision-making; sensorimotor control; embodied cognition; Bayesian modeling

Introduction

How do people make decisions under risk? Such decisions are characterized by a single choice between alternative actions for which the outcomes are uncertain. Because of this inherent uncertainty, decision alternatives can be characterized by the expected outcome of each of the available actions. According to statistical decision theory, the rational choice is then to select that action, for which the expected outcome is highest among the alternatives (Von Neumann & Morgenstern, 1944; Savage, 1972). Decisions under risk are ubiquitous in everyday life, such as deciding whether to play a lottery or deciding which insurance to take out. However, more recently, scenarios with sensorimotor decision under risk involving motor actions have been investigated, blurring the the strict dichotomy between decision-making and sensorimotor control. Indeed, such situations are more closely related to everyday tasks, such as the decision to take a turn in navigation or whom to throw a pass in sports. While the prescriptions of statistical decision theory can be evaluated in all of these cases, people's behavior has been shown to deviate systematically from these prescriptions depending on a multitude of factors.

Classically, decisions under risk in economic domains or involving higher cognition are studied in experimental paradigms using repeated putative lotteries, in which monetary reward obtained by participants is often tied to the overall accumulated outcomes from their individual decisions. In such tasks, information about outcome uncertainties are provided explicitly, often verbally, such as that a gamble has a 30% chance of an outcome of 1$ and a 70% chance of an outcome of 0$. People have been shown to exhibit a multitude of biases (Kahneman, Slovic, Slovic, & Tversky, 1982) with pervasive violations of statistical decision theory (Von Neumann & Morgenstern, 1944) including violations that seem difficult to reconcile with statistical decision theory, such as violations of stochastic dominance (Kourouxous & Bauer, 2019).

Decisions under risk in economic scenarios are often contrasted with decisions under risk involving motor control, i.e. implicit sensorimotor uncertainties. In perceptual and motor domains, many studies have shown that people are well calibrated to their internal visual and motor uncertainties and that they take these uncertainties into account when carrying out visuomotor decisions under risk (Ernst & Banks, 2002; Körding & Wolpert, 2004), but see the review by Rahnev and Denison (2018) for numerous deviations. In a motor task where people quickly move their finger towards targets displayed on a screen, yielding different rewards dependent on which target was hit, Trommershäuser, Maloney, and Landy (2008) have shown that people integrate their motor variability with explicit economic outcomes according to statistical decision theory. Even when variability is artificially increased, people are still able to perform close to optimally (Trommershäuser, Gepshtein, Maloney, Landy, & Banks, 2005). However, further experiments have shown that the accuracy of responses depends on the amount of training (Neyedli & Welsh, 2013), how often one target configuration is presented consecutively (Neyedli & Welsh, 2014) and how large the ratio of expected outcomes, i.e. gains and losses is (Adkins, Lewis, & Lee, 2022). In a direct comparison between the domains, Wu, Delgado, and Maloney (2009) find that in sensorimotor control people tend to be risk-affine which they attribute to a different weighting of probability.

In M. Goldwater, F. K. Anggoro, B. K. Hayes, & D. C. Ong (Eds.), *Proceedings of the 45th Annual Conference of the Cognitive Science Society*.

However, many real world sensorimotor decision scenarios are governed by the laws of physics, and thus the question arises, how people make sensorimotor decisions under uncertainty in scenarios with physical dynamics. The field of intuitive physics exhibits a similar dichotomy as economic decision-making. In explicit reasoning tasks, it has been found that people fail at predicting physical dynamics in coherence with Newton's laws (McCloskey & Caramazza, 1980) or at least show biases (Todd & Warren, 1982). These biases could be partly explained by assuming that people apply heuristics to predict physics (Gilden & Proffitt, 1994). However, it seems that human capabilities of predicting physical dynamics are strongly dependent on the task context, as prediction is better in familiar situations (Kaiser, Jonides, & Alexander, 1986) and when situations are displayed dynamically (Kaiser, Proffitt, Whelan, & Hecht, 1992; Smith, Battaglia, & Vul, 2018). More recently, peoples' understanding of physics has been found to be in coherence with Newton's laws when accounting for perceptual and internal model uncertainty, which has been called the 'noisy Newton' framework (Sanborn, Mansinghka, & Griffiths, 2013). This has lead to the hypothesis that people posses an internal noisy physics engine, which they apply to make judgements of situations with a physics context (Battaglia, Hamrick, & Tenenbaum, 2013; Bates, Yildirim, Tenenbaum, & Battaglia, 2015).

When viewing physical object interactions in the context of decisions under risk, a central question is whether people can integrate knowledge about physical dynamics with their sensorimotor capabilities. Neupärtl, Tatai, and Rothkopf (2020) have shown that people can make use of inferred physical object properties during subsequent object interactions, under the right circumstances they even show correct priors about object dynamics (Neupärtl, Tatai, & Rothkopf, 2021). Still, it remains open how people cope when object interaction yields economic outcomes in the form of explicit gains and losses.

Here, we investigated whether people are able to make use of their intuitive knowledge of Newtonian physics to make informed choices in an object interaction task under risk. For this purpose, we used a paradigm where subjects slide a hockey puck at a target, which yielded a positive or negative economic outcome. The task is inspired by the finger pointing paradigm of Trommershäuser et al. (2008) but adds nonlinear physical dynamics and elicits signal-dependent motor variability in task relevant responses (Neupärtl et al., 2021). This results in an increase in endpoint variability for longer slides, which needs to be taken into account to maximize the expected reward. By building a Bayesian actor model that includes these factors and comparing it against an alternative model without any notion of physics or signal-dependent variability, we test the hypothesis that people make use of an internal model of Newtonian physics and integrate it with prospective economic outcomes when sliding pucks.

Our results suggest that people take into account the increase in variability introduced by the physics of sliding pucks and compensate for it. This implies that they are generally able to include considerations of Newtonian physics in their motor planning. Still, we find that people diverge from the predictions of the Bayesian actor model, especially for high prospective loss. Additionally, we observe high inter-subject variability in behavior, which we account for by introducing subjective utilities in our model.

Method

Participants

We recruited 9 undergraduate students who participated in our study for course credit. Additionally, all participants were awarded a bonus payment of $3-8$€ proportional to their cumulative reward earned during the experiment. All of them were naive with regard to the goals of the study. The experiment was approved by the Ethics Committee of the Technical University of Darmstadt and all participants gave informed consent.

Apparatus

In our experimental setup, participants were placed in a virtual representation of the room they were standing in, presented through the *HTC Vive Eye Pro* and the *Unity* game engine. They were tasked to slide a real common hockey puck, which was tracked by a passive tracking system (6 Cameras operating with $150Hz$, *Qualysis Oqus 500+ and 510+*), across a table. The puck was modified with weights such that its mass amounted to $250g$ and equipped with felt at the bottom to enhance its sliding properties. To track the puck, four markers were placed on top of it. Thus, participants could only grab it from the side.
In the real world, the puck's trajectory was stopped short to make it easily available for multiple consecutive slides. However, just before stopping, its velocity was measured, enabling a virtual continuation of the trajectory by simulation. This transition took place after 50cm of the tables' lenghth, which was visually marked by a virtual line for the subjects. To ensure a timely release of the puck, we tracked the subjects' hand position.

Physics simulation

The virtual trajectory of the puck was realized by the physical approximation of motion with constant deceleration, which is given by the following quadratic relationship:

$$s = f(v) = \frac{1}{2a}v^2, \tag{1}$$

where s is the traveled distance of the puck, a the deceleration given by $a = 9.81c$ with the friction coefficient c and the initial velocity v. To simplify the problem, we eliminated angles from the simulation, i.e. after passing the measurement line, the puck's trajectory was directed parallel along the depth of the table. Still, to keep the behavior as close as possible to reality, we matched the surface qualities of the table in the simulation by recording multiple trajectories with the

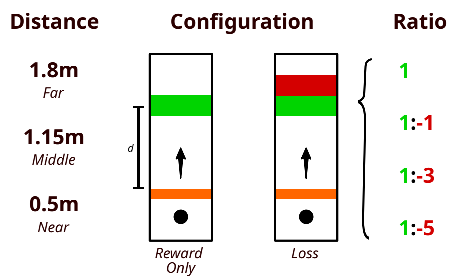
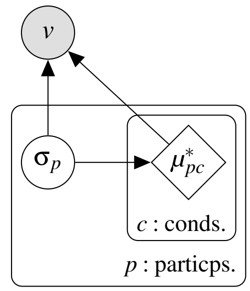


Figure 1: Subjects had to slide pucks at targets and received points for hitting the green *Reward Area (RA)* or the *Loss Area (LA)*. Rewards and losses were presented in 4 different ratios, and the center of target was located at 3 different locations. Each of the 12 possible target configurations was completed in blocks of 30 trials each.



$$\sigma_p \sim Halfnormal(0, 0.1)$$

$$\mu^*_{pc} = arg \max_{\mu} \mathbb{E}_v[r|\mu, \sigma_p, c]$$

$$v \sim Lognormal(\mu_{pc}, \sigma_p)$$

Figure 2: Probabilistic graphical model of the *Physics* model with a *Lognormal*-distribution for the release velocities v. Every participant p has their own variability σ_p, under which the optimal μ^*_{pc} is determined for every condition c by maximization of expected reward, taking the non-linear physical relationship into account.

tracking system and then estimated the friction coefficient between the table's surface and the puck $c = 0.29$.

Task

Subjects had to slide the puck across the table to hit a target (see Figure 1), a green area as wide as the table and 20 cm in depth, named the *Reward Area (RA)*. A hit of this area was rewarded by 1 point. In some trials, a red area, the *Loss Area (LA)*, of the same size was placed right behind the *RA*. Hitting this area would amount to either -1, -3 or -5 reward points, made apparent to the subject by a display above the table. The center of the *RA* was placed at one of three distances 0.5m, 1.15m, or 1.8m with respect to the measurement line. If neither the *RA* nor the *LA* was hit, the subjects received 0 points. The final puck position was shown for 1s. At the same time, feedback about the reward achieved in the current trial and the cumulative reward was shown on a display above the table. Trials in which the subjects overreached the measurement line had to be repeated.

Procedure

Subjects participated in the task on two consecutive days. On day one, the subjects began with unrewarded training trials where only the *RA* was presented. First, they completed 100 trials with variable distances ranging from $0.2 - 2$m in order to learn the puck's dynamics. Afterward, trials were presented in blocks of 30 trials to avoid sequence effects such as sensorimotor regression to the mean (Petzschner & Glasauer, 2011) and to ensure optimal performance (Neyedli & Welsh, 2014). To accustom the subjects with the specific distances used in our task, they had to complete two blocks of training trials per distance.
After the training phase, subjects began with the rewarded phase of the experiment. As there were 4 different loss conditions and three distances, this design amounted to 12 blocks of different configurations in randomized order, and therefore 360 trials in total. On the second day, subjects were only given 10 training trials per distance, and then the rewarded phase of the experiment was repeated. With this procedure, we aim to investigate how well people have learned the physical properties of sliding pucks, because they had to transfer their gained knowledge from the training to novel cost functions in the rewarded phase of the experiment (Maloney & Mamassian, 2009).

Modeling

We build a normative model of human sensorimotor actions based on *statistical decision theory* (Trommershäuser et al., 2008). In the classical finger pointing paradigm used by Trommershäuser, Maloney, and Landy (2003), the movement variability is independent of the target location, which allows modeling the movement endpoints as homoscedastic normal distributions. In puck sliding, however, Neupärtl et al. (2021) find that variability increases with distance. In our model, we assume that this increase in variability stems from two sources. First, we assume that subjects regulate the puck's velocity v at release by controlling the location parameter μ of the distribution

$$v \sim Lognormal(\mu, \sigma), \tag{2}$$

with variability parameter σ. The *Lognormal* distribution was chosen to account for signal-dependent motor variability (Schmidt, Zelaznik, Hawkins, Frank, & Quinn Jr, 1979; Harris & Wolpert, 1998).

Second, we need to account for the fact that puck sliding involves non-linear dynamics. Specifically, the puck's velocity determines its final position $s = f(v)$ via the quadratic relationship in Equation (1), which defines a distribution $p(s|\mu, \sigma)$ and further scales the endpoint variability with increasing distance.

With this formulation of variability, we can define the optimal location μ^*_c of the velocity distribution in a particular reward condition c as the one which maximizes the expected reward of slides:

$$\mu_c^* = arg\max_{\mu} \mathbb{E}_v[r|\mu,\sigma,c] \quad (3)$$

$$= arg\max_{\mu} \sum_A p(A|\mu,\sigma) r_c(A), \quad (4)$$

where r is the reward of a slide. The distribution $p(A|\mu,\sigma) = p(s \leq A_u|\mu,\sigma) - p(s \leq A_l|\mu,\sigma)$ is the probability of hitting an area A defined by upper and lower bounds (A_u, A_l), and $r_c(A)$ is the reward (or negative reward in the case of loss) received when hitting the area. For the loss configurations in our experiment (Figure 1), this model makes two qualitative predictions about the shifts in endpoint positions with respect to the center of the *RA*. First, endpoints should be shifted away from the center of the *RA* more at larger target distances, because of the distance-dependent increase in endpoint variability. Second, shifts should also be larger at a higher ratio between loss and reward, because the model maximizes the expected reward, resulting in more conservative shots for higher prospective losses.

The reward-maximizing model based on Newtonian physics, which we will refer to as the *Physics* model, has only one free parameter: the variability σ. As an alternative model, we consider a model without a notion of physics, which we will refer to as the *Normal* model, as it simply assumes a normal distribution $s \sim Normal(\mu,\sigma)$ with one free parameter σ for the position-independent endpoint variability (Trommershäuser et al., 2008). Additionally, we consider subjective versions of both models, which maximize subjective utility instead of the actual reward. For this purpose, we introduce a parametric subjective utility function (Tversky & Kahneman, 1992):

$$u(r,a,b) = \begin{cases} r^a, & \text{if } r \geq 0 \\ -(-r)^b, & \text{if } r < 0, \end{cases} \quad (5)$$

and assume that the agent maximizes the expected subjective value u instead of the reward r. As we only have one positive reward, we fix $a = 1$, but since we want to weight the negative rewards (-1, -3 and -5) against the positive reward, we treat b as an additional free parameter of the subjective models. We assume that all participants have their own b_p. Thus, we end up with four models, the *Physics* model, the *Normal* model, and their respective *Subjective* value versions.

The four models constitute different computational-level descriptions of the task and its optimal solution from the subject's perspective. From the researcher's perspective, we build a probabilistic model of the subject's behavior (Figure 2) and estimate the free parameters of the subject's model using Bayesian methods. Specifically, we implemented the models with the Python probabilistic programming package `numpyro` (Phan, Pradhan, & Jankowiak, 2019) using Metropolis-Hastings sampling. For each model, we drew 500000 samples in 4 chains, with 10000 burn-in steps and thinning rate of 50. To compare the models, we use Pareto-smoothed importance sampling as an approximation of leave-one-out cross validation (PSIS-LOO) (Vehtari, Gelman, & Gabry, 2017) as implemented in the Python package `arviz` (Kumar, Carroll, Hartikainen, & Martin, 2019). Importantly, PSIS-LOO is an estimate of the out-of-sample prediction accuracy and therefore takes model complexity into account.

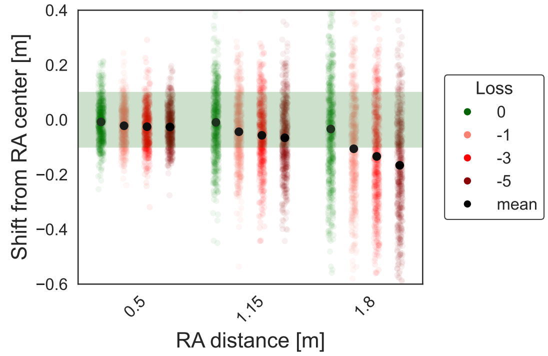


Figure 3: Slide endpoint shifts from the center of the *Reward Area* (*RA*, highlighted in green), aggregated for all subjects.

Results

For all analyses, we consider the data from both rewarded sessions, except for three trials, which had to be excluded because of malfunction of the tracking system. The central quantity of interest is the shift of the slide endpoints relative to the center of the *RA*, because it indicates how strongly subjects adapt their behavior in response to different target distance and loss conditions.

Influence of experimental conditions

We first compare the distributions of the endpoint shifts relative to the center of the *RA* across conditions (Figure 3). The endpoint variability increases with target distance (std: $0.5m$: $0.08m$; $1.15m$: $0.13m$; $1.8m$: $0.20m$), which indicates that the modeling assumptions of incorporating position-dependent variability are appropriate.

To quantitatively estimate the influence of the two manipulations (amount of loss and target distance) on the slide endpoints, we fitted a Bayesian mixed-effects model with the Python package `bambi` (Capretto et al., 2022). For this purpose, we assumed a normal distribution of the endpoint shift from the *RA*, treated both conditions as categorical variables and included random effects across subjects for both conditions. In the following, we report the posterior mean parameters and 95% credibility intervals.

We find that subjects perform shorter slides with increased distance ($\beta_{1.15} = -0.2, CI = [-0.04, -0.01]$; $\beta_{1.8} = -0.9, CI = [-0.12, -0.06]$; $\beta_{1.8} - \beta_{1.15} = -0.07, CI = [-0.10, -0.03]$). Figure 3 suggests that this difference could be attributed to the increased shift for higher losses at larger distances. The presence of loss in general leads to shorter slides ($\beta_{-1} = -0.04, CI = [-0.05, -0.03]$; $\beta_{-3} = -0.05, CI = [-0.07, -0.04]$; $\beta_{-5} = -0.07, CI = [-0.09, -0.05]$). Furthermore, comparing the effects be-

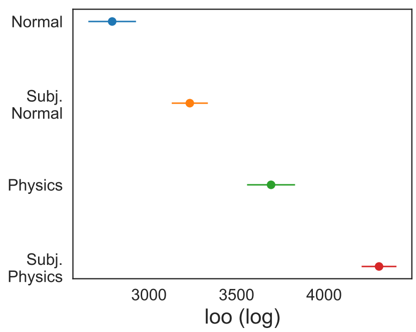


Figure 4: Model comparison with LOO, higher means better.

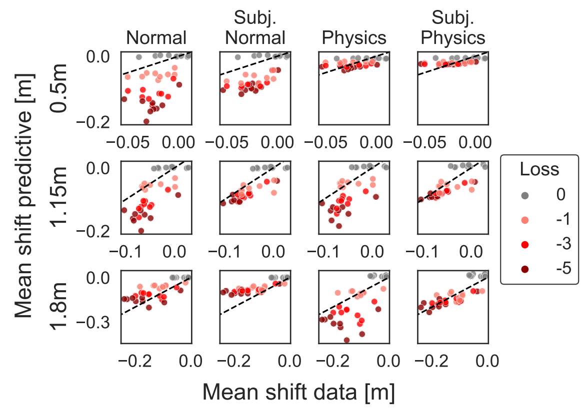


Figure 5: Mean shifts from the center of the *Reward Area (RA)* compared with the posterior predictive means of the four models. Each point in the plot shows the mean shift for one subject.

tween loss conditions suggests that the exact amount of loss does have an influence on the shift, but not a large one ($\beta_{-1} - \beta_{-3} = -0.01, CI = [0.00, -0.03]$; $\beta_{-3} - \beta_{-5} = -0.01, CI = [0.01, -0.03]$). Still, when comparing the smallest loss -1 against the largest, -5 the influence is more apparent ($\beta_{-1} - \beta_{-5} = -0.03, CI = [-0.01, -0.05]$).

Model comparison

As the central test for whether subjects use an internal model of Newtonian physics, we compare a Bayesian actor model that includes the physical relationship (the *Physics* model) against an alternative model without any notion of physics (the *Normal* model). Bayesian model comparison with PSIS-LOO (Figure 4) shows that the *Physics* model has a higher predictive accuracy than the *Normal* model ($d_{loo} = 907.00$, $se_d = 85.25$). Comparing the mean predicted shifts in individual conditions with the model predictions (Figure 6), one can see that even the *Physics* model does not predict the high loss conditions well, at least in some subjects. This motivated the extension of both models to versions with subjective losses that differ from the actual losses in the experiment. In both cases, the *Subjective* versions outperformed their respective non-subjective models (*Normal*: $d_{loo} = 443.12$, $se_d = 41.04$; *Physics*: $d_{loo} = 616.37$, $se_d = 46.66$). The *Subjective Physics* model outperforms the *Subjective Normal* model ($d_{loo} = 1080.25$, $se_d = 63.95$). Importantly, even the *Physics* model without subjective losses still has a higher predictive accuracy than the *Subjective Normal* model ($d_{loo} = 463.88$, $se_d = 88.36$).

Model predictions

To investigate the differences between the models more precisely, we compare the subjects' slide endpoint shift means against the means of the posterior predictive shifts per condition in Figure 5. The *Normal* model cannot account for the fact that many subjects adjust the magnitude of their shifts between the different target distances. Especially, for $0.5m$, the *Normal* model strongly overestimates the magnitude of the shifts, especially for high loss conditions. This overestimation is still present at $1.15m$, while the prediction in the $1.8m$ condition is relatively accurate. The addition of subjective losses does not improve the *Normal* model much, as it leads to an underestimation of the shift magnitude in $1.8m$ distance condition.

The predictions of the *Physics* model are more accurate than those of the *Normal* and *Subjective Normal* models, especially in the $0.5m$ condition. It accurately predicts the data of all participants at equal reward-loss ratios (-1 loss condition). However, for larger losses we see that some subjects do not shift as much as predicted, while others are still rather close to the prediction. These individual differences can be accounted for by introducing the subjective value function to the *Physics* model, resulting in accurate predictions in all conditions and subjects.

Individual differences between subjects

The deviations between model predictions and data (Figure 5) show that there are differences between the subjects' strategies. To investigate these individual differences, we show a detailed comparison between the data and the prediction of the *Physics* model for each subject in Figure 6. Some subjects (e.g. 2, 5, 6) are quite close to the shift predicted by the *Physics* model, but others do not shift as much as predicted (e.g. 1, 8, 9). As noted before, this is especially true for conditions with higher losses and at larger distances. These differences also become apparent in the parameters estimated from the *Subjective Physics* model, which can be found in (Table 1), where participants 2, 5, and 6 have the highest values for β_p (posterior means: .36, .65, .48, respectively), while participants 1, 8, and 9 have the lowest values (.03, .03, .02). Furthermore, we also find differences in how sensitive subjects are to increased prospective loss, as for example participant 3 compensates for larger distances but does not distinguish the amount of prospective loss.
Additionally, we conducted a model comparison on an individual subject level. For 6 out of 9 subjects, we find the same pattern as described in the group level model comparison. For the others, differences are not as clear or the pattern

Table 1: Posterior subjective loss parameters β_p for individual subjects, estimated using the *Subjective Physics* model.

Subject	1	2	3	4	5	6	7	8	9
mean ± std	.03 ± .03	.36 ± .08	.36 ± .08	.06 ± .05	.68 ± .09	.48 ± .09	.30 ± .08	.03 ± .02	.02 ± .02

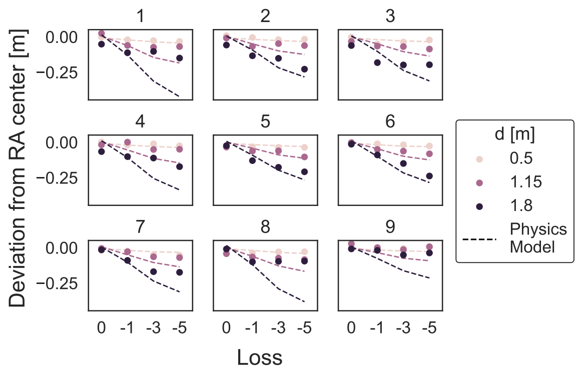


Figure 6: Shifts from the center of the *Reward Area (RA)* compared with the posterior predictive means of the *Physics Model*. Each point in the plot represents the mean shift for one subject.

is changed. But, the *Subjective Physics* model performs best for every subject.

Discussion

In this paper, we investigated whether people's visuomotor actions when sliding pucks at targets for monetary rewards take Newtonian physics into account. Specifically, the physics of sliding pucks makes the variability of the slide endpoint depend on the distance of the target. Accordingly, if people took the physics into account in their puck slides, they should shift their endpoints more at larger distances to avoid hitting the loss region because of the larger variability. We tested this prediction by building Bayesian generative actor models. A model with knowledge of this physical relationship accounts for the data better than an alternative, physics-unaware model with position-independent Gaussian variability. This is consistent with the finding that people can account for artificially increased motor noise in reaching movements (Trommershäuser et al., 2005). Note, however, that in the original study by Trommershäuser et al. (2005), the experimental design was such that the variability due to motor control led to an approximately Gaussian distribution around an aim point. In our task, instead, the variability is better described by a log-normal distribution combined with the physical dynamics of the puck sliding task, because of the signal-dependent motor noise playing out in the dimension of the movement direction. Here, we show that people can adapt to this increased variability.

However, as previous studies have observed (Adkins et al., 2022; Trommershäuser et al., 2005), subjects deviated from the normative reward-maximizing ideal when losses were high relative to gains. We accounted for this by extending the models to include a subjective loss function, which has been successful at describing subjective utilities in economic decision-making tasks (Tversky & Kahneman, 1992; Wu et al., 2009). While the subjective loss versions of the models explained the data better than their counterparts with veridical losses, we nevertheless found that all models including physics performed better than all physics-unaware models. While the subjective loss parameters estimated using the *Subjective Physics* model were able to account for the subjects' behavioral sensitivity to losses, the specific values for some of the participants are lower than what is commonly reported in the economic decision-making literature (Kahneman et al., 1982; Abdellaoui, 2000). We are therefore cautious in attributing the observed deviations from the *Physics* model exclusively to subjective losses, and think that further research on the reasons for these deviations is necessary.

Intuitive physics has mostly been investigated in the context of physical reasoning, e.g. when making judgments about trajectories (McCloskey & Caramazza, 1980), object masses (Sanborn et al., 2013), liquid dynamics (Bates et al., 2015), or the stability of object configurations (Battaglia et al., 2013). Recent work has suggested that people also use intuitive physics during actual interactions with objects in naturalistic tasks (Bramley, Gerstenberg, Tenenbaum, & Gureckis, 2018; Neupärtl et al., 2021). Here, we have combined interaction with objects in a naturalistic setting with a task with explicit monetary rewards. We thereby extend the result that people take their motor variability into account when pointing their finger at targets on a screen (Trommershäuser et al., 2003) to a naturalistic physical interaction task. This task requires subjects to include intuitive physics, which has usually been regarded as a higher cognitive process, in their motor planning. Taken together, these results suggest that sensorimotor behavior, intuitive physical reasoning, and economic decision-making might not be fundamentally distinct domains, but instead rely on common cognitive processes.

Further research should consider intuitive physics in the context of motor planning, as this intersection is a good opportunity to investigate the interplay of different cognitive abilities. We find that individuals show considerable differences in their strategies, which opens up ample room for further empirical and computational investigations. To this end, we see methods for inverse modeling, that allow inference over the internal, cognitive parameters in sensorimotor decisions under risk as a particularly fruitful avenue, as they reconcile normative and descriptive models of behavior (Schultheis, Straub, & Rothkopf, 2021).

Acknowledgments

This research was supported by 'The Adaptive Mind,' funded by the Excellence Program of the Hessian Ministry of Higher Education, Science, Research and Art. We additionally acknowledge support by the European Research Council (ERC; Consolidator Award 'ACTOR'-project number ERC-CoG-101045783).

References

Abdellaoui, M. (2000). Parameter-free elicitation of utility and probability weighting functions. *Management science*, *46*(11), 1497–1512.

Adkins, T., Lewis, R., & Lee, T. (2022). Heuristics contribute to sensorimotor decision-making under risk. *Psychonomic Bulletin & Review*, 1–14.

Bates, C. J., Yildirim, I., Tenenbaum, J. B., & Battaglia, P. W. (2015). Humans predict liquid dynamics using probabilistic simulation. *Cognitive Science Society*, 172–177.

Battaglia, P. W., Hamrick, J. B., & Tenenbaum, J. B. (2013). Simulation as an engine of physical scene understanding. *Proceedings of the National Academy of Sciences*, *110*(45), 18327–18332.

Bramley, N. R., Gerstenberg, T., Tenenbaum, J. B., & Gureckis, T. M. (2018). Intuitive experimentation in the physical world. *Cognitive psychology*, *105*, 9–38.

Capretto, T., Piho, C., Kumar, R., Westfall, J., Yarkoni, T., & Martin, O. A. (2022). Bambi: A simple interface for fitting bayesian linear models in python. *Journal of Statistical Software*, *103*(15), 1–29.

Ernst, M. O., & Banks, M. S. (2002). Humans integrate visual and haptic information in a statistically optimal fashion. *Nature*, *415*(6870), 429–433.

Gilden, D. L., & Proffitt, D. R. (1994). Heuristic judgment of mass ratio in two-body collisions. *Perception & Psychophysics*, *56*, 708–720.

Harris, C. M., & Wolpert, D. M. (1998). Signal-dependent noise determines motor planning. *Nature*, *394*(6695), 780–784.

Kahneman, D., Slovic, S. P., Slovic, P., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge university press.

Kaiser, M. K., Jonides, J., & Alexander, J. (1986). Intuitive reasoning about abstract and familiar physics problems. *Memory & Cognition*, *14*(4), 308–312.

Kaiser, M. K., Proffitt, D. R., Whelan, S. M., & Hecht, H. (1992). Influence of Animation on Dynamical Judgments. Journal of Experimental Psychology:. *Human Perception and Performance*, *18*(3), 669–690.

Körding, K. P., & Wolpert, D. M. (2004). Bayesian integration in sensorimotor learning. *Nature*, *427*(6971), 244–247.

Kourouxous, T., & Bauer, T. (2019). Violations of dominance in decision-making. *Business Research*, *12*, 209–239.

Kumar, R., Carroll, C., Hartikainen, A., & Martin, O. (2019). Arviz a unified library for exploratory analysis of bayesian models in python. *Journal of Open Source Software*, *4*(33), 1143.

Maloney, L. T., & Mamassian, P. (2009, January). Bayesian decision theory as a model of human visual perception: Testing Bayesian transfer. *Visual Neuroscience*, *26*(1), 147–155.

McCloskey, M., & Caramazza, A. (1980). Curvilinear motion in the absense of external forces: Naive beliefs about the motion of objects. *Science*, *210*, 1139–1141.

Neupärtl, N., Tatai, F., & Rothkopf, C. A. (2020). Intuitive physical reasoning about objects' masses transfers to a visuomotor decision task consistent with newtonian physics. *PLoS Computational Biology*, *16*(10), e1007730.

Neupärtl, N., Tatai, F., & Rothkopf, C. A. (2021). Naturalistic embodied interactions elicit intuitive physical behaviour in accordance with Newtonian physics. *Cognitive Neuropsychology*, *0*(0), 1–15.

Neyedli, H. F., & Welsh, T. N. (2013). Optimal weighting of costs and probabilities in a risky motor decision-making task requires experience. *Journal of experimental psychology: human perception and performance*, *39*(3), 638.

Neyedli, H. F., & Welsh, T. N. (2014). People are better at maximizing expected gain in a manual aiming task with rapidly changing probabilities than with rapidly changing payoffs. *Journal of Neurophysiology*, *111*(5), 1016–1026.

Petzschner, F. H., & Glasauer, S. (2011). Iterative Bayesian estimation as an explanation for range and regression effects: A study on human path integration. *Journal of Neuroscience*, *31*(47), 17220–17229.

Phan, D., Pradhan, N., & Jankowiak, M. (2019). Composable effects for flexible and accelerated probabilistic programming in numpyro. *arXiv preprint arXiv:1912.11554*.

Rahnev, D., & Denison, R. N. (2018). Suboptimality in perceptual decision making. *Behavioral and brain sciences*, *41*, e223.

Sanborn, A. N., Mansinghka, V. K., & Griffiths, T. L. (2013). Reconciling intuitive physics and newtonian mechanics for colliding objects. *Psychological Review*, *120*(2), 411–437.

Savage, L. J. (1972). *The foundations of statistics*. Courier Corporation.

Schmidt, R. A., Zelaznik, H., Hawkins, B., Frank, J. S., & Quinn Jr, J. T. (1979). Motor-output variability: a theory for the accuracy of rapid motor acts. *Psychological review*, *86*(5), 415.

Schultheis, M., Straub, D., & Rothkopf, C. A. (2021). Inverse optimal control adapted to the noise characteristics of the human sensorimotor system. *Advances in Neural Information Processing Systems*, *34*, 9429–9442.

Smith, K. A., Battaglia, P. W., & Vul, E. (2018). Different Physical Intuitions Exist Between Tasks, Not Domains. *Computational Brain & Behavior*, *1*(2), 101–118.

Todd, J. T., & Warren, W. H. (1982). Visual perception of relative mass in dynamic events. *Perception*, *11*(3), 325–335.

Trommershäuser, J., Gepshtein, S., Maloney, L. T., Landy,

M. S., & Banks, M. S. (2005). Optimal compensation for changes in task-relevant movement variability. *Journal of Neuroscience*, *25*(31), 7169–7178.

Trommershäuser, J., Maloney, L. T., & Landy, M. S. (2008). Decision making, movement planning and statistical decision theory. *Trends in cognitive sciences*, *12*(8), 291–297.

Trommershäuser, J., Maloney, L. T., & Landy, M. S. (2003). Statistical decision theory and the selection of rapid, goal-directed movements. *J. Opt. Soc. Am. A*, *20*(7), 1419–1433.

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

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*(5), 1413–1432.

Von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior.* Princeton, NJ, US: Princeton University Press.

Wu, S.-W., Delgado, M. R., & Maloney, L. T. (2009). Economic decision-making compared with an equivalent motor task. *Proceedings of the National Academy of Sciences*, *106*(15), 6088–6093.