Using physics simulations to predict children's and adults' preference for physical interactions

Anonymous CogSci submission

Abstract

Curiosity is a fundamental driver of human behavior, and yet because of its open-ended nature and the wide variety of behaviors it inspires in different contexts, it is remarkably difficult to study in a laboratory context. A promising approach to developing and testing theories of curiosity is to instantiate them in artificial agents that are able to act and explore in a simulated environment, and then compare the behavior of these agents to humans exploring the same stimuli. Here we propose a new experimental paradigm for examining children's–and AI agents'–curiosity about objects' physical interactions by letting them choose which object to target when dropping a given object. We compared adults' (N=155) and children's choices (N=66; 3-7 year-olds) and found that adults show a strong preference for choices affording a containment relation, a preference that is also shown by children. Adults alone also make choices consistent with achieving support relations. We contextualize our results using heuristic models based on physics simulations of the same scenarios judged by participants.

Keywords: curiosity; novel objects; object interactions; intuitive physics

Introduction

Curiosity is a hallmark aspect of human intelligence. From infants exploring the objects in their environment to scientists exploring the frontiers of our solar system, humans are highly motivated to seek out new knowledge and experiences. However, although such exploratory behavior has long been recognized as a critical component of human learning (James, 1983) and cognitive development (Gopnik, Meltzoff, & Kuhl, 2009; Piaget, 1952), formal theories that explain human curiosity and how it drives exploratory behavior have remained elusive (Kidd & Hayden, 2015). Moreover, extant theories have rarely provided quantitatively precise enough predictions to be directly compared to empirical measurements of curiosity-driven behavior in humans.

The goal of the current paper is to help close this gap by proposing a novel paradigm to advance our theoretical understanding of curiosity, specifically within the domain of physical object interactions (Kubricht, Holyoak, & Lu, 2017). First, we present an empirical investigation of the pattern of actions taken by children and adults in a novel physical exploration task. We then present a set of heuristic models of curiosity based on a variety of metrics of simulated physical interactions (e.g., likelihood of a dropped object coming to rest on a target object), and test the degree to which these features predict children and adults' behaviors in the same task.

We take inspiration from a large body of prior work in developmental psychology investigating the development of knowledge about physical objects, their properties, and how they interact (Baillargeon, 2007; Hespos & VanMarle, 2012; Smith, Jayaraman, Clerkin, & Yu, 2018). Children both spend a remarkably amount of time across exploring how different objects and surfaces interact during naturalistic play (Fenson, Kagan, Kearsley, & Zelazo, 1976) and spend longer time exploring objects that appear to violate physical laws (e.g., an object that appears to pass through a wall; Stahl & Feigenson (2015); Baillargeon (2007)). In other words, children seem to actively learn about physical interactions by intervening on the world and observing the consequences of their actions (Gopnik et al., 2009; Gureckis & Markant, 2012; Needham, 2000). However, relatively little work has examined what types of physical interactions children are most interested in testing, or linked children's actions to formal theories of exploration or of physics learning. Instead, most work that has investigated exploratory behavior in children has done so by examining how they play with relatively complex objects – for example, documenting the number of functions discovered while playing with a novel toy (e.g., Cook, Goodman, & Schulz, 2011; Bonawitz, Schijndel, Friel, & Schulz, 2012; Gweon, Pelton, Konopka, & Schulz, 2014).

We thus developed a novel physical exploration task in which children, adults, or AI agents can choose which series of physical experiments to perform, and then demonstrate how this paradigm can be used to test theories of curiosity about physical interactions. First, we measured people's choices in a novel physical exploration task, in which participants were told that they would drop a given object (e.g., a sphere, a torus; see Figure 1) onto one of two target objects (e.g., a dumbbell, a pentagonal prism; see Figure 2), with the goal of the creating the most interesting physical interaction. We recorded adults' and children's (3-7 years of age) choices for a set of trials in which some of the drop objects could plausibly end up *supported* by one of the target objects, and for a set of trials in which some of the drop objects could end up *contained* by one of the targets – although the other potential targets likely also offered affordances of interest. After examining the consistency of people's preferences, we tested the predictive power of a variety of heuristic models of curiosity that operate on simulations of this task with these same objects in a 3D environment. Our results suggest that using detailed measurement of human action selection and computational models based on simulations of the same tasks promises to lead to more robust and precise theories of human curiosity about the physical world, and how it develops.

Experiment 1: Adults

To investigate the systematicity of people's preferences for physical interactions between objects, we began by studying adults, whom we might expect to be less idiosyncratic and thus more consistent in their choices than children. Our design is motivated by the results of a pilot study conducted in-person in January, 2020, in which we asked adults to select which of a pair of 3D-printed toy blocks (see Figure 1) they would like to drop on a given target object from the set, or vice-versa: on which of a given pair of target objects would they like to drop a given object. In the pilot study (N=15), the pairs of target or drop objects were chosen essentially at random, but were the same for all participants. We were surprised to find consistency in adults' preferences for many of the trials: especially when given a drop object and asked to choose one of two target objects, adults were quite often (75-90%) targeting that object that would either *contain* or *support* the dropped object (i.e., the pipe could contain the cone; the pentagonal prism could support the octahedron). This consistency in their choices is remarkable given that there are many other possible goals that people might choose in order to make something "interesting" happen: they might attempt to make the dropped object roll or bounce far from the target, or rebound in an unexpected direction, but in fact most people settled on attempting support or containment relations. Thus, we set out to examine the development of these preferences, first in a large adult sample in order to have high reliability for later model comparisons, and then in young children.

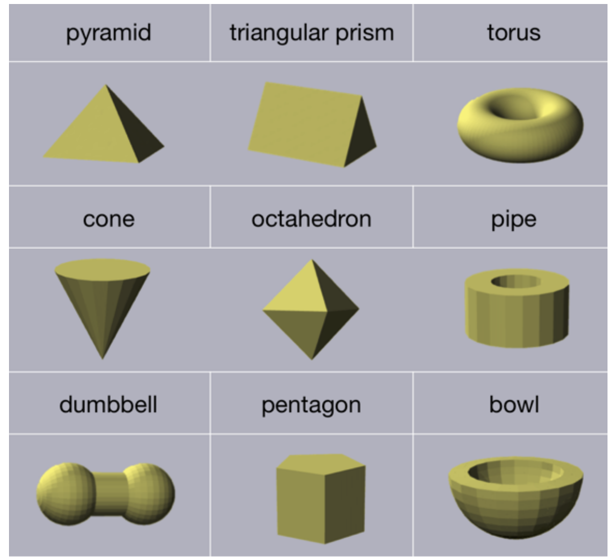

Figure 1: Nine of the 10 3D objects used for dropping and as targets (not pictured: ball).

Method

Participants 200 adults were recruited via Amazon Mechanical Turk and were paid $1 for participating.

Materials Stimuli were images of 3D objects produced using Blender 3D-modeling software. The nine objects, depicted in Figure 1, were bowl, cone, dumbbell, octahedron, pentagon (pentagonal prism), pipe, pyramid, torus, triangular prism, and ball (sphere; not pictured).

Design The experiment consisted of 20 drop trials, completed by each participant in one of four pseudorandom orders. Participants were randomly assigned to each order. Each drop trial displayed an object X that is to be dropped on one of two other objects (Y or Z), as described in the following procedure. In the 20 trials, each of the above 3D objects was used twice as the drop object (X), and appeared four times as potential targets. Instead of randomly sampling the target objects (Y or Z), each trial was designed to allow for one of two goal relations (or affordances): containment, or support. That is, the target objects were chosen so that one of them would be capable of either supporting or containing the dropped object. For example, if asked to drop the cone on either the torus or the octahedron, a containment relation could be achieved between the cone and the torus, but not the octahedron (and support is unlikely due to the small surface area of the octahedron). An example support relation is choosing to drop the pentagonal prism on the (equal diameter) pipe rather than the pyramid. 10 of the 20 trials were designed to afford containment relations, and the other 10 afforded support relations. We refer to the objects affording the designed containment and support relations as *targets*, and the alternative objects as *distractors*. Distractors for each trial were the same for all participants, and were selected to 1) not afford containment/support of the dropped object, and 2) roughly equate the frequency of appearance of all 10 objects.

Procedure Participants were instructed that they would be helping choose which toys to include in a new set of children's blocks in order to make them the most interesting. Participants were then given a practice trial (see Figure 2), in which they were told that they should imagine dropping a given object (the torus) on each of two toys (the dumbbell or the pentagonal prism) in a bin. They were then asked to choose which toy to drop the torus on, and prompted to choose the most interesting or surprising combination. After making their choice on the practice trial, participants were shown a 10-second video recording of 3D-printed plastic toys carrying out their chosen interaction (e.g., if they chose the dumbbell, they would see the torus dropped on the dumbbell). This was done to ensure that they understood the consequences of the choice they made. After the video of the torus drop, participants were given a sequence of 20 more drop trials asking them to choose which toy (X or Y) they would like to drop object Z on. Four catch trials were interspersed among the 20 drop trials, which asked them to indicate which object they had just dropped on the previous trial

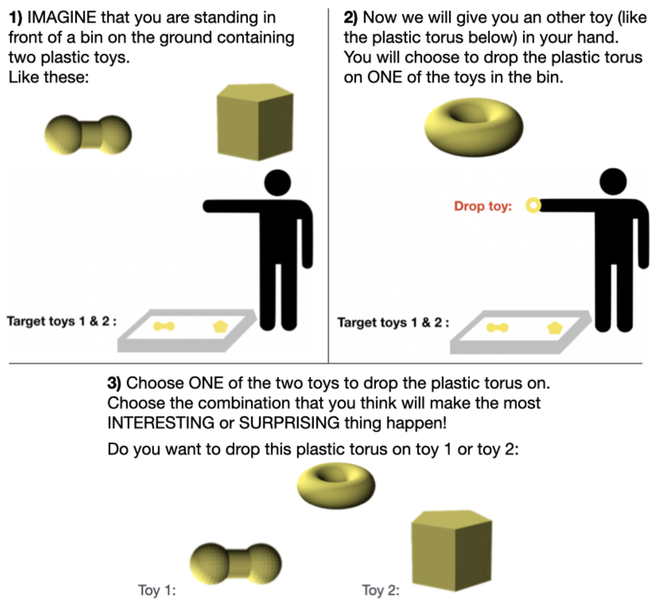

Figure 2: Example of a trial given to adults in Experiment 1.

(3-alternative forced choice). The catch trials were meant to encourage attention to the objects, and participants who were incorrect on two or more of the catch trials were excluded.

Results

We analyzed data from the 155 adults who completed the experiment and answered at least 3 of the 4 catch trials correctly (45 participants were excluded for not meeting this criterion). Averaging each subject's binary responses (1=target relation, 0=alternative) for each trial type revealed a stronger preference for containment relations ($M = 0.87$) than support relations ($M = 0.63$; paired $t(154) = 12.69$, $p < .001$, $d = 1.02$). Table 1 shows the proportion of participants that chose the designed target relation for each of the 20 trials. Based on the binomial distribution, any of the trials on which more than 90 of the 155 participants agree (i.e., >0.59 or <0.41) significantly differ from chance. As can be seen in Table 1, adults participants (*adult* column) significantly preferred the target relation for all 10 of the containment trials, and significantly preferred five targets on the 10 support trials; the other five support trials did not significantly differ from chance, suggesting that many participants found the prospect of dropping on the distractor object at least equally enticing.

Further, these trial effects were quite reliable across participants. We examined the split-half reliability of adults' choices by repeatedly splitting the samples in half and testing the correlation between the halves. Based on 100 random samples, the split-half reliability for adults was $r = 0.95$ (sd=0.02). The split-half reliability of adults' choices on containment trials was $r = 0.85$ (sd=0.07), and on support trials was $r = 0.9$ (sd=0.05).

relation	drop	target	child	adult
contain	bowl	pyramid	0.72	0.96
contain	cone	torus	0.73	0.94
contain	dumbbell	pipe	0.67	0.92
contain	octahedron	pipe	0.58	0.90
contain	pentagon	bowl	0.69	0.88
contain	pipe	cone	0.58	0.88
contain	pyramid	torus	0.71	0.87
contain	sphere	bowl	0.80	0.86
contain	torus	cone	0.67	0.81
contain	trig prism	bowl	0.65	0.71
support	bowl	torus	0.71	0.85
support	cone	trig prism	0.45	0.82
support	dumbbell	pentagon	0.38	0.74
support	octahedron	pentagon	0.45	0.64
support	pentagon	pipe	0.57	0.62
support	pipe	torus	0.60	0.56
support	pyramid	trig prism	0.52	0.55
support	sphere	pipe	0.58	0.54
support	torus	bowl	0.70	0.53
support	trig prism	pentagon	0.62	0.46

Table 1: Children's and adults' target preferences per trial.

Experiment 2: Children

Experiment 1 demonstrated that adults show consistent preferences for dropping objects on target objects that afford containment relations, and to a lesser extent support relations. Experiment 2 investigates whether these strong preferences are present even in young children, recognizing that children may find different types of physical interactions (e.g., rolling, bouncing, unpredictability) of greater interest than adults, or may simply show more idiosyncratic choice patterns.

Method

We adapted the same materials and procedure used in Experiment 1 for use in an online experiment with children, in order to directly compare the results for children and adults.

Participants Participants were 73 children recruited online via outreach through a local nursery school and targeted Facebook ads over the course of 6 months. Participant exclusions were made based on cases where i) the participant did not complete more than half of the study play session or ii) the parent did not consent for video recording of study. After exclusions, results from 66 were analyzed, including 17 3-year-olds, 15 4-year-olds, 16 5-year-olds, 16 6-year-olds, and 2 7-year-olds.

Materials The materials were the same as those used in Experiment 1, except that the trials were adapted for presentation via Zoom in a slide presentation as shown in Figure 3.

Procedure After the parent provided informed consent, children were assigned to one of two pseudorandom trial orders in counterbalanced order. To accompany the practice trial, children were shown 3D-printed instances of the three physical objects held by the researcher, to ensure that children

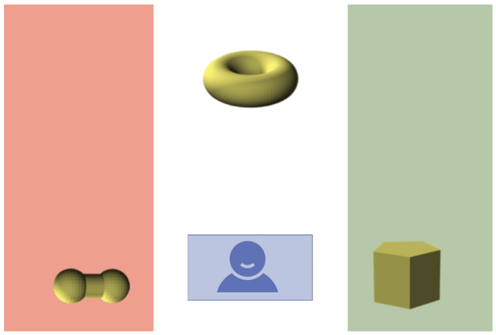

Figure 3: Zoom screen configuration for children in Experiment 2. Parents were asked to place the experimenter's video feed in the bottom center so the experimenter could point up to the drop object and left and right at each target choice.

understood their physicality. Children were asked to verbally select target object Y or Z, and then asked to confirm whether they wanted to select the object on the red or green side of the screen, in order to prevent left/right confusion. The sides on which target objects and colors appeared were counterbalanced across trials.

Results

Similar to adults, averaging each child's binary responses for each trial type revealed a stronger preference for containment relations ($M = 0.68$) than support relations ($M = 0.56$; paired $t(154) = 12.69$, $p < .001$, $d = 1.02$). Unlike adults, however, children did not show a significant preference for choosing the support relation. Figure 4 shows the proportion of participants' choice of the designed target relation broken down by relation type and age group, showing a preference for the designed relations that increased with age and was overall stronger for containment.

We next examined trial-level effects in children. Table 1 shows the proportion of children ("child" column) choosing the designed target relation for each of the 20 trials, alongside the adult choice proportions from Experiment 1. Based on the binomial distribution, any of the trials on which more than 41 of the 66 participants agree (i.e., >0.64 or <0.36) significantly differ (p<.05) from chance. Children significantly preferred the designed relation on eight of the 10 containment trials, while only significantly preferring two of the 10 support relation choices. On the remaining two containment trials and the other eight support trials, children's preferences also did not significantly differ from chance against the designed relation. These item effects were relatively reliable, though noisier than that of adults: the split-half reliability for children's choices was r = 0.61 (sd=0.09). The split-half reliability of children's choices on containment trials was r = 0.32 (sd=0.22), and on support trials was r = 0.64 (sd=0.14).

Comparison of Children's vs. Adults' Preferences

Finally, we compared the trial-level preferences of children and adults. Figure 5 shows adults' (Experiment 1) vs. children's (Experiment 2) choice proportions for the target relations, colored by relation type. (visualizing the same data presented in Table 2). If they corresponded perfectly, they would fall along the dotted $y = x$ line, but children's preferences mostly fall short of that line, lying closer to the chance line ($y = 0.5$). At a glance, these results seem to support the hypothesis that "children are noisy adults" in this task and suggests some consistency in the trial-level effects across development. This consistency also confers additional motivation for attempting to understand what drives human interest in particular physical interactions in this task through computational models.

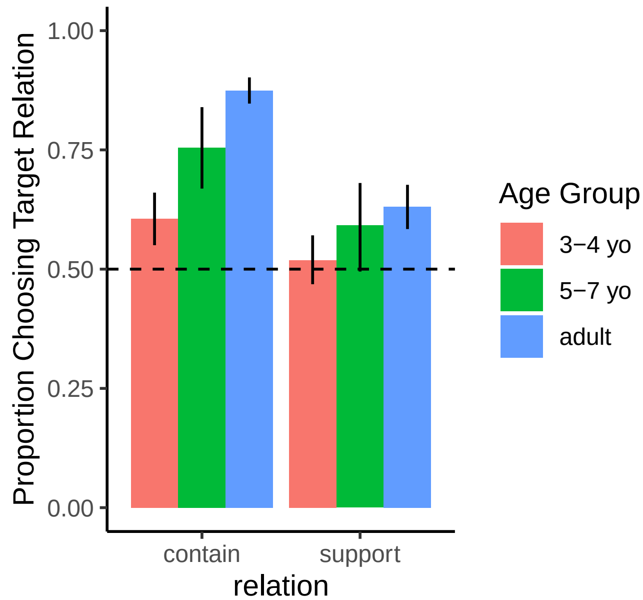

Figure 4: Children's vs. adults' choices for each type of trial, with bootstrapped 95% confidence intervals.

Comparison to Physics Simulations

Using a physics engine (Gan et al., 2020) and 3D models of the objects that were shown to participants, we constructed a simulation of each drop interaction in each trial. We then assessed how well a variety of heuristic models based on these simulated physical interactions could predict children's and adults' choices. For each trial's two possible drop object choices, we ran 250 simulated drops, and for each drop we calculated a variety of features measuring the state of the model after the drop was completed. We selected features that we thought may provide good metrics for what people could find interesting, for instance, the mean amount of time before both objects come to rest (*M(Move Time)*), as well as the standard deviation of that time (*SD(Move Time)*). Some features were calculated separately for drop and target objects, such as how variable each object's final positions tend to be (e.g., the inverse SD of each object's final position (*1/SD(Drop Obj Pos)* and *1/SD(Target Pos)*), the mean and maximum final distance of each object from the drop location (e.g., *M(Target Dist)* and *Max(Target Dist)*), and how variable the speed of each objects tend to be after collision (e.g.,

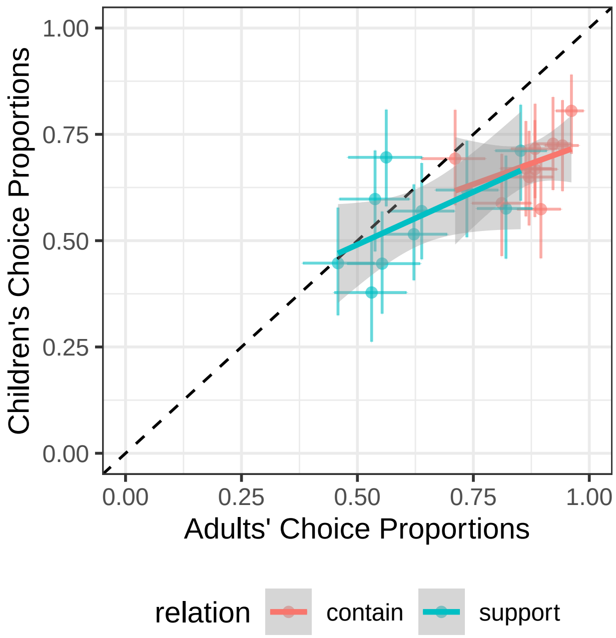

Figure 5: Comparison of children's vs. adults' preferences on each trial (dot), with bootstrapped 95% confidence intervals.

Vel(Target)). We also tested a variety of features based on the likelihood of the dropped object coming to rest atop the target object–$Pr(support)$–and the robustness of this likelihood to small perturbations in drop position (*Supp. Sharpness*). Note that the model's definition of support does not explicitly distinguish support from containment.

We measured each of these features in 250 simulations of each possible drop in the experiment, and then used the resulting values to generate relative preferences for the drop choices on each trial. A model's preference on any given trial was assumed to be proportional to the relative magnitude of the feature values for the possible physical interactions on that trial, scaled by a softmax parameter β. For each model (feature), we optimized β separately to find best-fitting values for children's and adults' choice proportions, with the objective of minimizing mean squared error (MSE) between model and human choice proportions across all 20 trials.

Results Examination of the fitted model preferences revealed that none of them achieved a good fit to human preferences. For example, while the best-fitting feature, *Pr(support)*, captured both adults' and children's overall mean preference for the designed target relations, but explained no trial-level variation and was in fact negatively correlated with people's choices, overall. Thus, instead of reporting predictions from fitted βs for each feature, we show in Table 2 the correlation between model preferences (with softmax $\beta = 1$) vs. adults' and children's choice proportions, both to all trials and separately for containment and support trials. The feature with the strongest correlation to adults is *Vel(Target)* ($r = .33$), but adults' support trials were more correlated with *1/SD(Target Pos)* ($r = .39$), while contain-

Table 2: Correlations (r) of model and human responses.

feature	Adult: All	Child: All	Adult: Support	Child: Support	Adult: Contain	Child: Contain
Vel(Target)	**0.33**	-0.11	0.1	-0.51	0.34	-0.09
1/SD(Target Pos)	0.14	-0.08	**0.39**	**0.41**	0.16	-0.52
M(Target Dist)	0	0.13	0.11	0.22	0.42	0.42
Max(Target Dist)	-0.01	0.17	0.11	0.33	0.41	**0.43**
Supp. Sharpness	-0.02	**0.18**	-0.26	0.14	0	0.18
M(Move Time)	-0.07	0.04	-0.08	-0.08	-0.02	0.29
Vel(Drop Obj)	-0.1	0.17	-0.27	0.3	**0.54**	0.41
SD(Move Time)	-0.18	-0.19	-0.01	-0.29	-0.37	0.13
Pr(support)	-0.36	-0.48	-0.48	-0.54	-0.39	-0.51
Max(Drop Obj Dist)	-0.45	-0.28	-0.39	-0.29	-0.09	0.18
M(Drop Obj Dist)	-0.47	-0.31	-0.45	-0.35	-0.04	0.2
1/SD(Drop Obj Pos)	-0.48	-0.32	-0.49	-0.33	-0.1	0.12

ment trials were most correlated with *Vel(Drop Obj)* ($r = .54$). The feature with the strongest correlation to children is *Supp. Sharpness* ($r = .18$), but like adults, children's support trial choices were better correlated with *1/SD(Target Pos)* ($r = .41$). Children's containment trial choices were most correlated with *Max(Target Dist)* ($r = .43$), but *Vel(Drop Object)*, the most related to adults' containment trials, was not far behind ($r = .41$). Many of the other features show weak or even moderate negative correlations with people's choices.

Discussion

This study aimed to 1) measure the consistency of children's and adults' preferences for particular object interactions, and 2) determine whether people's interest was predicted by particular features of the imagined physical interactions between objects. In an online study that gave adults the opportunity to make drop choices that could result in either a likely support or likely containment relation on each trial, we found that adults consistently chose targets likely to contain the dropped object, and to a lesser degree chose target objects that were likely to support the dropped object. Experiment 2 found the same pattern in children, but with greater noise – even to the extent that younger children were at-chance at choosing the support relation on most trials. In sum, our behavioral study found that infant's early-emerging interest in containment (Casasola, Cohen, & Chiarello, 2003) may extend through childhood and persist into adulthood, along with a weaker interest in support relations.

Given the high reliability of choices on this task, particularly for adults ($r = .95$, children $r = .61$), we tested how well heuristic models of curiosity based on simulations of the physical interactions could predict participants' preferences of target objects on each trial. We tested a wide range of features that we thought might be proportional to people's interest in particular object interactions (e.g., how far a dropped object might end up from the drop location), but not one of these features explained much of the trial-level variance in people's choices. Instead, we found a few features that were partially correlated with people's choices: for example, the inverse standard deviation of the target's final position was the best predictor of both children's ($r = .41$) and adults' choices ($r = .41$) on support trials. For containment trials, the normed velocity of the drop object after first collision was most correlated with adults' choices ($r = .54$) and moderately with children's ($r = .41$), but children's choices were also correlated with the maximum and mean distance traveled by the target ($r = .43$ and $r = .42$). On balance, although much systematic variation in this dataset is unaccounted for, it is somewhat encouraging that people's interest in physical interactions can be in part accounted for by simple heuristic models based on simulations of the same physical task we asked participants to merely imagine.

At the same time, the fact that these results are not fully explainable by simple heuristic models suggest that this paradigm may fruitfully serve as a test bed for evaluating more complex computational theories of curiosity. For example, in one proposal learners prefer to explore stimuli that are "moderately discrepant" in relation to their current knowledge state, thereby providing an opportunity to learn (Kinney & Kagan, 1976), and curiosity changes as the gap between the learner's knowledge develops and the state of the world closes (Loewenstein, 1994). These theories are beginning to be implemented in deep neural networks, which are now capable of learning forward and inverse physical dynamics (i.e., "intuitive physics") from images when given the ability to "poke" the objects in the scene (Agrawal, Nair, Abbeel, Malik, & Levine, 2016), and have more recently been used to test which "curious" policies for generating actions result in robust and effective learning of intuitive physics in deep reinforcement learning agents (Haber, Mrowca, Fei-Fei, & Yamins, 2018). In future work, we aim to examine the development of curiosity in such curious artificial agents, and compare whether these agents behave similarly to people and "drop it like it's hot" (Dogg, 2004). The multifaceted nature of curiosity has fascinated researchers for decades, but only recently have we developed the means to factorize and test these theories. We propose that the development of parallel tasks for children, humans, and embodied agents is a promising way forward towards modeling curiosity in the real-world.

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