MIT Press • Open Encyclopedia of Cognitive Science

Intuitive Physics

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MIT Press

Published on: Jul 01, 2026

URL: https://oecs.mit.edu/pub/m27ympza

People reasonably predict how things will fall, slide, ooze, drape, and crash, and they do so quickly, easily, and automatically. People do not have to be trained physicists to reason in this way about the everyday dynamics of everyday objects. However, people are also not perfect in their physical reasoning, and they make systematic mistakes and errors. This overall sense of intuitive physics is an important part of commonsense reasoning and a current target for building more human-like artificial intelligence. Several competing frameworks attempt to explain both the successes and failures of human physical reasoning. Although there is no strong consensus yet on which framework is correct, two of the main current approaches to intuitive physics emphasize either mental simulation (a process that updates an internal model of the world) or features and heuristics (which map a given perceptual input to a physical judgment).

History

The basic notion that people have internal, simplified copies of the world that they can manipulate by different cognitive operations predates the advent of cognitive science as a field (Craik, 1943). However, the specific interest in physical reasoning, prediction, and inference did not coalesce until several decades later. The early work of Shepard and colleagues (Shepard & Cooper, 1986; Shepard & Metzler, 1971) proposed that the mind acts on object representations using mental transformations that obey real-life restrictions for the purposes of planning and reasoning. The argument was that mentally simulating how a scene will unfold allows an organism to plan its actions accordingly, avoiding literal (and metaphorical) pitfalls that would be hazardous if the action were taken in reality. However, such a simulation only works if mental transformations (rotations and motion) are in accordance with reality.

This work was later folded into the *imagery debate*, a running argument over the format of perceptual images. During the 1970s and 1980s, much of the work on intuitive physics focused on simple scenes and the search for the right combination of heuristics and features that may underlie this reasoning (Gilden & Proffitt, 1989). An example of the kinds of situations, properties, and features studied in this line of work would be showing people a scene in which two simple spheres approach each other with different velocities, collide, and bounce off. Then, one could examine how people's estimations of object weight and elasticity vary as a function of the angle of dispersion or the ratio of initial and final velocities of the spheres (see Figure 1-I).

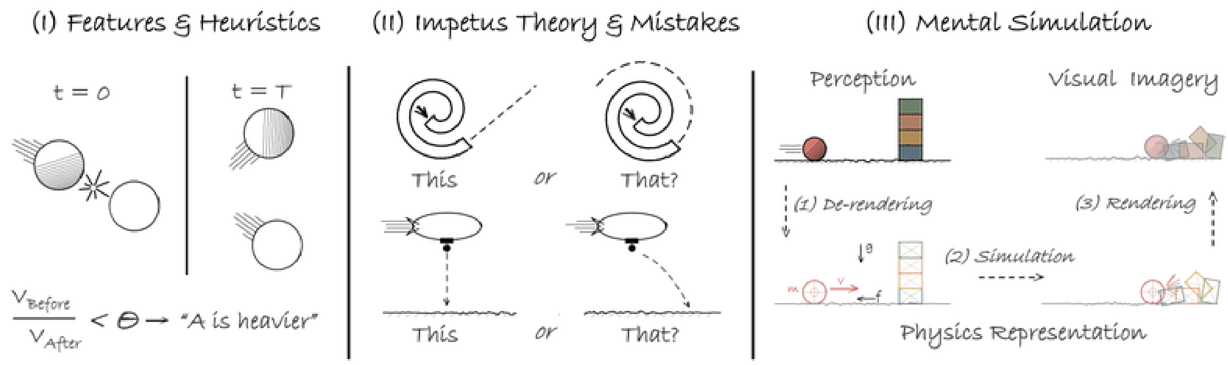

Figure 1

(I) Early work on intuitive physics focused on simple scenes (such as two balls colliding) and trying to find how people might infer the physical properties of objects (such as weight) from simple heuristics or perceptual features (such as the ratio of velocities before and after a collision). (II) From the 1980s onwards, a great deal of work in intuitive physics has emphasized people's systematic mistakes. Imagine a ball went into the spiral loop depicted here; would it come out like the path on the left or the right? Or suppose a flying blimp dropped a cannon ball; would its trajectory look like the left or the right? Many people get this wrong, thinking the paths on the right are the correct ones. Previous research has proposed such mistakes are the result of people intuitively thinking the world works according to a pre-Newtonian "impetus theory." (III) A more recent approach to intuitive physics has suggested people may rely in part on a process of mental simulation similar to how a computer game or animation might create somewhat realistic videos. The proposal is that people turn a perceptual scene into an object-centric, spatial/physical representation. They can use this representation to simulate how the world might turn out. Optionally, people can also imagine what such new world states would be perceived as, visually or in other modalities.

Around the same time, a very influential framework by Caramazza and McCloskey (McCloskey et al., 1980) instead focused on the characteristic mistakes that people make across a wide variety of scenarios. A typical example involves showing people a sketch of a spiral enclosure (like the shell of a snail) and the motion of a ball in this enclosure, asking them to continue the motion of the ball past the enclosure (see Figure 1-II). Many people, including students studying physics, indicate the ball will continue its curvilinear motion. Caramazza and McCloskey argued for a unified framework, according to which people have a *theory* of physical motion but one that is pre-Newtonian and involves scientifically outdated notions of impetus. This work was hugely influential on the field of education, in which the focus continues to be on people's mistakes, and the primary task of pedagogy is seen as identifying and eradicating intuitive but incorrect notions of physics, and replacing them with correct and scientific notions (Hartshorne & Jing, 2025). Several other important directions in the 1980s, 1990s, and early 2000s included the development of qualitative reasoning (Forbus et al., 1991) and findings and models related to mechanical reasoning. Around this time, findings in cognitive development suggested that much of children's basic physical reasoning is early developing (Spelke, 2022).

The early 2010s saw the revival and updating of an approach to intuitive physics that suggested it was based on a *mental simulation* over internal models of the outside world (Battaglia et al., 2013; Hegarty, 2004). In a basic version of this approach, perceptual scenes are first *derendered* into physical scene representations (i.e., they are turned from pixel-based perceptual representations into amodal, spatial/physical representations). Such scenes are then advanced step by step as the basis for answering questions such as, "What will happen next in this situation?" (see Figure 1-III). This *mental game engine* framework takes inspiration from game engines and physics engines, the programs and software tools used to create approximate world simulations (Ullman et al., 2017). As opposed to the work in education, the mental game engine approach emphasizes people's overall successes in physical reasoning, noting that even the seeming systematic mistakes pointed out by previous work are largely absent when scenes are presented and assessed in a dynamic, realistic way rather than through vignettes and sketches (Smith et al., 2013). The mental simulation approach has since been used to capture people's physical reasoning across a wide variety of dynamic situations (including, but not limited to, collisions, stability, fluids, two- and three-dimensional situations, sliding, friction, soft bodies, and fabrics) and cognitive domains including common sense, counterfactuals, causality, imagination, prediction, inference, and more (Hartshorne & Jing, 2025). Findings from neuroscience over the past decade have also found correspondence with the mental simulation approach, mapping the brain architecture of intuitive physics (Pramod et al., 2022).

Core concepts

Mental models

Mental models are inner cognitive representations of the world, which relate hidden variables to external observable data [see Causal Reasoning]. Mental models are an old idea, but in recent decades, progress has been made on formalizing these as probabilistic, generative programs [see Bayesian Models; Intuitive Theories]. When the relevant variables and data are objects and their interactions, a mental model can support intuitive physics.

Mental simulation

Mental simulation updates a mental model step by step, from initial conditions to a hypothesized or counterfactual outcome. The initial, intermediary, and final steps along this simulation are themselves representations that correspond to the world, had it taken the simulated path. Mental simulation can happen over physical variables but is not limited to that. Also, not every step-by-step computation is a simulation. Many computations exist in which the intermediary representations do not meaningfully correspond to a relevant state in the world. For example, rotating an object represented as a matrix of coordinates in space can be achieved by switching the rows and columns of a matrix in a particular way. In such a computation, the initial and final matrices correspond to the first and final state of the object, but each intermediate matrix does not correspond to a rotation in between those two states.

Heuristics

Heuristics are simple, rough-and-ready rules or snippets of computation that are easy to carry out. They are oftentimes successful, but within a limited domain. Consider, for example, the judgment that a tower of blocks is unsteady. One could either create an internal mental model of the tower of blocks and then mentally simulate its trajectory over time, arriving at the conclusion that it will probably fall down because many runs of the mental simulation ended that way (Battaglia et al., 2013), or one could use a rough estimate of the visual features of the tower along with a simple heuristic that corresponds to something like, "If it's tall, it'll fall." Such a heuristic will likely be less general, and more error prone than mental simulation, but is also less costly and faster to compute (Gigerenzer et al., 2000).

Questions, controversies, and new developments

Researchers are continuing to map out both people's successes and mistakes across different domains and continue to try and reconcile the views that emphasize people's systematic errors with those that emphasize their competence. Further, although many intuitive physical principles (e.g., solidity, cohesion, and permanence) appear to be present early in development for both human and nonhuman animals, it remains a topic of controversy whether and to what degree such principles are acquired from experience or present through innate cognitive constraints.

There are also major open arguments about the format of the mental computations that underlie intuitive physics, with much of that controversy surrounding the possible use of mental simulation. Mental simulation is also not the only current approach to intuitive physics. Other frameworks emphasize a variety of other possible mental computations, including large combinations of bottom-up perceptual features and deep learning approaches (Piloto et al., 2022), logical rules (Davis, 2014), or qualitative physics (Forbus et al., 1991). Critiques of mental simulation also do not have to propose alternatives and can simply point out seeming human inconsistencies and mistakes that are not predicted by realistic mental simulation (Ludwin-Peery et al., 2020). A current direction in intuitive physics examines the *approximations* and *workarounds* of mental simulation, arguing that both engineers and the human mind are under similar constraints of time, memory, and computation to produce good enough approximations of the physical world, predicting both successes and systematic failures at the limits of these approximations (Bass et al., 2021). In addition, several current approaches to intuitive physics adopt a pluralistic approach to mental simulation and heuristics. Such hybrid approaches suggest that the mind contains various modules for dealing with different aspects of intuitive physics, and trades those off or combines them based on context (Smith et al., 2023; Sosa et al., 2025).

Side by side with the research in cognitive science, the fields of artificial intelligence and machine learning have also taken a keen interest in intuitive physics. In these fields, some researchers take inspiration from people's competence in intuitive physics and try to build more human-like physical reasoning systems in machines. Other researchers remain agnostic about the desired format of physical reasoning in machines, emphasizing the use of benchmarks and allowing artificial systems to come up with whatever models and algorithms achieve the highest scores on these benchmarks. Developmental benchmarks have been particularly influential here, and current useful physical benchmarks include Physion, IntPhys, PHYRE, and CLEVRER. It is also unclear to what degree video-generation models align with human cognition (especially the currently popular ones based on diffusion architectures).

Broader connections

Intuitive physical reasoning is a major pillar of common sense reasoning and, as such, relates to many other basic domains in cognitive science, including, for example, causal reasoning, tool use, decision-making, and object tracking [see Causal Reasoning]. The basic sense of predicting what will happen next in a real or imagined scene is also intimately tied to imagination, imagery, and pretense [see Mental Imagery]. The foundations of physical reasoning likely lie in innate or early-developing concepts that are shared with other animals and across cultures (Spelke, 2022), and a better understanding of development will inform the understanding of adult intuitive physics. How people think intuitively about everyday physics relates also to formal scientific theories of physics and what even counts as a satisfying explanation within such theories (Ullman & Tenenbaum, 2020). To get a quick sense of this, consider that although a formal framework of electromagnetism may be fully specified by a set of abstract formal equations, both the discovery of this formal theory and its intuitive understanding are based in the imagination of everyday entities like balls colliding or liquids sloshing.

Acknowledgments

The author thanks the Jacobs Foundation as well as the Kempner Institute for the Study of Natural and Artificial Intelligence for their support. A combination of Claude Code (Sonnet 4.6) and Gemini 3.1 Pro were used to create the code that was the basis for Figure 1.

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