Physical reasoning during motor learning aids people in transferring mass, but not motor control mappings

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Abstract

When people interact with objects, they show incredible flexibility in learning novel motor control mappings or adapting their known control mappings to variables like object mass. Such motor learning can benefit from intuitive physical reasoning, as novel contexts of object interaction could be a new combination of a previously experienced control mapping with a different object with known mass. In this work, we present a novel object interaction paradigm in which subjects learned to slide pucks at targets by releasing kinetic energy from a compressed spring in a computer game. Participants needed to learn how their motor actions related to the final positions of the puck, while also adapting to the mass of different pucks. With a Bayesian regression model, we inferred participants' beliefs about object mass and control mappings, and show that they could transfer information about previously experienced puck mass but not the motor mappings of the springs.

Keywords: intuitive physics; sensorimotor learning; transfer learning; function learning

Introduction

Almost every day, people interact with objects, tools, and devices they have never interacted with before. Oftentimes, they are remarkably flexible and fast at learning how to manipulate these objects. One reason for this might be that they have encountered similar situations in the past and can now transfer or combine knowledge from their experience. For example, people might know how to play shuffleboard by sliding pucks with their hands, but not yet know how to play a similar game in a pinball machine. Some parts of the task, such as the friction and knowledge about puck mass might transfer, but other properties, such as the controls of the automaton need to be learned from experience. Quick and flexible learning in such a task requires a combination of motor refinement, memory and physical reasoning (Tsay, Kim, et al., 2024).

Motor learning has often been studied in adaptation paradigms such as reaching under a constant force field (Heald, Lengyel, & Wolpert, 2021) or reaching with a rotation or translation of the visual field (Braun, Aertsen, Wolpert, & Mehring, 2009; Helmholtz, 1924; Taylor, Krakauer, & Ivry, 2014). Human learning in these experiments is usually modeled with error-based learning (Wolpert, Diedrichsen, & Flanagan, 2011). In many cases, this means a sequential approximation of a target value based on the visual movement errors (Tsay, Kim, et al., 2024), e.g., approximating the visuomotor translation or rotation. Classically, this learning mechanism has been regarded as an implicit process, with the cerebellum playing a major role in implementing adaptation in the brain (Marr, 1969; Sokolov, Miall, & Ivry, 2017).

Error-based learning is similar to temporal difference learning algorithms, which have been impactful in explaining mechanisms in human reinforcement learning (Wilson & Collins, n.d.). There, instead of motor perturbations, agents learn to approximate the expected value of actions based on rewards in the task. In both cases, a target value is approximated by computing a sequential average weighting recent experience with a learning rate. These implicit learning mechanisms have been successful in explaining many behavioral phenomena, but at the same time cannot account for the full complexity and flexibility of human motor learning in naturalistic tasks, as such tasks might require reasoning (Tsay, Kim, et al., 2024), more specifically intuitive physical reasoning (Neupärtl, Tatai, & Rothkopf, 2020), model-based learning (Daw, Gershman, Seymour, Dayan, & Dolan, 2011; Haith & Krakauer, 2013), contextual inference (Heald, Lengyel, & Wolpert, 2023), hierarchical abstraction (Eckstein & Collins, 2020) and memory (Eckstein, Summerfield, Daw, & Miller, 2024).

Sensory motor control strongly benefits from having an internal model of the task (Wolpert, Ghahramani, & Jordan, 1995). This also extends to object interaction like sliding pucks in shuffleboard, as it has been shown that people have good prior intuition in such tasks (Neupärtl, Tatai, & Rothkopf, 2021), and can even apply a correct model of friction when planning actions under risk (Tatai, Straub, & Rothkopf, 2025). But what happens if they encounter this known situation in a novel context? Suppose that people are required to shoot the puck by compressing and releasing a spring instead of manipulating it by hand.

First, people would need to recognize a new context and adapt to it (Heald et al., 2023). However, in the case of a change in control mapping, adaptation might not suffice and require the agent to pick up an entirely new model of the task. This is called structural learning (Braun et al., 2009; Wolpert et al., 2011), as an agent needs to learn how its motor actions, like the amount a spring is compressed, relate to the action outcome, the puck's final position. Very similar to that is the paradigm of function learning (Schulz, Tenenbaum, Duvenaud, Speekenbrink, & Gershman, 2017; Broadbent, FitzGerald, & Broadbent, 1986) only that in this case the inputs and outputs are often explicit numbers or visual displays of functions.

But in the case of switching the control mapping of puck manipulation, learning of input-output mappings might not be the only relevant skill. Aspects like the puck mass might transfer from one context to another, and therefore, intuitive physical reasoning possibly with the use of noisy representations (Sanborn, Mansinghka, & Griffiths, 2013) or simulation (Battaglia, Hamrick, & Tenenbaum, 2013; K. R. Allen, Smith, & Tenenbaum, 2020) could speed up the learning process. Certainly, within one control mapping people can transfer knowledge about mass in sensorimotor control (Davidson & Wolpert, 2004; Neupärtl et al., 2020) and they even have intuitions about novel objects belonging to the same family (Cesanek, Zhang, Ingram, Wolpert, & Flanagan, 2021). However, it is unclear whether such information might also transfer across control mappings.

Here, we investigated whether people are able to transfer knowledge across object control tasks with shared properties. We present a novel object interaction paradigm which combines implicit adaptation and learning of new non-linear motor control mappings, with intuitive physical reasoning. In our task, people compressed different types of springs in order to slide pucks at targets. They learned to control different combinations of puck masses and physical spring properties. We systematically varied the order in which participants interacted with combinations of pucks and springs in order to investigate whether people were able to transfer the two properties of puck mass and the spring control between different contexts. We find that people can learn novel mappings of their motor action as they learn how to interact with the different spring. Furthermore, people were able to transfer information about puck mass across different control mappings, i.e., different springs. But, on the contrary to that, they were not able to transfer their knowledge about springs to novel new pucks. This hints at a difference between learned models of physics like those of the springs and aspects of physics like mass people have ample experience with.

Method

Participants

We recruited 16 participants over Prolific. Participants were required to be located in the UK or USA and to meet technical criteria, including using a desktop device with a monitor larger than 1500×800 pixels and a keyboard as the input device. In addition to the base payment of 12.50 \$ per hour, all participants were awarded a bonus payment of 2.80 to 4.50 \$ proportional to their precision in sliding pucks. The experiment was approved by the Ethics Committee of the local university, and all participants gave informed consent.

Task

In our experiment, participants slid pucks at targets by releasing the energy stored in a compressed spring (see Fig. 1a). The amount the spring was compressed, i.e., the length of displacement, increased linearly with the duration they pressed the space button. If a spring is compressed, it stores elastic energy, which at its release at lifting the hand off the space button in our experiment, is converted into kinematic energy of the puck. Then, the puck slides across the surface towards the target and, slowed by friction, it stops moving at its final position. In our task, press time x of the space button and the final puck position y are related as follows:

$$f(x) = y = \frac{1}{m} \cdot x^k, \quad (1)$$

whereby $k > 0$ describes the characteristics of the spring and $m > 0$ the mass of the puck. This functional relationship can be derived from the conservation of energy between elastic energy stored in the compressed spring and the kinetic energy of the puck, combined with the quadratic properties of friction, modeled as velocity with constant deceleration.

While for classic springs the force required for compression scales linearly with the distance it is compressed, there exist many other spring characteristics, as for example modern compound bows or shock absorbers in cars. Because of a pulley system, compound bows require less force to hold the bow string after the string surpasses a certain amount of stretch, which enables more precise aim. Car shock absorbers, on the other hand, must effectively handle both small bumps responsively and large impacts stiffly, requiring a non-linear force response. In our experiment, participants are required to learn 3 different spring characteristics (see Fig. 1b), as press duration always causes the same amount of compression, but depending on the spring characteristics, the amount of energy stored varies. Learning different spring characteristics can be seen as new motor contexts. Additionally to the different springs, people handled 3 pucks with different masses, resulting in 9 possible contexts of spring-puck combinations. Note, however, that these contexts shared features, as some parts like the surface friction remained constant, and a particular puck and spring could be encountered in multiple contexts. Therefore, a participant could be in a context where they already knew the puck and the spring from separate contexts, but needed to combine the prior knowledge over both in a novel context.

Procedure

We used 3 puck masses ($m_1 = 0.45\,\text{kg}$, $m_2 = 0.3\,\text{kg}$ $m_3 = 0.6\,\text{kg}$) cued to the subject by the puck size and a colored symbol, and 3 spring characteristics ($k_1 = 1$, $k_2 = 2$, $k_3 = 0.5$) cued to the subjects by a colored texture (see Fig. 1c). This resulted in 9 possible spring and puck combinations, i.e., 9 functional relationships of button press time and final puck location (see Fig. 1d). At the beginning of the experiment, participants were shown all pucks and springs and were informed that they would encounter each combination once in the experiment. Each combination was completed for a block of 50 trials. All blocks started with a depiction of the puck and spring, and the background of surrounding the sliding surface changed to the color of the spring as a further cue.

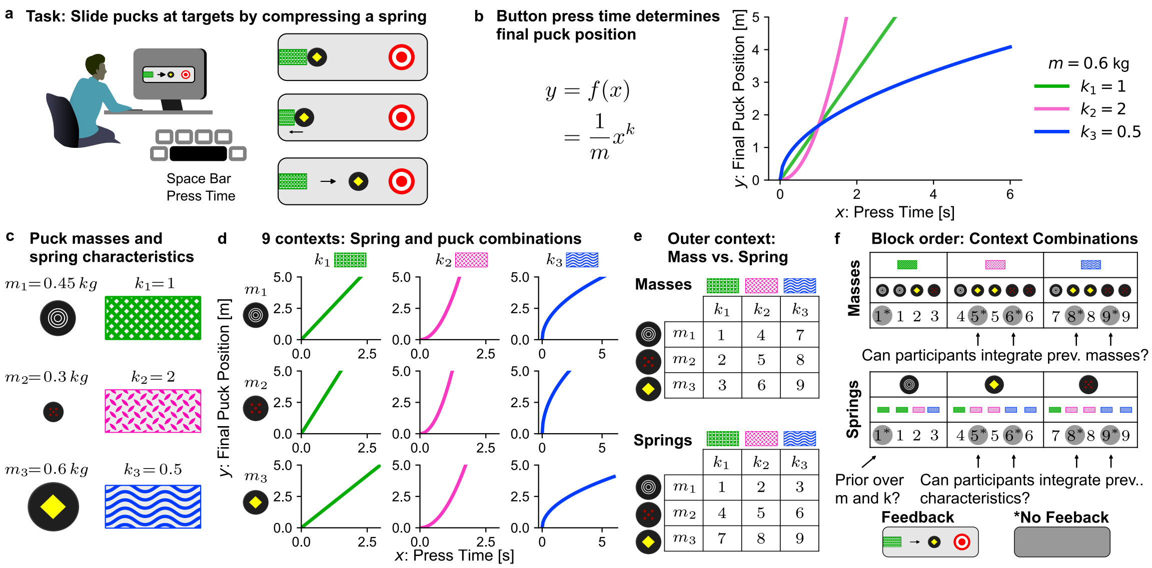

Figure 1: Task overview. a) 16 participants learned to slide pucks at targets in a computer game. b) Button press time x controlled the amount of spring compression. Spring characteristics, puck masses and surface friction determined the final puck position y as a function of x. Target distance was randomly sampled in the range $[0.2, 5]$. c) The puck masses and spring characteristics used in our experiment, and d) the 9 resulting contexts, i.e., functions of x and y people had to learn. e) Contexts were completed in blocks of 50 trials. The masses condition investigates participants' ability to extrapolate over masses, whereas the springs condition investigates participants' ability to extrapolate over springs. Therefore, for three consecutive blocks we defined an outer context and kept mass or spring constant depending on the condition. f) Some blocks were preceded by 25 trials without visual feedback of the puck's trajectory and end position to evaluate prior beliefs over the function relationship and extrapolation to context combinations to investigate whether people could integrate previously experienced masses and spring characteristics.

Note that the sliding surface stayed the same color to ensure the impression of unchanged friction. In each trial, the target distance was randomly sampled from a uniform distribution in the range 0.2 m – 5.0 m and displayed at a scale of 200 px per meter. The participants were instructed to get the puck as close to the target as possible. Additionally, at the end of each trial, they received a score of their precision determined by the following function score $= 10 - 4|y_i - d_i|$, where y_i is the final puck position and d_i the target distance in trial i. The sum of this score was translated to a final bonus payment in the task (10 points $\rightarrow$ 1 cent), about which they were informed before the beginning of the experiment.

Participants were assigned to one of two conditions: *masses* or *springs* (see Fig. 1e). In each condition, either masses or springs formed the outer context, which changed every three blocks, while the other feature formed the inner context, which changed on every block. (see Fig. 1f). This design allowed us to test whether participants used mental task models that inferred masses m and spring characteristics k separately from each other, allowing them to extrapolate to never-seen contexts that presented previous masses and spring characteristics in new combinations. In the *masses* condition, this means that participants learn how to play with one spring characteristic and all three pucks before switching to a new spring, to test whether people could transfer their knowledge about mass to another spring. In the *springs* condition, people experienced all springs with one puck, and then had to transfer the knowledge about springs to a new puck mass.

To test peoples' prior intuitions about the task and their transfer capabilities, we included 25 *no feedback* trials at the beginning of some blocks. In those trials, participants saw a gray screen after releasing the space button instead of receiving visual feedback about the puck's trajectory and final position. These trials were also counted towards the total score of the subjects, but the total score of the no feedback trials was only revealed after completing all of them. This was done in order to incentivize subjects for optimal performance in transferring information, without giving them the opportunity to learn the novel context combination. In total, 5 blocks started without feedback: block 1 investigated peoples' prior intuitions, blocks $5, 6, 8, 9$ featured combinations of already known inner and outer contexts and, therefore, allowed for testing transfer.

Modeling

People produced button press times x_i in trial i subject to signal dependent noise (Harris & Wolpert, 1998), which we model with a log normal distribution $\log x_i \sim \text{Normal}(\log a_i, \sigma_x)$, where a_i is the intended button press time of the agent and σ_x the agent's motor noise. Consider that press times and final puck positions are related by Equation

1, which in log space becomes a linear function

$$\log y_i = \log(f(x_i)) = k \log x_i - \log m. \quad (2)$$

Consider now that the agent's task can be framed as learning the parameters m and k given the intended press times $A = \{a_1, ..., a_i\}$ and the final puck position $Y = \{y_1, ..., y_i\}$. We assume that after a certain number of trials, participants have formed a fixed representation of the task. With this assumption, we can infer their beliefs about masses and spring characteristics.

As researchers, we would like to estimate which beliefs m' and k' led to a participant's press time x_i in that trial, given the target distance d_i. If we assume that participants have learned an internal model of the task, the action they should choose is $a_i = f^{-1}(d_i; m', k')$, if we consider that they would like to minimize the absolute error of their actions. Therefore, in order for us to infer participants' beliefs, we get the following regression problem:

$$\log x_i \sim \text{Normal}(\log f^{-1}(d_i; m', k'), \sigma_x). \quad (3)$$

As this problem is formulated in log space and the function is linear there (see Equation 2), this becomes a standard linear regression problem, where the slope of the function represents the participants' belief about the spring characteristics, and the offset the participants' belief about mass.

Results

Participants can learn the different contexts

The first question that arises in our paradigm is whether people are at all able to learn the different mappings between button press time and final puck position. For this purpose, we took the last 25 trials per block across all participants and fitted a standard Bayesian linear regression in log space (see Equation 3) in order to estimate the participant's beliefs about the spring characteristics and puck masses. We only included the last 25 trials, as we want to show that participants can arrive at the correct functional relationship. The model included a separate parameter for mass and spring characteristics for each block and condition, but the noise was shared across blocks and conditions. To quantify model fits, we estimated the mean absolute error in button press time across the target distances used in the experiment from 0.2 to $5m$ between the ground truth functional relationship and the model fit: $\overline{\Delta_x} = \frac{1}{N}\sum_Y |f^{-1}(y; m, k) - f^{-1}(y; \overline{m'}, \overline{k'})|$, where m, k and $\overline{m'}, \overline{k'}$ are the true underlying values and their estimates, and Y an evenly spaced set of target distances in the range of $[0m, 5m]$ with $|Y| = 10^5$.

The results of the linear fit are shown in Fig. 2a and b. In the following, we report means and 95% confidence intervals of the parameter estimates. Before receiving any visual feedback participants had a close to linear belief over the mapping of button press time and final puck position in block 1* (*masses*: $\overline{k} = 1.25$ $[1.12, 1.38]$, *springs*: $\overline{k} = 1.18$ $[1.06, 1.30]$). This enabled them to learn the first spring $k_1 = 1$ (*masses*: $\overline{k} = 1.118$ $[1.04, 1.30]$, *springs*: $\overline{k} = 1.12$ $[1.01, 1.12]$) as well as the mass $m_1 = 0.45kg$ of the first puck (*masses*: $\overline{m} = 0.393$ $[0.36, 1.42]$, *springs*: $\overline{k} = 0.42$ $[0.39, 0.45]$) yielding a close functional fit $\overline{\Delta_x} = 0.1s$, *springs*: $\overline{\Delta_x} = 0.17s$).

In the *masses* condition, participants played with one spring over three consecutive blocks. First, the played with a linear spring $k_1 = 1$, followed by a quadratic spring $k_2 = 2$. For the quadratic relationship small increments in press time have little effect of puck displacement when overall press times are short, but they have large effects when overall press times are large. Already in block 4, when they first encountered the quadratic spring $k_2 = 2$, participants have picked up on the fact that the exponent was larger than one $\overline{k} = 1.64$ $[1.41, 1.85]$ (see also Fig. 2a, first plot in the second row). Over the next two blocks, this estimate is also good (block 5: $\overline{k} = 1.83$ $[1.56, 2.11]$, block 6: $\overline{k} = 1.79$ $[1.48, 2.11]$). On the other hand, in the *springs* condition, at the first encounter in block 2, participants are able to estimate $k_2 = 2$ ($\overline{k} = 1.96$ $[1.62, 2.32]$), whereas the third time around in block 8 they are less precise ($\overline{k} = 1.24$ $[1.14, 1.42]$), indicating that the switching between springs might have an impact on performance. Considering, however, that the participants have learned the masses well across all blocks in both conditions, the overall functional fits are still quite close to the actual function $\overline{\Delta_x} = 0.2s$.

Next, participants encountered the square root spring $k_3 = 0.5$, with the opposite pattern to the quadratic: small increments of press time have a big effect on puck displacement for short press times, whereas when they are large only big increments in press time have an effect. With this spring participants show more difficulties in learning mapping. Even in the *masses* condition, after playing with the spring three consecutive times, the participants only partly picked up the square root relationship $k_3 = 0.5$ and stayed with a rather linear approximation (block 9: $\overline{k} = 0.84$ $[0.78, 0.91]$). As the performance in the *springs* condition was similar (block 9: $\overline{k} = 0.88$ $[0.81, 0.94]$) this leads to a larger error between model fit and ground truth (*masses:* $\overline{\Delta_x} = 1.38s$, *springs:* $\overline{\Delta_x} = 1.33s$) compared to the quadratic spring. Consider, however, that in contrast to the quadratic relationship with a steep slope, where small deviations in press time could mean a large difference in final puck position, bigger errors do not have as much impact with the square root function because of its shallow slope. Additionally, this error largely stems from undershooting farther targets while still being precise when shooting at closer targets (see Fig. 2a, top figure bottom row, bottom figure right most column).

Participants can transfer information about mass, but not spring characteristics

In order to investigate how well participants were able to transfer their knowledge about spring characteristics and masses, we inserted 4 no-feedback blocks to assess participants' ability to extrapolate to new contexts. Each no-feedback block combined a puck of a mass that had been encountered before with a spring characteristic that had been

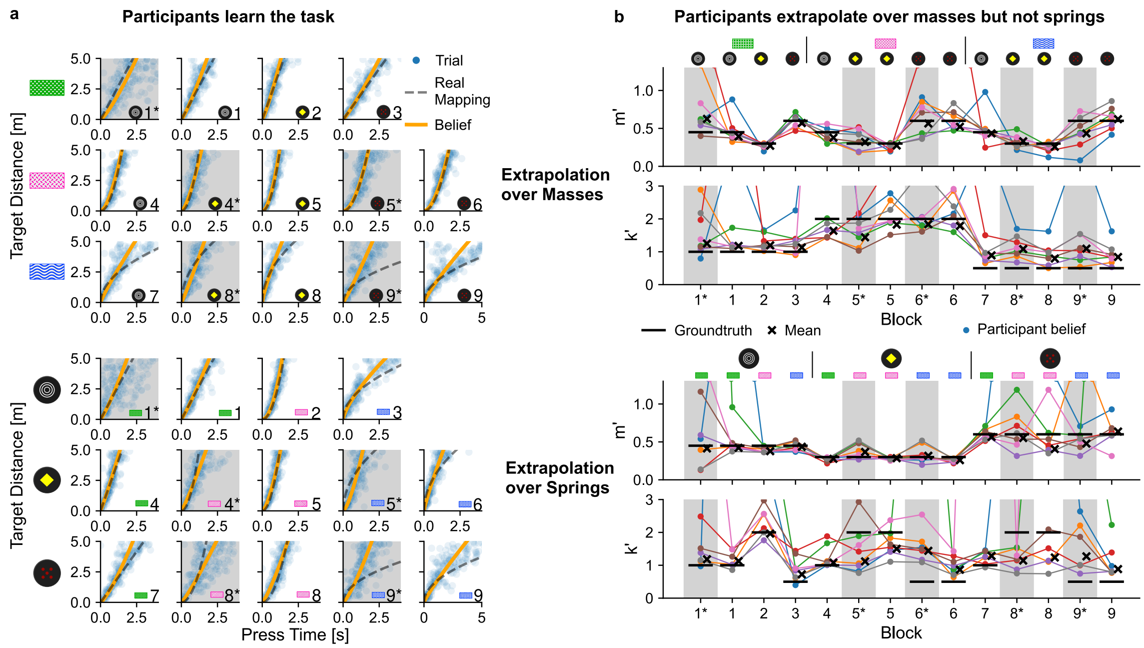

Figure 2: Main results of the task: a) button press time, compared to the target distance in the last 25 trials across all participants per block (dots are one trial). The orange lines show the fit of a linear regression in log space estimating the subjects beliefs about mass and spring characteristics. Participants adapted to the ground truth functional relationships (dashed line), but showed difficulties with the exact functional form of the square root springs. (bottom row in masses condition; fourth/fifth column in springs condition) b) The mean estimates of mass m' and spring characteristics k' of the linear fit across all participants (black) and for each individual separately (colored). Participants were able to extrapolate information about mass, but not the springs, in the no-feedback blocks (gray background).

encountered before, but never in this combination. If participants' had formed accurate representations of these masses and spring characteristics, they might be able to plug them into their mental physics model and perform correctly from the start in no-feedback blocks. To quantify this, we estimated how their belief changed in the no-feedback blocks with respect to the previous block. For this purpose we calculated the differences of mean beliefs over mass $\Delta_{\overline{m'}}$ and spring characteristics $\Delta_{\overline{k'}}$ and their 95% confidence intervals.

In the *masses* condition when participants switch from the first puck $m_1 = 0.45kg$ to the second $m_2 = 0.3kg$, we would expect that subjects decrease their estimate about the puck mass $m_2 - m_1 = -0.15$. For both transitions, we find this decrease: ($4 \rightarrow 5^*$: $\Delta_{\overline{m'}} = -0.05$ $[-0.11, 0.00]$, $7 \rightarrow 8^*$: $\Delta_{m'} = -0.10$ $[-0.14, 0.07]$). We find that the reverse of this holds for the transition from $m_2 = 0.3kg$ to $m_3 = 0.6kg$ ($m_3 - m2 = 0.3kg$: $5 \rightarrow 6^*$: $\Delta_{\overline{m'}=0.29}$ $[0.21, 0.38]$, $8 \rightarrow 9^*$: $\Delta_{\overline{m'}} = 0.17[0.14, 0.21]$. This shows that subjects are able to understand that the next puck is lighter or heavier. While the participants adjust their estimates for masses, it seems that for the quadratic spring people can hold their belief of the spring characteristics relatively constant ($4 \rightarrow 5^*$: $\Delta_{\overline{k'}} = -0.19$ $[-0.50, 0.09]$, $5 \rightarrow 6^*$: $\Delta_{\overline{k'}} = 0.01$ $[-0.44, 0.46]$), whereas for the square root they increase their belief towards a more steep functional relationship ($7 \rightarrow 8^*$: $\Delta_{\overline{k'}} = 0.19$ $[0.06, 0.33]$, $8 \rightarrow 9^*$: $\Delta_{\overline{k'}} = 0.30$ $[0.18, 0.43]$).

On the contrary to the puck masses, people were not able to transfer information about the spring characteristics in the *springs* condition. When switching from the linear $k_1 = 1$ to the quadratic spring $k_2 = 2$, one would expect a big increase of the mean belief over the spring characteristics $\overline{k'}$ ($k_2 - k_1 = 1$). But we do not find this in the data, as the belief changes only little or not at all ($4 \rightarrow 5^*$: $\Delta_{\overline{k'}} = 0.03[-0.11, 0.18]$, $7 \rightarrow 8^*$: $\Delta_{\overline{k'}} = -0.14$ $[-0.33, 0.04]$). A change in belief should be even more apparent in the switch from the quadratic spring $k_2 = 2$ to the square root spring $k_3 = 0.5$, as there should be a large difference in how participants treat slides to targets which are farther away ($k_3 - k_2 = -1.5$). Again, this is not the case ($5 \rightarrow 6^*$: $\Delta_{\overline{k'}} = -0.06$ $[-0.33, 0.19]$, $8 \rightarrow 9^*$: $\Delta_{\overline{k'}} = 0.03[-0.18, 0.24]$). In the *springs* condition, participants play with the same puck three times in a row. Therefore, participants' belief about the puck mass should not change between blocks and stay relatively constant. This is also what we find in the data, as changes are either rather small ($4 \rightarrow 5^*$: $\Delta_{\overline{m'}} = 0.09$ $[0.05, 0.13]$, $8 \rightarrow 9^*$: $\Delta_{\overline{m'}} = 0.07$ $[0.02, 0.12]$) or not there at all ($5 \rightarrow 6^*$: $\Delta_{\overline{m'}} 0.03 =$ $[-0.02, 0.08]$, $7 \rightarrow 8^*$: $\Delta_{\overline{m'}} - 0.01 = [-0.08, 0.05]$). This gives another indication that participants have a good understanding of mass in our task.

Individual Differences

Looking at the mean absolute error of final puck position across all blocks excluding the no-feedback trials, we find considerate differences in performance among participants, as the worst participant shows a mean absolute deviation of pucks to target center $\overline{\Delta_y} = 1.27$ and the best participant $\overline{\Delta_y} = 0.52$. Possible reasons for this could be that some subjects learned the functional relationships better than others, or that they have different motor variabilities. To estimate how well participants learned the functional relationships individually, we fitted a separate linear regression model (see Equation 3) to the data of each participant. Some participants were clearly better able in learning the functional relationships than others (see Fig. 2b). Some subjects were even able to learn the square root relationship, indicating that learning this control mapping, is possible but not easy. A further source of error, might the variability of press times σ_x, which is partly influenced by the individuals' motor variability. We find that σ_x lies within the range of 0.24 and 0.65 across participants, indicating considerable difference in performance. Consider, however, that this could also be, because these subject were still learning during the trials, i.e., that their belief of the functional relationship still changed.

In blocks with the square root spring $k_3 = 0.5$, which came rather towards the end of the experiment, participants needed to press comparatively long for far targets. However, for some subject we find the opposite i.e. considerable higher beliefs k' (see Fig. 2b), indicating relatively short presses for long target distances. While this could be due to the participants not being able to learn the task, it could also be due to fatigue and wanting to decrease the duration of the experiment by pressing quickly.

Discussion

In this paper, we investigated whether people can use physical reasoning to combine knowledge about object mass with knowledge about different motor mappings of object interaction. In a puck sliding game, people learned how to compress different types of springs in order to slide pucks at targets. As the pucks could have different masses, people could encounter several combinations of springs and pucks during the experiment. When people encounter a new combination of a spring and puck, where they have experienced the puck's mass and the spring's characteristics separately before, correct physical reasoning would enable them to extrapolate how these two combine within a novel context. Using a Bayesian regression model to infer participants' beliefs about mass and spring characteristics, we found that people extrapolated information about mass to new motor mappings of interacting with objects. However, at the same time, we found that people have difficulties with extrapolating motor mappings of object interaction to novel objects.

Our results are in accordance with past findings that have shown that people can reason about object masses (Sanborn et al., 2013) and even integrate this reasoning within motor control (Neupärtl et al., 2020; Davidson & Wolpert, 2004). We extend these findings in that reasoning about masses does not only work within one control mapping, but also across different motor mappings, like the springs used in our experiment. But our results also show that this does not extend to the extrapolation of motor mappings. Although participants except for the square root relationship are able to learn the characteristics of the springs within a block, it was difficult for them to extrapolate these properties to a novel puck. Possibly this could be improved with more learning trials, or with an alternative block structure more beneficial for structural learning, interleaving different motor mappings with small trial numbers structural (Braun et al., 2009). Another reason for this could be that studies conducted online can be more noisy in comparison to lab studies (Thomas et al., 2024), although they offer the advantage of opening the research to a more diverse study group (Tsay, Asmerian, et al., 2024). Additionally, one needs to consider that embodied motor interaction elicit correct motor mappings (Neupärtl et al., 2021), whereas in our case spring characteristics need to be learned with error learning from visual feedback without any embodied force feedback.

This shows the complexities of physical object interaction, as they require a combination of adaptation, learning of a novel model and physical reasoning (Tsay, Kim, et al., 2024). However, it seems that there is a difference between tasks requiring models of physics, as in our experiment people showed a good explicit understanding of mass but not the springs. People are in contact with object masses on a daily basis, and people are therefore adjusted to cues like object size that we used in our experiment. However, the springs were only cued by color and symbols require the participants to learn a novel model of how their motor actions are connected to 30 outcomes in the world. Although physical reasoning is an important aspect of human object interaction (Neupärtl et al., 2020; K. R. Allen et al., 2020), it requires a correct model of the physics in question. Our results show, that people are able to learn novel physical relationships based on their errors, however, they were unable to generalize the functional relationship. Learned models of physics might, therefore, be a further limit to intuitive physical reasoning (Ludwin-Peery, Bramley, Davis, & Gureckis, 2021).

Taken together, even seemingly simple object interactions might combine different cognitive faculties including motor learning and physical reasoning, as we have shown that people can transfer information about mass to novel motor mappings. Studying these within immersive games (K. Allen et al., 2024), seems like a fruitful way of shedding light on the interaction of these processes. The present paradigm offers many further opportunities to study motor learning not only in the combination with physical reasoning, but also in interaction with other fields of study in cognitive science like function learning (Schulz et al., 2017), meta learning (Binz et al., 2024), or economic decision-making (Tatai et al., 2025).

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