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Review article

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Insights into cognitive mechanics from education, developmental psychology and cognitive science

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Abstract

Humans reason implicitly and explicitly about the physical world, which enables them to successfully interact with and manipulate objects in their environment. This reasoning is studied under different names across three main literatures: education, developmental psychology and cognitive science. At a high level, education researchers examine the acquisition of formal scientific knowledge, developmental psychologists explore children's emerging understanding of their physical surroundings and cognitive scientists analyse the structure of the mind. These different disciplines have reached divergent conclusions about what children and adults know about 'cognitive mechanics' and developed parallel scientific theories of these phenomena. In this Review, we describe the findings of these three literatures and conclude that each literature contributes robust and reliable findings that must be taken seriously even when they seem to be contradictory. We suggest that further progress requires reconciling these literatures; one avenue is to consider multiple interlocking cognitive mechanisms that are differentially engaged across scenarios and across development. Finally, we outline a research programme to further reconcile these literatures.

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Introduction

Adult humans — and nearly all mature macroscopic animals — are equipped with cognitive abilities that enable them to interact with the physical environment. Whether or not this knowledge directly encodes the laws of physical mechanics, it must be sufficiently aligned with how the world works to enable the organism to accomplish its goals. For instance, without an untutored 'cognitive mechanics', humans could not predict what surfaces will support their weight, whether objects placed in particular locales will stay there on their own or what actions will remove or create physical obstacles. The complexity of these problems has been highlighted by decades of robotics and artificial intelligence research that seeks to induce mechanical understanding in artificial agents[1–3].

By cognitive mechanics, we mean something distinct from 'intuitive physics', a term commonly used to describe people's intuitive knowledge that underlies their understanding of and interaction with the physical world[4,5]. Cognitive mechanics is both broader and more narrow than intuitive physics. Cognitive mechanics is broader in that it includes not just untutored intuitions but also beliefs about physics that derive from education ('tutored'). For instance, in asking how people think about collisions between rigid bodies, we are equally interested in infants playing with balls, pool sharks setting up complex billiards shots and college students diagramming collisions using Newton's equations. All of these examples are cognition applied to mechanics and therefore within scope. Note that this definition also includes what is sometimes called 'tacit physics', which underlies the ability to catch balls, navigate obstacles and otherwise interact with the physical world (as opposed to explicit or verbalized knowledge). Cognitive mechanics is narrower than intuitive physics in that it encompasses only classical mechanics, not all of physics. In practice, the bulk of intuitive physics research has focused on classical mechanics, so this distinction might seem like splitting hairs. Nonetheless, we have found that the term intuitive physics is opaque to experts in physics education, where 'physics' includes other topics such as electromagnetism and general relativity.

Much of the vast body of work on cognitive mechanics draws inspiration from a spate of studies from the late 1950s through to the early 1980s that seemed to reveal deep confusions about mechanics on the part of children, lay adults and even physicists[5–14]. For example, when asked to judge the forces acting on a cannonball fired in the air, laypeople and even students with a year of undergraduate physics class reported that the cannonball will continue upwards as long as the upward force imparted by the firing (believed to exist in the upward trajectory) is greater than the downward force of gravity (Fig. 1a). In fact, according to Newtonian mechanics, once the cannonball has been set in motion, the only force acting on it is the downward force of gravity.

From this common origin of foundational studies, several independent literatures have emerged that in the past quarter of a century rarely if ever cross-cite each other. Cognitive psychologists and artificial intelligence researchers focus on characterizing tacit and explicit mechanics knowledge in adults (and machines) outside an education context[4,15–17], whereas developmental psychologists focus

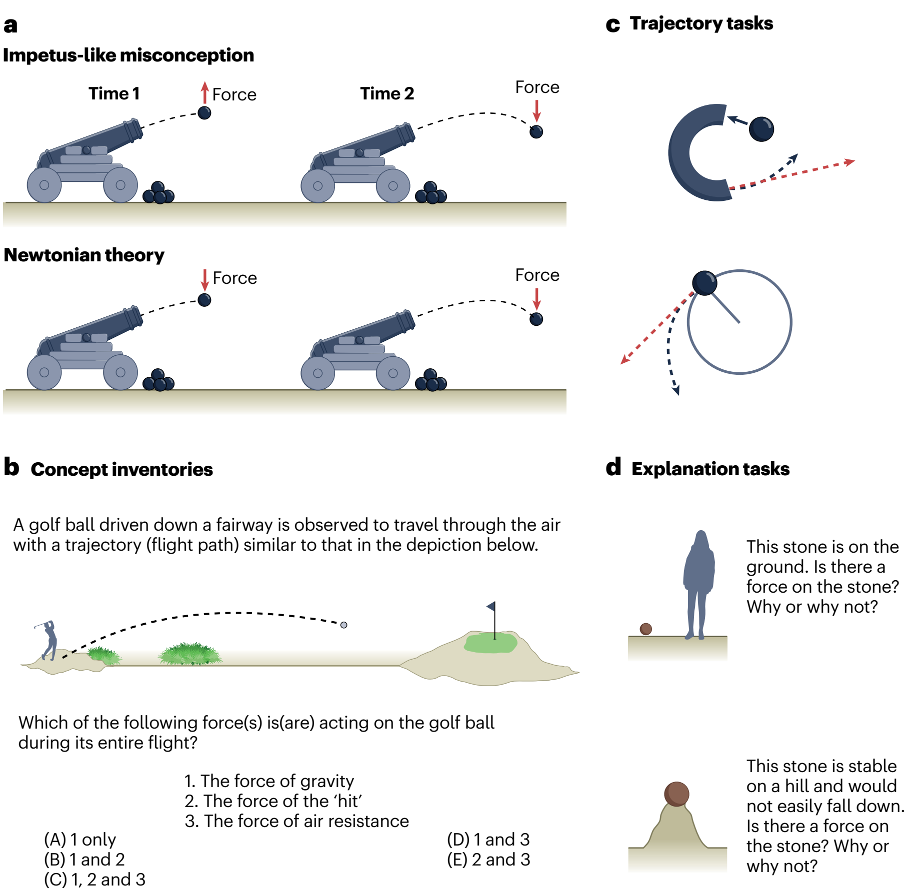

Fig. 1 | Examples of cognitive mechanics problems and common misconceptions. a, In considering the forces acting on a cannonball, many people endorse an account in which total force is always in the same direction as motion (upper panel), roughly consistent with the impetus theory. By contrast, the correct answer is to endorse the Newtonian theory (lower panel), in which there is no acceleration without a force causing it and therefore a downwards force (gravity) is operating on the cannonball throughout its flight (time 1 and time 2). **b**, Concept inventories, typically resembling multiple-choice classroom exams, probe basic concepts and thereby conceptual knowledge. An example problem involves asking what forces are acting on a hit golf ball. Many participants incorrectly report that the force of impact remains in effect throughout the ball's flight[207]. **c**, In trajectory tasks, participants are asked to draw or judge the expected trajectories of objects, such as balls rolled through a curved tube or a ball swung in a circular motion on a string and then released. A common mistake is an expectation for the circular motion to continue (black dashed lines) even after the ball leaves the tube (top) or is released (bottom), whereas the correct path is straight (red dashed lines)[8]. **d**, In explanation tasks, participants provide free-response explanations of their thought processes. Here, participants are asked to explain the forces acting on a stone and often incorrectly respond that no force is acting on the stone, whereas both gravity and the ground are imparting (equal but opposite) force[87]. Although the two questions here are normatively identical, participants often vary in their answers (reviewed elsewhere[88]). Part **b** adapted with permission from ref. 207, AIP Publishing.

Table 1 | Properties of three contemporary literatures in cognitive mechanics

	Education literature	Developmental psychology literature	Cognitive science literature
Literature-specific questions	Why are adults' and children's cognitive mechanics systematically erroneous? How can physics instruction be designed to dispel error or misconception?	What do infants know about the physical world? How do infants and children acquire veridical cognitive mechanics?	Under what conditions does adult cognitive mechanics fail? What algorithms and neural processes underlie cognitive mechanics?
Theoretical perspectives	Framework theory[94] Knowledge in pieces theory[32,97]	Core knowledge theory[64,126] Theory theory[22,63] Rule assessment theories[14,122,123]	Video game engine in the head theory[15] Heuristics and biases theories[4,43,46] Information integration theory[17]
Primary participant populations	Advanced physics students Naive physics students Physics experts	Infants and young children	Adults who are not physics experts
Common methods	Classroom observation Standardized exams	Preferential looking paradigm Dishabituation paradigm Balance beams, balance scales and block stacks Prediction tasks	Drawing tasks Perceptual judgements Prediction tasks Action tasks
Strengths	External validity Ecological validity Large-sample studies Frequent replication Longitudinal data	Experimental manipulation Diverse measures	Experimental manipulation Diverse measures Computational modelling

on development of tacit (and, to a lesser extent, explicit) cognitive mechanics in early childhood[18–22]. Similar to developmental psychologists, education researchers study learning – but primarily explicit, verbalized knowledge of mechanics[23–29]. These researchers often have an added interest in whether and how children's cognitive mechanics informs their learning of the scientific discipline of physics and how cognitive mechanics might be leveraged in pedagogy[23,30,31]. As a mnemonic and for simplicity, we refer to these three literatures as the contemporary cognitive science, developmental and education literatures, to reflect the outlets in which the bulk of their output has been published. However, these are not natural kinds with rigid boundaries in their questions, methods or researcher affiliations. For instance, there are members of the 'education' literature who are interested in development and members of the 'cognitive science' literature who have primary appointments in schools of education. Because a goal of this Review is to collapse the boundaries between these intellectual communities, any imprecision in our grouping should soon become moot. Prominent reviews published in the past decade[4,15,17,19,23,27,32–34] illustrate the degree to which the literatures have become distinct. Although these reviews cite many of the same foundational studies from the past century, their discussions of the past 25 years are much more restricted. An exception to this pattern is a 2021 review of the cognitive science literature that acknowledges the contemporary developmental literature but declares most of it out of scope[17].

Surprisingly, despite their common twentieth century origins and shared domain, these three literatures have also reached very different conclusions about the empirical phenomena in need of explanation. As a result, the theoretical debates in one literature frequently make no sense in the context of the others. For instance, education researchers describe striking errors in cognitive mechanics made by both laypeople and even professional physicists and a protracted struggle that individuals go through in (only partly) correcting their physical reasoning[23,24,27,28,32]. The theoretical work in this literature is focused on explaining why humans find cognitive physics so difficult and how humans eventually achieve accurate understanding, to the extent they ever do[23,24,28,29,32,35,36]. By contrast, cognitive science research on adult cognitive mechanics has found that adult reasoning is often accurate[15,16,37–42] and theoretical debates focus on explaining why it is not always accurate[4,16,17,39,43–46]. Notably, although the scope of the cognitive science literature is broader than the education literature – it includes tacit reasoning in perception and motor control – it includes extensive studies of the same kinds of tasks studied in the education literature, such as explicit reasoning about pendulums or projectiles[39,44]. Thus far, the cognitive science literature has had little to say about learning, and the most successful theory (the 'video game engine in the head'; discussed subsequently) does not easily admit of a learning theory: the most straightforward prediction is that even infants have a roughly veridical cognitive mechanics. By contrast, the developmental literature largely takes at face value that infants have a non-veridical cognitive mechanics but acquire an essentially veridical understanding of classical mechanics by middle childhood, with the research focus being on characterizing how that happens[18,19,47]. Unfortunately, the differences between these literatures are not easy to reconcile. All three literatures are impressive collections of rigorous, replicable, cumulative and systematic investigation by generations of scientists.

In this Review, we provide a comprehensive discussion of cognitive mechanics across these literatures this century (for reviews covering only one of the three literatures, see refs. 4,15,17,19,23,33,34). We first review each literature (Table 1), systematically highlighting the differences across them and addressing concerns that contributors to one literature might have about the others. We then sketch one possible reconciliation: that cognitive mechanics involves a cluster of cognitive mechanisms that are differentially invoked for different tasks. We conclude with suggestions for future work to reconcile the literatures and test this hypothesis.

The education literature

What we refer to as the contemporary education literature is a body of interlocking work focused on students' struggles to understand physical mechanics. Systematic errors ('misconceptions') such as those reported for the cannonball scenario described earlier (Fig. 1a) have been documented in hundreds of studies. These misconceptions arise in the reasoning of advanced physics students and even faculty members[5,48]. Furthermore, these findings are reliable enough across individuals to have been collected in standardized paper-and-pencil assessments such as the force concept inventory[49], which are used in both research and educational contexts to characterize physics understanding[24–26,49–56] (Fig. 1b).

Beyond concept inventories, further evidence for non-Newtonian misconceptions comes from language: linguists have noted that the semantics of language is decidedly non-Newtonian[57]. Although in Newtonian mechanics it makes no sense to describe one participant in an event as being the cause or applying the force because all actions are met by equal and opposite reactions, this asymmetry is built deep into the structure of many – possibly all – languages. For instance, the phrases 'my hand pushes a box' and 'a box pushes my hand' are understood as describing different scenarios, whereas according to the laws of physics, whenever one is true the other must be true, too. This fact would make sense if people think about mechanics in a non-Newtonian manner.

Inspired by classical scholars[58,59], one early line of theorizing ascribed this behaviour to people holding incorrect theories that are not aligned with Newtonian mechanics[5,60,61]. According to this perspective, humans understand the world in ways very similar to scientific theories and these 'intuitive theories' can be wrong[5,8,9,62–66]. The key idea is that although people's beliefs about mechanics can be non-veridical, they are coherent, predictable and explicable. Some researchers have argued that untutored intuitions about classical mechanics resemble the medieval impetus theory (that moving objects are kept in motion by an internal 'impetus' or force, which gradually dissipates)[5,60]. Others have described these misconceptions in terms of an earlier precursor to the impetus theory (that objects move only when acted upon by a force and come to rest when the force is removed)[61]. Such a misconception is explicable: many researchers note that impetus theory is more consistent with day-to-day observations of objects moving through the world than is Newtonian mechanics[43] (but see ref. 67, which finds that the reverse is true for adults reasoning about forces acting on one's own body). Importantly, successfully learning Newtonian theory in school requires changing one's beliefs about mechanics; for this reason, we refer to these accounts as 'theory-change' accounts.

The reach of the theory-change account within physics education is demonstrated by the large literature that has grown up around the aforementioned concept inventories, which are designed to capture misconceptions[24–27,49–56,68–85]. These assessments are widely accepted in undergraduate physics education as a valid measure of cognitive mechanics (or at least the aspects relevant to undergraduate-level physics) and are used to assess changes in student understanding across the semester[86], evaluate education reforms[26], compare pedagogical approaches[26,27,49,73,76,77] and compare instructors[86].

Over time, however, evidence accumulated that suggests a more complex picture than envisioned in the twentieth century theory-change accounts. For example, numerous studies revealed that both children and adults give different answers to questions that are identical from the perspective of impetus theory and Newtonian theory[4,16–18,32,34,87,88]. For example, in a study in which undergraduate students were asked to predict the trajectory of a moving object, 28% of the students succeeded in drawing the trajectory for water exiting a curved hose but failed when to draw the trajectory for a ball exiting a curved tube[88] (Fig. 1c). Similar evidence[89–91] led researchers to believe that a single individual can simultaneously hold true and false conceptions regarding essentially the same mechanical phenomenon[92] (for related work embedded in the contemporary developmental psychology literature, see also ref. 93). Several theories have emerged to explain this variability. Framework theory keeps some aspects of the theory-change account but argues that children's untutored cognitive mechanics constitutes something less than a coherent theory[94]. Rather, the beliefs underlying cognitive mechanics are initially organized into frameworks – skeletal, incomplete conceptual systems. Misconceptions arise as students try to interpret what they learn in school in light of their pre-existing frameworks, which are often incompatible[23,94]. Even if students eventually acquire the normative scientific theory, it does not replace but coexists with the untutored frameworks.

Although framework theory asserts that (untutored) cognitive mechanics is fairly coherent but not entirely theory-like, other theories assert that cognitive mechanics consists of fragmented knowledge elements[95–97]. For example, the knowledge in pieces theory argues that cognitive mechanics is internally inconsistent and fragmented, consisting of many potentially useful knowledge elements: an 'ecology' of narrow, semi-independent beliefs, named 'p-prims' ('phenomenological primitives')[32,87,88,97]. P-prims are abstractions of familiar events and sensorimotor experiences. For example, children might notice that objects usually stop moving unless something keeps them moving and adopt a p-prim that encodes this belief. When reasoning about a cannonball launched from a cannon, activating this p-prim would give rise to the impetus theory-like belief that an upward force is operating on the cannonball throughout its upward trajectory[98]. Successfully learning to apply Newtonian theory involves not just acquiring the necessary p-prims (often prior to any formal physics education) but also finding the right ones to apply the right way in the right contexts[29,32,99]. Consequently, immature cognitive mechanics is highly context-sensitive, and explanations offered by students will depend in subtle ways on which particular knowledge elements happen to be triggered in particular situations. For instance, according to the dynamic system theory (an elaboration of knowledge in pieces), students' conceptions emerge dynamically from the interactions of conceptual resources (that is, smaller bits of knowledge or intuition students have)[28,29,35,36,100]. Thus, conceptions at a particular point in time and applied to a particular problem might display something of the coherence of a theory, whereas conceptions over time and across situations are not necessarily stable or consistent, as they are shaped by the dynamic interplay of contextual factors and the activation of different conceptual resources.

Another line of work similarly distinguishes between having knowledge and successfully deploying it. Inspired by the heuristics-and-biases literature that explores how people use mental shortcuts (heuristics) that are useful but sometimes result in systematic errors or biases in judgement and decision-making[101], these researchers argue that untutored cognitive mechanics consists of a set of probabilistically correct heuristics that must be suppressed to use school-derived knowledge of Newtonian physics[102–107]. Inconsistencies in reasoning over time can result from the fact that the heuristics – like p-prims – do not themselves form a coherent system.

Even work on concept inventories – which were inspired by the twentieth century misconception account – has increasingly suggested that cognitive physics is fragmented rather than consisting of coherent theories. In particular, factor analysis has been used in conjunction with the inventories to decompose student struggles, often revealing five or more factors[50,51,55,78–82]. Although it is often the case that one of these factors explains much more of the variance than others and some of the factors are scientifically uninteresting (for instance, two of the factors in ref. 55 correspond to a preference to respond 'A' or 'C' on a multiple-choice inventory), overall the effect is to paint a more complex picture than a transition from an incorrect impetus-like theory to a normatively correct Newtonian one. Indeed, some analyses identify multiple factors that are related to impetus-like reasoning but are dissociable from one another[55], suggesting that impetus-consistent errors do not all have a single cause. Conversely, there is increasing evidence that a major impediment to success on the concept inventories is understanding Newton's third law specifically, rather than all three laws or their interactions[80,81]. Overall, it is not yet clear exactly what sort of theory would be supported by the factor analysis work – interpreting factor analyses is complex and comparison across studies is difficult – but this discussion illustrates one more way in which the contemporary education literature has moved away from accounts on which cognitive mechanics consists of coherent theories and learning involves replacing one theory wholesale with another.

In summary, the contemporary education literature has been primarily concerned with explaining why learning to successfully solve classical mechanics problems in school is difficult and slow and apparently only imperfectly even among professional physicists. Theoretical work is further driven by a desire to explain what appears to be inconsistent and even incoherent behaviour on the part of students, laypeople and experts alike.

The developmental literature

The literature that we refer to as the contemporary developmental literature (primarily published in developmental psychology journals in the past 25 years) grew out of many of the same foundational studies that seeded the education literature[6,7,62]. However, although contemporary work in the education literature tries to account for why adults struggle to comprehend Newtonian mechanics even after formal instruction, contemporary work in the developmental literature tries to account for an incompatible set of observations that people's untutored cognitive mechanics becomes roughly Newtonian by middle childhood without any dedicated instruction. This inconsistency between the literatures persists in part because contemporary papers in the two literatures do not cite one another.

The developmental literature has probed children's knowledge of many mechanics phenomena, including motion on an inclined plane, collision events, lifting objects, balance and support[14,18,19,108–123]. Although this work has invariably shown that children eventually behave in ways consistent with knowledge of Newtonian mechanics (such as correctly identifying whether a stack of blocks is stable or will collapse), it also reveals systematic errors on the part of younger children.

Children's understanding of balance and support relationships among objects has received the most comprehensive scrutiny, in part because of the puzzling developmental trajectories uncovered. In particular, researchers have developed three different tasks for probing children's understanding of the mechanical principle of torque: the balance beam task, the balance scale task and the block stack task (Fig. 2). All three tasks involve determining whether one object placed on another object will balance and differ in the nature of the objects: asymmetric blocks balanced on a fulcrum (balance beams), levers with weights placed on a fulcrum (balance scales) or children's toy blocks placed on other toy blocks (block stacks). For all three tasks, the age at which children succeed varies wildly: around 1 year old for block stacks[19,117,118], 6–7 years old for balance beams[7] and 14 years old for balance scales[14,122] (but see refs. 115,116). For all three tasks, early work suggested a series of developmental stages that children go through on their way to success, with each stage characterized by different patterns of response. However, the stages described for each task are distinct. For instance, for the balance beam task, at the earliest stage children seem to believe (incorrectly) that a block will balance at its geometric centre[7] (Fig. 2a). No such stage has been described for balance scales[14,122] (Fig. 2b), and for block stacks it is one of the last stages[19,117,118] (Fig. 2c).

The discrepancies in the results of these tasks do not seem susceptible to simple explanations, such as differences in methods. Although block stack studies use passive measures such as eye-tracking, whereas balance scales tasks involve overt predictions and balance beams involve overtly acting on the physical world, this difference does not seem to determine performance. For instance, young children (age 3–6 years) performed worse than infants in block stacks in both overt tasks and eye-tracking[116,119,120]. Furthermore, a large sample ($n = 1{,}587$) of children across a wide age range performed differently on two superficially different versions of the same balance scales task[121]. Thus, methodological differences might not be sufficient to explain the distinct development trajectories revealed across studies.

Although early studies of cognitive mechanics in children were initially embedded in the theory-change account described in the previous section[7], this account proved untenable. For instance, the initial and intermediate developmental stages described for balance beams, balance scales and block stacks[7,14,19,117,118,122] are better described as rules or heuristics ('blocks balance at their geometric centre' or 'the side with more weights falls' or 'if any part of an object is supported from below, it does not fall') than rich, coherent theories such as impetus theory or Newtonian theory. In any case, the initial evidence for distinct, clearly defined developmental stages has not always held up well under further investigation. For instance, large-scale data-driven analyses of children's behaviour on the balance scales task failed to reveal a simple ordered transition from rule to rule over development, suggesting instead mixed strategies within individual children that are not easily characterized[122,124] (for a more sceptical interpretation, see ref. 125).

Perhaps for these reasons, developmental researchers – such as education researchers – have increasingly explored alternatives to theory-change accounts. For instance, some developmentalists argue that infants' representations of mechanics are impoverished early in development but go through refinement and elaboration with experience (the exact details of these theories vary, particularly with respect to the learning process)[20–22,117,126]. Although these theories are similar in some respects to the framework theory, they posit that children's cognitive mechanics approaches the veridical theory much earlier in development – indeed one explicitly argues that children acquire Newtonian theory[22] – and without explicit instruction. Other researchers have argued that the behavioural transitions observed in the literature are more gradual, emergent phenomena consistent with connectionist learning[127].

Yet other researchers have explored the possibility that humans have two cognitive mechanics systems, which work differently and are differentially applied in different circumstances, although the theories differ in the details[128,129]. For example, one group of researchers has suggested that depending on the task or even scenario, cognitive mechanics differentially recruits tacit knowledge and explicit, socioculturally influenced beliefs derived from media and other sources;

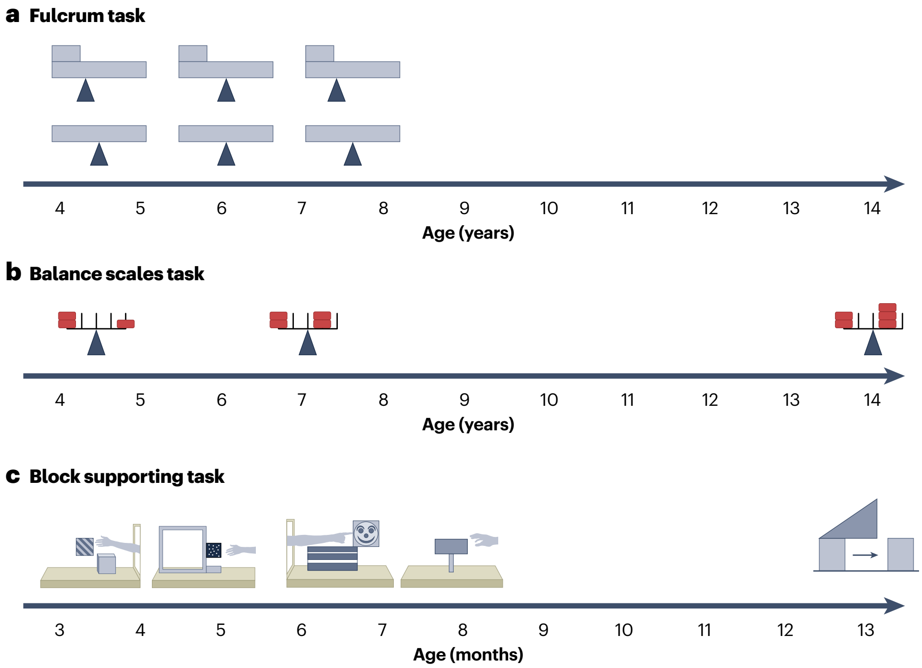

Fig. 2 | Developmental timelines for children's understanding of torque. **a**, In the balance beam task[7], children must place a beam so it will balance on the fulcrum. Children younger than 6 years of age generally balance both asymmetrical (top row) and symmetrical (bottom row) blocks using a system of trial and error and end up correctly balancing both blocks ('no theory'). Around age 6, children begin to balance all blocks using the geometric centre of a block, regardless of whether the block is symmetric or asymmetric ('centre theory'). Around age 7 or 8, children begin to use the centre of mass as the balance point, for both symmetrical and asymmetrical blocks ('mass theory'). **b**, In balance scales tasks, children must predict whether the scale will balance on its fulcrum. The typically observed developmental trajectory is depicted[14,122] (but see refs. 115,116 for somewhat different timing). By 4–5 years old, children can recognize that the scale will tip towards the side with more weight. By 8 years old, children recognize that if weights are equal, the scale will tip towards the side where the weights are farthest from the fulcrum. By sometime in adolescence, they recognize that the scale will tip towards the side with more torque. **c**, In block stack tasks[19,117,118,208], 3-month-old infants expect objects that are at least partly supported from below or the side will not fall until 5 months, when only lower surface support (of any amount) will prevent falling. By 6.5 months, infants expect stability only when >50% of the lower surface is supported. By 8 months, infants do not expect an object to fall if <50% of the lower surface is supported as long as the lower surface centre is supported, and at 13 months infants' expectations match the predictions of Newtonian mechanics. Part **c** adapted with permission from refs. 209,210, Elsevier and ref. 211, The MIT Press.

whether the individual answers correctly depend on which system prevails and whether it supports the correct answer[129]. A computational model of performance on the balance scales task splits up cognitive mechanics differently, modelling cognitive mechanics as a strategic tradeoff between 'intuitive' (connectionist) reasoning and application of the normative torque rule; developmental changes in performance are explained by learning-related changes to both intuitive reasoning and strategic tradeoff[128]. We return to this idea of multiple cognitive mechanics systems in the next two sections.

In summary, much like the contemporary education literature, the contemporary developmental literature has largely abandoned the theory-change accounts of the previous century in favour of a more fragmented picture of cognitive mechanics. However, it differs in that it is generally agreed — and the data seem to show — that children eventually converge on something close to (or identical to) Newtonian mechanics without requiring explicit instruction. As a consequence, the debates and the theories proposed look quite different from those of the contemporary education literature.

The cognitive science literature

We refer to the third literature we review as the cognitive science literature due to its prevalence in cognitive psychology and artificial intelligence publications. Whereas the education and development literatures are focused on learning and development, the cognitive science literature focuses on mature adults. There is essentially no cross-citation between the contemporary cognitive science literature and the contemporary education literature and only scattered cross-citation with the contemporary developmental literature (compare the citations in refs. 15,17,19,33,126,130). For instance, a 2023 review of the cognitive science literature[33] includes only one paragraph on the contemporary developmental literature.

The cognitive science literature has become increasingly embroiled in a debate about whether untutored cognitive mechanics is ever not Newtonian (reviewed elsewhere[4,15,16]; for prominent earlier work, see refs. 90,131). Although there are certainly plenty of researchers who argue that adult cognitive mechanics is not always Newtonian[17,33,34,43,132,133], the existence of the debate demonstrates the distance between the contemporary cognitive science literature and both the contemporary education literature (where it is agreed that adult cognitive mechanics — especially untutored cognitive mechanics — is rarely if ever Newtonian) and the contemporary developmental literature (where the opposite is concluded).

The cognitive science literature is replete with studies that present adults with the same kinds of mechanics questions that reliably elicited misconceptions in the foundational twentieth century studies but obtain responses consistent with Newtonian mechanics (reviewed elsewhere[4,15]) (for a more sceptical take on how Newtonian adult cognitive mechanics is, see ref. 33). It is tempting to suggest that this outcome is because the tasks used in the cognitive science literature are arguably more intuitive and naturalistic. For example, rather than ask adults to diagram the trajectory of a ball released from a pendulum from a static line drawing – something adults struggle with – one study presented participants with realistic videos and asked them to position a virtual barrel so that the released ball will land in it, something they did quite accurately[43]. Whether all classic misconception results disappear when more natural tasks are used is not yet known, and it is not clear whether the key factor is the naturalness of the task or some other difference, such as the degree to which the task relies on explicit reasoning[4,15–17,33,39,45].

In any case, there is general agreement in the cognitive science literature that adult judgements of mechanics are at least sometimes wrong even in highly naturalistic settings. However, there is disagreement as to whether this pattern actually reflects non-Newtonian reasoning. Indeed, a number of studies have shown that people might answer classical mechanics questions incorrectly even if their cognitive mechanics implements Newtonian mechanics[4,38,39,41,44,134–137]. Building on theories that view mental representations as image-like[37,138,139], these researchers argue that cognitive mechanics involves a high-level architecture that interactively simulates the physics of real-world scenes in a way that approximates the Newtonian mechanics[15,38] (Fig. 3). These simulations can be used to predict what will happen in the future as well as to evaluate different hypotheses about what caused current state of affairs. This theory is frequently referred to as the video game engine in the head theory[15,140], reflecting the fact that computational implementations of the theory are built using Newtonian simulators designed for video games. The theory has been supported by a variety of behavioural and neural measures[15,37,38,40,41,141–144]. Perhaps surprisingly, computational modelling shows that even with the ability to conduct veridical Newtonian calculations, performance on common tasks still shows characteristic errors. One source of error is lack of omniscience[4,38,39,41,134,135], which, for instance, results in both the model and humans to be susceptible to 'physics illusions': reliably expecting certain block towers to fall even though the towers are in fact stable[38] (Fig. 4). These illusions arise in cases in which slight perturbations of the exact positions of the blocks would result in an unstable tower. Because humans cannot perceive the exact configuration of blocks with perfect precision, most of their simulations will involve unstable configurations, leading them to infer that the tower will fall. Similarly, perceptual biases and noise seem to explain adults' tendency to judge animations of non-Newtonian collisions between rigid bodies (such as billiard balls) as plausible[39].

A second reason a cognitive physics based in Newtonian mechanics would still produce errors is that perfect simulation requires implausible levels of computational power[41,44,136,137]. Rigorously applying Newton's laws is often intractable and even professional physicists often take shortcuts in calculations, hence the classic physics problem: 'Estimate the gravitational attraction between two cows standing 10 feet apart. Assume they are perfect spheres'. Video game engines and other simulators similarly make use of numerous shortcuts and approximations to make computation of Newtonian mechanics tractable[145]. Building on a long tradition of research that argues that cognition is resource-rational[146], researchers working in the video game engine in the head tradition have proposed that similar approximations are involved in cognitive mechanics[15]. For instance, people seem to simplify complex objects when predicting how they will interact – imprecisions that are often harmless but can lead to predictable mistakes[136]. A more complex example of resource-rational cognition within a video game engine in the head account involves partial simulation[137]. When deciding how to strike a billiard ball to achieve a particular trajectory, simulating the entire universe would be both intractable and overkill: the physics of most of the world and often most of the billiard table and its contents can be safely ignored because they have no impact on the outcome. However, these partial simulations can give rise to what appear to be non-Newtonian judgements[137]. For instance, in the 'physical conjunction fallacy'[43] adults who are asked whether a particular event will happen (such as a projectile falling in a hole)

a **b**

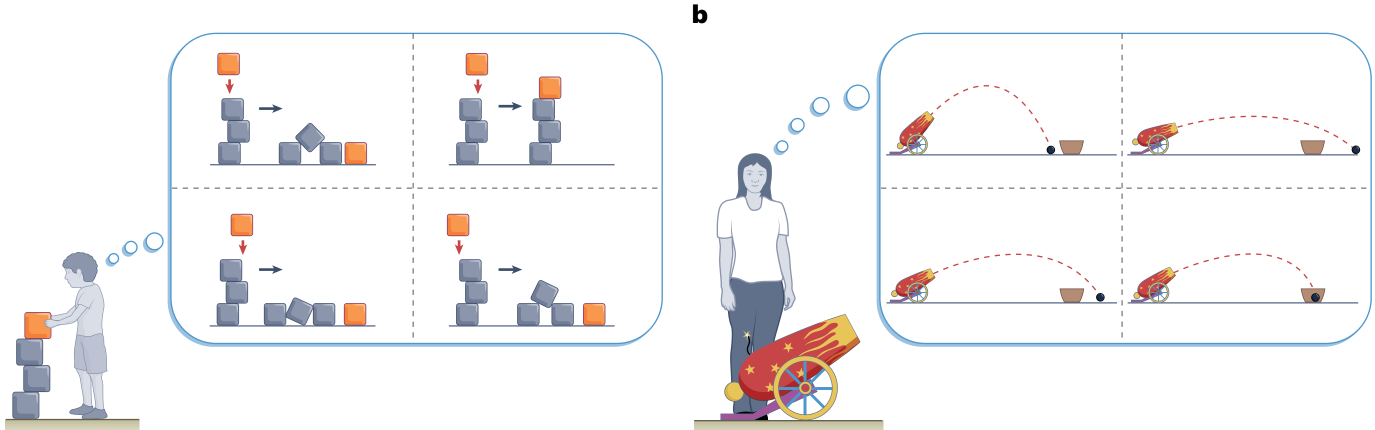

Fig. 3 | A simulation-based approach to action planning. a, An example of simulation used to inform action. When attempting to build a stable block tower, simulations might be used to decide whether to add an additional block. Each simulation is slightly different due to perceptual uncertainty, uncertainty about where exactly the new block will be placed, and perhaps due to stochastic noise in the simulation. In this case, the tower collapses in 75% of simulations and the individual concludes it is a risky manoeuvre and elects to do something else. **b**, An example of simulation used to make predictions. When considering whether a ball shot from a cannon will land in a barrel, simulations are again used to determine likely outcomes. In this case, the simulation results are also mixed and the individual is not confident about what will happen.

Fig. 4 | Physical illusions. This rock stack appears to be unstable but is actually very precisely balanced. The illusion comes from uncertainty about shape, mass and location[38]. Credit: Robert Taylor/Alamy Stock Photo.

give lower probabilities than adults who are asked whether both that event and another event will happen (such as the projectile bouncing off an obstacle and then falling in the hole): a logical impossibility that would not happen if participants were faithfully simulating the entire physical environment. However, the physical conjunction fallacy occurs precisely in cases in which the first event is only likely when the second also happens (the projectile only falls in the hole if it first bounces off the obstacle)[137]. In these cases, participants who neglect to include aspects of the scenario necessary for the second event (the obstacle) will judge the probability of the first event (hole-landing) to be negligible. Note that participants who are explicitly asked about the conjunction (that is, will the ball bounce off the obstacle and land in the hole) must necessarily include aspects of the scenario relevant to the second event (the obstacle) and will judge the probability to be higher. A computational model of partial simulation within the video game engine in the head framework not only accounted for the physical conjunction fallacy but also produced novel predictions that were then confirmed in humans. (For an application of partial simulation to spatial navigation, see ref. 147.)

In short, non-normative behaviour does not necessarily mean a non-normative cognitive mechanics. Nonetheless, it remains controversial whether resource-rational, noisy probabilistic simulation as exemplified by the video game engine in the head theory can account for all departures from normative Newtonian judgements. Some researchers working within the contemporary cognitive science literature have argued that some or all errors are better explained by a heuristics-and-biases theory similar to those proposed in the education literature[4,43,46,133]. In this case, heuristics are understood to be simple rules that apply in very specific circumstances, such as 'taller things are more likely to fall' or 'heavier objects fall faster'. Such heuristics do not fit together into a coherent package, and they typically do not refer to unobservable properties (for instance, they refer to observable features such as weight and height but not unobservable ones such as gravity or mass).

Other researchers argue for something more akin to the framework theory proposed in the education literature, in which cognitive mechanics consists of a set of non-normative beliefs that form something less than a coherent theory[33,34,148]. Researchers sometimes refer to these incorrect beliefs as 'heuristics', but it is useful to distinguish them from the rote rules based on observable features described in the previous paragraph. Instead, in these accounts, cognitive mechanics makes use of unobservable latent constructs — a hallmark of formal theories that is absent in prototypical heuristics. For instance, the proposed 'impetus heuristic'[34,148] refers to an unobservable feature impetus. Another account, based on information integration theory, uses rules based on the same unobservable features of Newtonian mechanics such as gravity, but the rules are mutually inconsistent and therefore cognitive mechanics lacks the coherence of a theory such as those invoked in the theory-change account[17].

Teasing apart the theories described in this section is complicated by the fact that most are not formal theories that can be directly implemented in math, making their predictions unclear (or at least debatable). This limitation is illustrated in the discussion of the video game engine in the head account: whereas earlier work had assumed that if cognitive mechanics implements Newtonian mechanics, human behaviour would be error free, computational modelling shows that this is not the case, that certain types of errors are in fact predicted on such an account. Even the more formalized accounts such as the video game engine in the head[15,38] and information integration theory[17] are frameworks rather than fully worked-out theories. For instance, although every empirical test of the video game engine in the head account involves a fully implemented computational model, implementing a model for each new task and domain often raises substantial technical challenges; whether an implementation is possible or exactly what its predictions will be is difficult to establish in advance. Thus, it is not currently clear whether the theory's impressive successes in accounting for human behaviour so far will fully generalize. Nonetheless, the video game engine in the head account is being rapidly fleshed out[15,42,134,136,137,147,149–152]; other theories will need to be similarly elaborated in order to determine whether they present viable alternatives.

The contemporary cognitive science literature also presents challenges to the contemporary developmental literature, which is aimed at explaining how children acquire a Newtonian cognitive mechanics. Even if the video game engine in the head theory is correct, it suggests a very different end state than seems to be considered in the developmental literature. If one of the other theories, in which adult cognitive mechanics is non-Newtonian heuristics or misconception or error theories, is correct, the contemporary developmental literature is even more misguided. Either way, it is unclear for any of the contemporary cognitive science theories whether there are learning theories that recapitulate the developmental trajectories described in the contemporary developmental literature and culminate in the cognitive mechanics proposed by the cognitive science theory. This state of affairs is mostly an absence of evidence: the cognitive science literature has had very little to say about learning or development. For some theories, such as the heuristics theories, standard approaches to modelling the learning of heuristics could be tested and compared with human data. The case of the video game engine in the head theory is more complex, because there are no well-developed learning theories that can be straightforwardly applied, although the contemporary developmental literature itself suggests some starting points[22]. There is one early but promising attempt to incorporate learning into the video game engine in the head theory, but it is not yet clear whether it can capture the attested developmental patterns[150].

In summary, the contemporary cognitive science literature accepts that adults' untutored cognitive mechanics is usually accurate but admits of systematic errors. The central debate is whether the systematic errors are due to cognitive mechanics being a non-normative approximation of Newtonian mechanics (such as heuristics) or a reflection of a resource-rational approach to computation (as suggested by the video game engine in the head account).

Cognitive mechanics across literatures

The three literatures we have reviewed here have reached different conclusions about the nature of cognitive mechanics. None is easily dismissed: all three bodies of literature have striking strengths relative to the others (as well as limitations), which we describe first. Then, we pick up on a theme from all three literatures: cognitive mechanics might involve multiple dissociable mechanisms that are differentially invoked in different contexts[16,17,23,42,50,51,55,78–82,94,101–107,128,129]. Although the proposals in the literature are too simplistic (they were designed to account for a simpler pattern of results than what we have reviewed earlier), the approach is promising and should be developed further.

Strengths and weaknesses by literature

One might be tempted to reconcile the three literatures by dismissing two of them. However, determining which two to dismiss would be difficult, as all three have compelling strengths as well as weaknesses.

The evidence in the contemporary education literature for pervasive misconceptions is backed by studies with thousands of subjects, including longitudinal data ideal for studying learning. The education literature also has the advantage of clear ecological validity in that most of the studies are directly measuring students' struggles in physics class using the same kinds of assessments used in physics class. There has been considerable attention paid to the psychometric properties of the concept inventories that constitute the primary measure for many studies[50,51,71,72,74,79–84]. In the light of current concerns about replicability[153,154], it is also notable that many findings have been repeatedly replicated using the same measures[26,73–76].

These compelling strengths make it difficult to dismiss the findings. However, features of the contemporary education literature that give rise to its strengths also make the findings less than fully conclusive. Most obviously, it relies primarily on two basic methods: paper-and-pencil classroom exams and qualitative analysis of explicit, verbalized reasoning and therefore is constrained by the limitations of those methods. For instance, performance on a concept inventory is necessarily modulated by (potentially learned) test-taking abilities[155–158] and also by design of the test (many of the commonly used concept inventories are indifferently formatted and involve interpreting line drawings).

By contrast, a strength of the contemporary developmental literature and especially the contemporary cognitive science literature is the use of a much wider array of methods, including eye-tracking, motor tasks, perceptual judgements and neural measurements. This diversity of methods provides a more robust picture of the phenomena than a few tasks, which helped researchers in this literature assess external validity and pin down exactly which findings generalize across methods[16,44,159,160]. This diversity is particularly true of the cognitive science literature. The developmental and cognitive science literatures have also prioritized high-quality, easy-to-understand tasks, decreasing the probability that errors on the part of the participants reflect confusion about the task. Both literatures use computational modelling, enabling more precise tests of theory than has been seen in the education literature. The cognitive science literature in particular boasts computational models of unusual sophistication, enabling evaluation and comparison of theories to a degree of precision and detail that would be otherwise impossible (see, for instance, the back-and-forth about the physical conjunction fallacy[43,133,137]).

These considerations make it difficult to dismiss either literature in favour of the education literature, although again their results are not beyond question. These two literatures have made less use of replication than the education literature: some basic findings in the developmental literature involving balance scale and balance beam tasks have been replicated, but not with the frequency of major education literature findings, nor across as many populations. Likewise, sample sizes are generally small apart from a handful of larger balance scale tasks in the developmental literature, and none of these reaches the massive scale of the larger education literature studies.

In total, we find no convincing argument to favour the results from one literature over the others. Rather, it is likely that the differences in findings are meaningful and something to be explained. Clearly, differences in methods explain some of the variance in results, both within and across literatures. Unfortunately, what those differences are is unclear. For instance, although performance sometimes improves when more easily-understood and ecologically valid tasks are used, it does not always[4,17,38,39,41,43,44,94,132–134] (reviewed elsewhere[33]). Moreover, although no doubt people underperform their actual knowledge in some studies because the task is not ecologically valid, is hard to understand or is otherwise poorly designed, suggesting that poor performance is always due to poorly designed measures implicitly posits that physics students actually understand Newtonian mechanics prior to instruction. This situation would imply that generations of instructors (and education researchers) have failed to notice this understanding due to confusing class discussions and poorly written exams, which would be a striking phenomenon in need of its own explanation, given that psychologists (who, it should be emphasized, are not professional physics educators) apparently have no such difficulty determining that this knowledge is present. Similarly, whereas the fact that humans struggle in physics class yet seamlessly move about the physical environment might suggest a distinction between inaccurate conscious reasoning and veridical tacit knowledge[16,159], this hypothesis fails to make sense of findings that participants sometimes struggle with implicit or tacit tasks, succeed at conscious reasoning or have differential success on what seem to be similar tasks[5,17,44,48,108,116,119–121,160–163] (reviewed elsewhere[33]). A related proposal is that accuracy tends to be higher on motor, perceptual and mental imagery tasks than on reasoning tasks, but there are many unexplained exceptions to this generalization[17]. Such data are similarly problematic for theories in which people trade off using quick-but-sometimes-inaccurate heuristics with more accurate but slower Newtonian reasoning[44,102–107]. Thus, the divergent findings across and within literatures defy simple explanations and do not fully align with any existing proposals.

Interlocking mechanisms for cognitive mechanics

Perhaps, the aforementioned proposals are not all wrong but rather all right. As reviewed earlier, researchers in each literature have suggested that the patterns of success and failure at mechanics tasks reflect humans reasoning about different problems in different ways; for instance, deploying veridical knowledge to some problems but not to others[34,42,102,107,128]. However, because of the disconnect between the literatures, these theories have been aimed at a much less complex pattern of results than what we review earlier.

Perhaps, there are not two but many mechanisms that vary in the degree to which they are tacit versus explicit; are differentially invoked in planning, perception and prediction; and develop on different timescales. This proposal is less far-fetched than it might seem: there are other domains where the brain has multiple ways of solving the same problem that are differentially involved in different tasks and have different characteristics. For example, in visual perception, there are over six separate mechanisms for depth perception (such as stereopsis, motion parallax and visual occlusion) that vary in their application (stereopsis is critical for motor control but visual occlusion has a greater effect on conscious perception of depth)[164]. Another example is long-term memory: episodic, semantic and procedural memory work differently, vary in their conscious accessibility and are used for different purposes[165]. Other examples might include decision-making[166].

Multiple mechanisms might be necessary because formally equivalent algorithms (which can solve all and only the same problems) can vary considerably in which problems they work well for. For instance, computer programming languages can in principle all do the same things, but in practice there are many programming languages because each has different strengths. For instance, javascript is asynchronous: instead of running one line of code at a time, it can try running all of them at the same time. This simultaneity is useful for displaying websites but would be disastrous for a physics simulator, in which the temporal order of events is critical. Natural languages also vary in how easily certain concepts are expressed. If we consider not just formally equivalent algorithms for a task but also good-enough approximations, there are even more options. Thus, it might be common or required for the brain to flexibly use different computational mechanisms for the same computational problems[167].

Similarly, there are many algorithms for obtaining at least approximate solutions to questions about Newtonian mechanics — algorithms that vary in their advantages, disadvantages and use-cases. Some questions can be quickly answered through closed-form solution of a few equations, whereas others are easier to solve through simulation. Neural networks can approximate the results of physics simulations in a fraction of the time[168]. However, neural networks work best for familiar situations and can produce nonsensical results in less familiar ones[169,170] (humans are likewise more accurate at solving classical mechanics problems embedded in familiar scenarios[17]). Similarly, computation-reducing simplifications (like treating a cow as a perfect sphere of uniform mass) and heuristics might work well enough in some situations (determining gravitational attraction between a cow and the sun) but be counterproductive in others (milking a cow). This list does not exhaust the options for (approximate) Newtonian reasoning but is sufficient to demonstrate there are many options that work better for different purposes. Note that by virtue of the fact that the world is Newtonian, any sufficiently well-specified theory of cognitive mechanics involves some algorithm (or set of algorithms) for (approximating) Newtonian mechanics. Given that different algorithms are better suited to different purposes, cognitive mechanics might involve many of them. Performance on any particular task need not involve only one but could involve a mixture of multiple mechanisms.

Of course, each cognitive mechanics mechanism need not be itself entirely unitary. For instance, there is good reason to suppose they might each combine real-time processing with stored, rote responses. The proliferation of computational models of cognition in the twentieth century[171–177] has driven home the computational difficulty of most problems solved by human brains. A great deal of current thought is directed at not just understanding how brains do what they do, but how they do it fast enough to be useful[151,178–184]. One approach to rapid calculation is to use classifiers to constrain the hypothesis space[184]; for instance, learning from experience to recognize likely points of failure on a block tower and then running simulations that target just those parts. Constraining the problem space simplifies the problem, making it faster and easier to solve, but at the risk of overlooking something important. Other approaches to rapid calculation, like using neural networks to approximate the results of simulations, similarly trade off speed with accuracy[151]. If humans use stored, learned knowledge to speed up calculation, then two individuals who both have veridical Newtonian simulations at their disposal might, nonetheless, give different answers because they have different experiences and different stored knowledge. Different answers could also occur from one individual at different times (with different stored knowledge) or in different contexts (which might trigger different aspects of stored knowledge to different degrees).

Patterns of behaviour for cognitive mechanics might also be complicated because of complex interactions with other cognitive systems. Mechanisms for cognitive mechanics need to interact with each other and also with input and output systems. As discussed in the cognitive science literature, some misconceptions might arise from imprecisions in perception rather than in cognitive mechanics[38,39,135]. It is also possible that errors arise in action: one might understand the physics of balance beams but have difficulty placing the beam in accordance with that knowledge.

In summary, the complexity of the findings across the three literatures and along a priori considerations about computational complexity and efficiency suggests that cognitive mechanics will not be well described by one or two simple cognitive mechanisms considered in isolation from the rest of the brain. It remains unclear what exactly the ultimate theory of cognitive mechanics should look like. Researchers are only just scratching the surface of two-mechanism theories[17,34,42,102,107,128], much less theories with more mechanisms. In the final section, we make some suggestions for next steps.

Summary and future directions

In the past three decades, research on cognitive mechanics has splintered into three largely unconnected literatures with incommensurate results, concerns and theories. This situation is unlikely to be resolved by overturning the findings of one or another literature, but rather by developing a theory of cognitive mechanics that involves multiple interlocking mechanisms with different affordances and pitfalls and that is differentially active across situations. Cognitive mechanics is complex because solving real-world mechanics problems is computationally complex. But critically, solving mechanics problems is complex in well-understood ways and researchers have an increasingly sophisticated understanding of the affordances of different computational approaches. There are several lines of research that are likely to advance understanding, including determining when cognitive mechanics is accurate, decomposing performance and formalizing models.

One key challenge is that it is not clear under what conditions human cognitive mechanics is accurate and under what conditions it is not. Partly, this answer is unclear because it has not received much systematic investigation. A few studies have carefully compared slight variations in method[44,45,131,132,160], but these cover only a small portion of a large, confusing body of work. For instance, one study reports that adults are strikingly accurate at understanding falling bodies[38], whereas another study concludes the opposite[132]. However, the studies differed in stimuli (stacks of blocks presented in 3D animations[38] versus rods presented in a mix of story problems, line drawings and physical objects[132]), the type and number of judgements (individual judgements about each stimuli[38] versus forced-choice comparisons[132]) and the specific question (whether the stacks would fall, and if so, which direction they would fall and how far away the blocks would land[38] versus which rod would be easier to balance on one's fingertip, and if the rod did fall, how fast it would fall[132]). The analyses of these studies are also not commensurate: the first study used the video game engine in the head theory and found that human performance was similar to an 'ideal observer' that is accurate within the constraints of perceptual uncertainty and processing constraints[38], whereas the second found that human performance was below that of an 'omniscient observer' with perfect knowledge of the stimuli (including exact mass distributions and positions), the circumstances (without wind or large vibrations) and Newtonian mechanics[132]. We suspect that the participants in the second study[132] probably also underperformed relative to the ideal observer, but we do not know. Systematically determining the determinants of accurate versus inaccurate behaviour is key to determining the nature of cognitive mechanics. Extending the systematic comparisons of studies (as done in refs. 44,132,160) is a large project. Although we think it is unlikely, it is possible that systematic study-by-study comparison will result in an uncomplicated story that does not require the interlocking systems account. Regardless, the point is that at the moment, we do not know exactly what theories need to explain and clarifying the phenomena is necessary for further progress.

Even if there are not multiple interlocking systems of cognitive mechanics, performance on any given task is a product of multiple underlying cognitive systems such as attention and working memory. This assumption is implicit in any suggestion that differences in results across studies are due to differences in tasks and extends well beyond the systems often invoked. For instance, performance on any task will rely on attention and cognitive control, working memory and meta-cognitive strategies. In one intriguing example of the relevance of meta-cognitive strategies, people with congenital limb differences thought longer than typically developing individuals before attempting to solve computerized mechanics puzzles but took fewer attempts to correctly solve them[185].

Research into interlocking mechanisms of cognitive mechanics could make use of the increasingly powerful statistical methods for mathematically identifying contributions of different cognitive mechanisms to performance in some tasks. These methods include factor analysis (for distinguishing latent variables such as reliance on different mechanisms) and item response theory (for characterizing differences across stimuli)[186,187]. These methods have been applied to concept inventories in the contemporary century education literature[50,71,72,83,84] and such work needs to be extended to cover the range of methods used in the literature. Use of more advanced Bayesian versions of factor analysis[188,189] might be particularly informative. Such work might provide some clarity on systematic differences in results across stimuli and tasks.

Similarly, cognitive science and developmental psychology researchers are highly experienced at teasing apart interlocking mechanisms through targeted experiments, neuroscientific methods and investigation of developmental trajectories[165,166,190–194]. Building on comparison studies[44,45,131,132,160], these methods need to be systematically applied to the range of findings and questions in the cognitive mechanics literatures. An emerging option derives from rapid advances in cognitive neuroscience. Tasks that invoke different cognitive mechanisms ought to involve different brain systems. Comparing implicated brain systems might historically have involved comparing functionally defined regions of interest; advances in analysis of neuroimaging data are providing a steadily more nuanced view of neural representation and processing, enabling tighter constraints on cognitive theories[174,195]. Indeed, the handful of neuroimaging studies of cognitive mechanics to date have already provided theoretically fruitful results[143,196–200]. We believe that a high-impact next step would be to systematically compare the neural systems involved in tasks that are known to give strikingly different behavioural results, to better clarify why.

Finally, researchers should formalize existing informal accounts to further test their predictions. As described in the review of the cognitive science literature, one of the great insights of the video game engine in the head approach was realizing that positing that cognitive mechanics involves veridical knowledge of Newtonian mechanics does not mean that humans can predict the physical world with infinite precision and therefore that they might not respond or behave in a Newtonian way. Perceptual uncertainty, processing capacity limitations and other practicalities necessarily distort theoretical predictions in ways that are hard to predict without creating a mathematical model of the theory[137]. Historically, it was intractable to develop computational models for theories as complex as some of those developed for cognitive mechanics. However, the sophistication of computational models has grown with leaps and bounds in the past several decades, enabling theories that are increasingly complex and precise[171–177]. Many of the theories that have not yet been formalized now likely can be, and the experience with the video game engine in the head account should make one wonder what unexpected insights might arise.

One question worth exploring is how limitations on computational resources influences theories that are not based on Newtonian simulation. For instance, one theory posits that cognitive mechanics involves augmenting perception with good-enough inferences based on a variety of sources, including experience with one's own motor planning[132,201,202]. As with the video game engine in the head theory, a sophisticated computational model is needed to know what such a theory predicts. The knowledge in pieces theory[29,32,88,97–99] is similarly complex, and it is likely that any computational version will make predictions that are not obvious. Certainly, implementing a computational model will require spelling out points that are currently unspecified (such as the set of p-prims and how they are selected for a specific task), but anecdotally the experience of many computational modellers is that during the process of specifying a theory in a model they really come to understand the theory. An additional advantage of comparing computational models is that it opens the door for 'optimal experimental design': choosing stimuli and experiments that maximally distinguish between models[203–206].

In conclusion, the study of cognitive mechanics has produced a dizzying array of findings and theories and a small but growing number of computational models. In the short term, collecting more data is less important than making better use of the data already collected, developing accounts that make sense of the full range of results. New data-collection efforts would be most profitable if focused on answering questions that will help reconcile the disparate results across and within literatures. Helpfully, the three literatures provide valuable methods, techniques and ideas that, in combination, should enable substantial, rapid progress in determining how people reason about the physical world.

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