Beyond Telling: Where New Computational Media is Taking Model-Based Reasoning

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Abstract The emergence of new computational media is radically changing the practices of science, particularly in the way computational models are built and used to understand and engineer complex biological systems. These new practices present a novel variation of model-based reasoning (MBR), based on dynamic and opaque models. A new cognitive account of MBR is needed to understand the nature of this practice and its implications. To develop such an account, I first outline two cases where the building and use of computational models led to discoveries. A theoretical model of the possible cognitive and neural mechanisms underlying such discoveries is then presented, based on the way the body schema is extended during tool use. This account suggests that the process of building the computational model gradually 'incorporates' the external model as a part of the internal imagination system, similar to the way tools are incorporated into the body schema through their active use. A central feature of this incorporation account is the critical role played by tacit and implicit reasoning. Based on this account, I examine how computational modeling would change model-based reasoning in science and science education.

1 Introduction

Modern science deals with entities and patterns that exist at size, time and complexity scales that are not available to human perception and action. Examples include galaxies, gravitational waves, DNA, molecular forces, evolution, plate tectonics, oscillating reactions, biological arms races, complex feedback loops etc. These entities and patterns are described using abstract external representations, such as equations, graphs, models, simulations, theories, etc., and experimentally

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investigated using complex and opaque instruments, which themselves embed abstract concepts and mathematical models. Learning modern science (and technology) thus requires learning to:

(1) Imagine detailed mental models
(2) Transform external models and related representations
(3) Integrate the mental models and external models

These three skills form the core of Model-Based Reasoning (MBR), which is now considered the dominant component of scientific reasoning (Hestenes 2011, 2013). Most discussions on MBR focuses on internal models, and not on external models. Until recently, most discussions about MBR-based science discovery (Nersessian 1999, 2010) and learning (Hestenes 2013; Lehrer and Schauble 2006) did not critically examine the media on which the external model is based, particularly the role this factor plays in discovery and learning. This is because most examined external models were based on static media (such as equations, graphs and physical models), and MBR was analysed from the perspective of these static media. Following this static media view, the knowledge encoded in external models was considered persistent and available for examination and analysis.

The current widespread use of computational modeling requires changing these static media assumptions, as computational models are both dynamic and opaque (Chandrasekharan et al. 2012). Following the shift to computational modeling in scientific practice, such models are now used in science education as well (Wilensky and Reisman 2006). Given its unique properties, computational modeling presents a novel variation of model-based reasoning (MBR), particularly MBR based on dynamic and opaque models, and a new cognitive account of MBR is needed to understand the nature of this practice and its implications. To develop such an account, I first outline two cases where the building and use of computational models led to discoveries. A theoretical model of the cognitive and neural mechanisms underlying such discoveries is then presented, based on the way the body schema is extended during tool use. This account suggests that the process of building the computational model gradually 'incorporates' the external model as a part of the internal imagination system. A central feature of this incorporation account is the critical role played by tacit and implicit reasoning.

2 The Nature of Computational Media

One way to understand the impact of science moving to new computational media is to examine other such media transitions in history. A recent and central one is the transition from orality to literacy. This shift, which emerged over 6000 years, changed the nature of cognition. Ong (2013) examines the nature of this shift, and highlights the following points:

1. Oral cultures never "looked up" anything; they only used recall. Writing lowered the need for recall, as well as memory techniques that supported this cognitive process (such as mnemonics, verse and rote learning).
2. Oral thought emphasized redundancy, as the spoken word does not persist. Sparse, linear, analytic thought is thus a product of writing.
3. Oral thought was conservative, as society regarded highly those wise old men and women who specialize in conserving knowledge. This conservation emphasis inhibited intellectual experimentation (a central value of science).
4. Oral thought was close to the human lifeworld, as learning or knowing meant achieving close, empathetic, communal identification with the known. Writing created distance, separating the knower from the known. This set up conditions for "objectivity", in the sense of personal disengagement or distancing.

Taken together, this view suggests that writing is a critical factor that *enabled* the development of science and its supporting values and practices. Hestenes (2011) argues that science and mathematics was made possible by writing. Rotman (2008) takes these points further, examining how the nature of writing is related to western cultural notions of the Self, God, and the Platonic nature of mathematics. Also worth noting is the key power shift associated with the move to writing, where the value of chanting (in Sanskrit/Latin/Arabic) was eroded, paving the way to the 'writing class' replacing the 'chanting class'. More broadly, writing enabled new institutional mechanisms, such as land titles, paper contracts, written law and paper money, which together made possible the economic framework within which science functions. The current pedagogical and institutional mechanisms for education, such as standardised curricula, lecture-driven classrooms, written-exams, and certification, are also shaped by the nature of writing and print media.

Similar to writing and print media enabling and reshaping oral knowledge, learning traditions and associated values, the rise of computing is leading to the emergence of a powerful new media system that is inherently dynamic, interactive, participatory and social—features not readily provided by static print media. These powerful features of new computing media allow re-imagining current discovery and learning practices, particularly model-based reasoning, and institutional mechanisms related to science and science education. Similar to the shift to writing, this move will bring in new value systems. This ongoing shift is widely understood and acknowledged, but what is not clear is the direction of this rapidly unfolding change. An analytic, particularly cognitive, understanding of this systemic shift is critically needed, as this will help society adapt more quickly. This is all the more important because the shift is happening in Internet time ($\sim$50 years), while the shift to writing happened over thousands of years.

As a starting point for the analysis of how new media would change the science and science education landscape, the following list captures some of the features supported by print media (text and graphics) and new computational media. It is worth noting that new computational media include text, which suggests that the transition from print would be different from the shift from orality. Particularly, print will not be replaced, but would be augmented.

Print media	New computational media
Static (i.e. does not move)	Dynamic
Non-manipulable	Manipulable and interactive
Individual focused	Social
Removed from the world	Can be hooked to the world
Linear navigation	Multiple navigation paths and trajectories
Explicit encoding of knowledge	Knowledge emerges from interaction

The following sections outline two cases studies and a theoretical model that could help understand the nature of the shift in science to computational media, and how this is changing model-based reasoning. The first section outlines how the building of a computational model led to a remarkable discovery in an interdisciplinary lab. The second section outlines the way basic science discoveries are made using new crowd sourcing games in biology. The third section examines a theoretical model of the possible cognitive/neural mechanisms involved in these two cases, and how interacting with computational models and games could lead to scientific discoveries. The final section examines the broader implications of this model, particularly one possible trajectory of change for science and science education.

3 Building to Discover

In the fields of biomedical engineering and systems biology, computational models are built to develop insights into the behavior of complex biological systems. Based on this understanding from modeling, new technologies are developed to control biological systems, such as neuronal populations (Chandrasekharan 2009) and metabolic pathways (Chandrasekharan and Nersessian 2015). In such cases, computational models are built to understand highly non-linear systems that are too complex to be modeled using traditional approaches based on equations and graphs. Since the phenomena they model are highly complex and dynamic, the models are highly complex and dynamic as well, which makes an explicit understanding of the multiple interactions between different variables (usually above 10) not feasible. However, fundamental discoveries about the natural phenomena have emerged from such 'opaque' (Di Paolo et al. 2000) models and control systems have been built based on this understanding (Lenhard 2006; Winsberg 2006). What is the nature of model-based reasoning in such cases of discovery and innovation? I briefly outline one such case of discovery below, see Chandrasekharan and Nersessian (2015) for details.

Understanding metabolic pathways (a network of biochemical reactions) is a key problem in systems biology, particularly when seeking to reengineer the pathways to develop new organisms, such as plants that allow cheap production of biofuel. One central problem in the production of biofuel is efficiently breaking down lignin, the key biochemical in the plant cell wall. Developing genetically modified plants with lower amounts of lignin would lead to more efficient biofuel production. Modeling would help in identifying systematic ways to lower lignin levels in plants. In the case we report (Chandrasekharan and Nersessian 2015) G10, an electrical engineer with no background in biochemistry, develops a model of lignin, in two phases, first for poplar, then for alfalfa. Based on these models, he made a series of modifications to the scientific understanding of the lignin pathway. One spectacular finding stood out: The modeling showed G10 that the traditional pathway—used by almost everyone in the field for 20 years—is incomplete, and an element (named X by G10) outside the standard pathway has a significant regulatory effect on the behavior of the lignin pathway.

G10's collaborators found this proposal provocative, and did experiments to test this proposal. The experiments identified a possible candidate metabolite that played the specific roles X played in G10's models. A paper outlining the modeling and experimental results was published in a high-impact modeling journal, and the paper was written jointly with the experimental collaborators. This result illustrates clearly the ideal case of modeling—of the model making a significant experimental prediction, which is then tested and validated by the experimentalists. It shows how modeling can lead to discovery, and the value modeling can provide for experimentalists.

Note that the original goal of the lignin project was tweaking a given pathway so as to make lignin break down more readily for biofuel production, which is an engineering goal. But G10 ended up changing the standardized pathway, the scientific consensus on the mechanism underlying lignin production. This is a basic biological science discovery, generated by an electrical engineer, based on a few months of modeling. The remarkable discovery shows that the built external model is not just a replica of an existing standardized structure (the pathway) for the purpose of tweaking. *The external model, and its building, is a mechanism that affords discovering unknown features of the pathway*. Approaching this discovery event from the point of view of understanding the role of computational models, and more broadly external representations, in science cognition, a key question is: What are the cognitive changes involved in building the external simulation model, and how could these changes lead up to the discovery?

We propose (see Chandrasekharan and Nersessian 2015 for details) that the key cognitive change is that within the course of many iterations of model building and simulation, the external model gradually becomes coupled with the modeler's inner mental system, particularly his imagination (simulative mental model) of the phenomena he is modeling. Based on this coupling, the modeler explores different scenarios. The building process thus slowly creates an "external imagination" that is closely coupled to the modeler's imagination system. This coupling allows "what if" questions in the mind of the modeler to be turned into detailed, and close to actual, explorations of the system.

It is important to note that the model acquires this external imagination role only in a gradual manner, through its incrementally acquired ability to enact the behavior of the system that it is modeling. As it is built over many iterations (such as the first poplar model), using many data sets, the model's output/behavior comes to parallel the pathway's dynamics. Each replication of experimental results by the model adds data, and by proxy, real-world complexity, to the model, and this process continues until the model fits all available experimental data well. At this point, the model can *enact* the behavior of the real system—the pathway that is being examined—and thus support detailed "what if" explorations that are not possible to do in the mind alone (see also Kirsh 2010) or in experiments. Importantly, the model's ability to enact the real system behavior is a very complex judgment made by the modeler, based on a large number of iterations, where a range of factors, such as sensitivity, stability, consistency, computational complexity, nature of pathway, and so on are explored. The gradual confidence in the model is thus a complex intuition about its overall performance, emerging over a long series of interactions and revisions, and does not depend just on data fitting, even though fitting is the most critical process leading to this judgment.

As the enaction ability of the model develops gradually through the building process, the model starts making manifest many behaviors the modeler might have only imagined previously. But, the model goes further, as it also makes visible many details of the system's behavior, which the modeler could not imagine (Kirsh 2010) because of the fine grain and complexity of these details. The gradual process of building creates a close coupling between the model and the modeler's imagination, with each influencing the other. The computational model now works as an external component of the imagination system. This coupling significantly enhances the researcher's natural capacity for simulative model-based reasoning (Chandrasekharan 2009; Chandrasekharan et al. 2012; Nersessian 2010), particularly in the following ways:

1. It allows running many more simulations, with many variables at gradients not perceivable or manipulable by the mind (say 0025 of metabolites a and b). These can then be compared and contrasted, which would be difficult to do in the mind.
2. It allows testing what-if scenarios that are impossible to do in the researcher's mind. Such as, what would happen if I change variable 1 and 2 downwards, switch off 6 and 21, and raise 7 and 11 with a time lag between 16 and 19?
3. It allows stopping the simulation in between and checking its state. It also allows tracking the simulation's states at every time point and, if something desirable is seen, tweaking the variables to get that effect more often and consistently. This "reverse simulation" is impossible to do in the mind or in experiments.
4. It allows taking apart different parts of the system as modules, simulating them, and putting them together in different combinations.
5. It allows changing the time at which some in-between process kicks in (say, making it start earlier or later), and this can be done for many processes, which is very difficult to do in the mind or in experiments.
6. It exposes the modeler to system-level behavior that experimenters would never encounter, as most of the above complex manipulations are not possible in experiments.

The process of building this distributed model-based reasoning system comprising researcher(s) and model leads to the creation of new or enhanced cognitive capacities. We thus propose an "incorporation" account of how computational models leads to discovery (see Chandrasekharan and Nersessian 2015), where the building process leads to two kinds of integration. First, incorporation of real-world data into the model, which allows the model to enact the behavior of the system it parallels. Second, incorporation of the model as part of the imagination system, such that imagined scenarios are tried out in the model, and the results are integrated into the internal model of the system the model parallels. This notion of incorporation is novel, and the cognitive mechanisms involved in this process would be wider than just perception, and would involve cognitive systems relating to the processing and understanding of motor control and tool use (see Chandrasekharan 2014). The possible cognitive/neural basis of incorporation is examined in the theoretical model that follows after the next section.

4 Building with Games

A second example of how new computational representations are radically changing the way scientific knowledge is generated, most notably in the biological sciences and bioengineering, is the case of *Foldit*, a video game (built on top of a computational model) that allows novel protein-folds to be designed by web-based groups of people not formally trained in biochemistry. Using *Foldit*, a 13-year-old player (Aristides Poehlman) designed protein folds that were judged better than the best biochemists' folds in CASP (Critical Assessment of Techniques for Protein Structure Prediction), the top international competition on protein-folding (Bohannon 2009). This remarkable result provides an interesting cognitive insight: the *process of building* new protein folds, using the video game interface, allowed the novice player to implicitly develop an accurate/veridical sense of the mechanics and dynamics of the protein folding problem. In this paper, I provide details of this process more generally, and develop a theoretical account of how discoveries could emerge from building.

The approach of 'crowd sourcing' difficult scientific problems to novices using novel interfaces is now widely accepted, especially after *Nature* published a paper (Cooper et al. 2010) where roughly 200,000 *Foldit* players were included as authors. The paper proposed that harnessing people's implicit spatial reasoning abilities using such model-based games could be a new method to solve challenging scientific problems. This proposal is now confirmed, with *Foldit* players making some remarkable discoveries, including building the structure of a protein causing aids in rhesus monkeys, which was an unresolved problem for 15 years (Khatib et al. 2011). The game is currently being refined to support the development of new drugs by the players. A spin-off game from *Foldit*, *EteRNA*, allows players to build RNA folds, and every week the most promising folds from the gamers are synthesized by a Stanford lab. The synthesis results are then fed back to the gamers, who use these real-world results to improve their designs. This closed loop building process has led to the gamers discovering fundamental design principles underlying RNA structure (Lee et al. 2014; Koerner 2012). Other similar crowd sourcing games include *Phylo* (helps optimize DNA sequences) *Eyewire* (helps map 3D structure of neurons). Eyewire recently helped answer some basic research questions about the way retinal cells detect motion (Kim et al. 2014).

These games mark an important shift in the direction of knowledge flow in science, which has traditionally been from implicit to explicit. For instance, in many areas of biology, the effort is to capture implicit procedural knowledge (such as flight patterns and navigation of birds) in explicit declarative terms (such as aerodynamics and signaling). In physics, procedural knowledge (such as the qualitative understanding of force) is considered to lead to misconceptions, and declarative knowledge (such as Newton's Laws) is used to explain many aspects of phenomenal experience. Given this procedural-to-declarative trajectory of scientific knowledge, the case of *Foldit* and similar games marks a new approach to discovering scientific knowledge, as such cases re-represent declarative knowledge using computational models and a manipulable interface, so that naive participants can use their procedural knowledge to build up novel patterns. At the heart of such games and other similar digital media for discovery is a re-representation—converting explicit conceptual knowledge, developed by science (structure of protein, possible folds, hydrophobic/hydrophilic interactions etc.) to build a *control interface* that can be manipulated using a set of actions. This interface allows building of new representations by novices, using their implicit spatial knowledge. These games thus present a fundamental shift in the practice of science, particularly an acknowledgment of the role played by tacit/implicit sensorimotor processes in scientific cognition (Polanyi 1958, 1966). The success of this approach suggests that there is a close connection between procedural and declarative knowledge.

This is a radical epistemic shift, and it is driven by two irreversible factors. One is the focus on understanding interdisciplinary problems such as climate change, where the phenomena under investigation are spread across many time-scales and spatial levels, and complex feedback loops are standard features of the domain. Existing theory and automated methods are not able to solve the multi-scale combinatorial problems that emerge in such areas. It is also possible that in these domains, as von Neumann (1951) observed, the phenomena are the simplest descriptions possible, and any good model would need to be more complex than the phenomena. A second factor is the emergence of 'Big Data', where petabytes of data are generated routinely in labs, particularly in biological sciences. It is not possible to analyze this avalanche of data without computational models and methods, which themselves fail to work for many problems. A good example is the classification of galaxies using data from the Hubble space telescope, a difficult problem that led to the development of Galaxy Zoo, the first effort to crowd-source science. This web-based citizen-science project has led to at least 30 peer-reviewed papers, and a new astronomical object (Hanny'sVoorwerp) named after the Dutch schoolteacher who identified it.

The crowd sourcing approach to scientific problem-solving is new, but the idea of using the human sensorimotor system to detect patterns, particularly in dynamic data generated by computational models, has been applied right from the beginning of computational modeling. Entire methodologies, disciplines, and phenomena challenging existing models have been built just from visualized patterns on computer screens. These include Complexity Theory (Langton 1984, 1990), Artificial Life (Reynolds 1987; Sims 1994), models of plant growth (Prusinkiewicz et al. 1988; Runions et al. 2005), computational bio-chemistry (Banzhaf 1994; Edwards et al. 1998), computational nanotechnology (reported in Lenhard 2004; Winsberg 2006), and climate change (Schneider 2012). All these novel areas of exploration are based on visualizing data from computational models. Apart from the visual modality, protein structure has been generated as music (Dunn and Clark 1999), and scanning microscope output has been used to generate haptic feedback (Sincell 2000).

This approach to making scientific discoveries, by coupling the sensorimotor systems of a crowd of novice humans to data embedded in novel computational media, raises a number of questions about MBR and cognition. Particularly, what cognitive mechanisms mediate the re-representation (and back) of scientific knowledge as manipulable on-screen structures? What is the relationship between declarative and procedural knowledge, such that this conversion is possible and new discoveries could emerge from this conversion process? At a more applied level, how could the visual and tactile manipulation of model elements on screen, by groups of non-scientists, quickly lead them to build valid structures representing imperceptible molecular entities they have never encountered, especially structures that have eluded practicing senior scientists for many years? What cognitive and biological mechanisms support this manipulation-based discovery process? How can these mechanisms be harnessed better, to develop other collaborative games/interfaces that address more complex and abstract scientific and engineering problems with wider applicability?

Answering these questions is critical for practicing as well as learning this new form of science and engineering. To address these questions, we require a general theoretical account that captures how discoveries could emerge from the building of new computational representations, particularly computational models, and re-representation of data from these models.

In the following section, I propose a novel theoretical account of how building and using such computational models could help in making new discoveries. This account extends the incorporation account sketched in the G10 case above, providing a specific model of the cognitive/neural mechanisms at work in the process of incorporation.

5 Incorporation: The Biological Mechanisms

Since the above cases show how novices can make discoveries in complex scientific domains by building computational structures, the mechanism underlying such discoveries cannot be domain-knowledge based. The computational model is helping the modelers extend their imagination to an external structure in the world, where manipulations can be tried out. The results from these manipulation are coupled seamlessly with the internal imagination system. What cognitive/neural mechanism makes this seamless coupling possible? I suggest that this is made possible by a version of the mechanism that extends the body schema during the use of tools.

A number of studies in monkeys have shown how the body schema is extended to incorporate external objects, particularly tools (for a review, see Maravita and Iriki 2004). One influential study (Irikiet al. 1996) examined the firing of bimodal neurons before and after a monkey learned to use a stick to gather food. Bimodal neurons in the intra-parietal cortex respond to both somato-sensory and visual input on or near the hand. That is, the bimodal neurons coding for the hand area will fire when the hand is touched, as well as when a light is flashed on the hand. Interestingly, this firing happens when the light is flashed not just on the hand itself, but also in the space close to the hand ("peripersonal space"), indicating that the neurons code for the space of possible activity, rather than just the hand. Iriki et al. examined whether this firing pattern changed when the monkey started using a stick as a tool. This investigation was done in three phases (see top panels, Fig. 1, adapted from Maravita and Iriki 2004).

In the first phase, there was no stick and the light was flashed on and near the hand, and the bimodal neuron fired. In the second phase, the monkey passively held

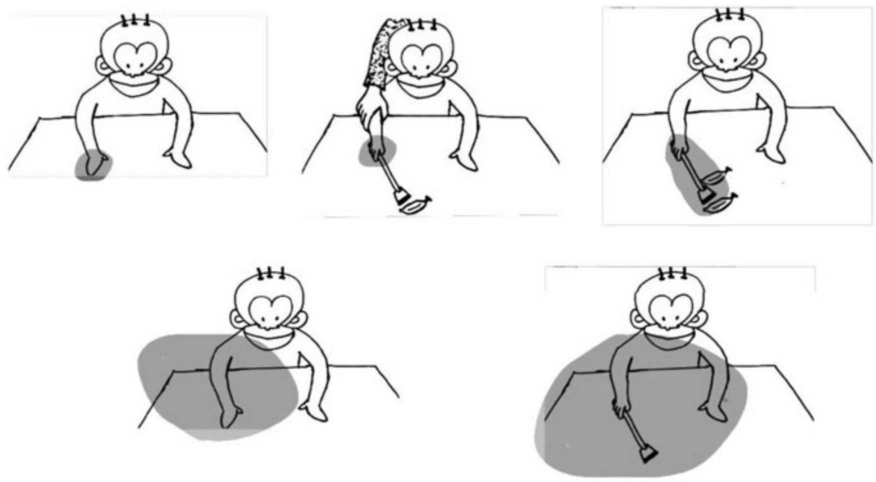

Fig. 1 Monkey with electrodes embedded in the intra-parietal cortex doing the tool task. *Top* panels show the three phases on the task, and how the per-personal space changes. The *bottom* panel shows the way the action-space of the monkey changes

the stick, and the investigators flashed the light near the monkey's hand, as well as at the end of the stick. The bimodal neuron fired only when the light was flashed near the hand. In the third phase, the monkey used the stick to retrieve food from a location that was not reachable by its hand. Immediately after this intentional action, the investigator flashed the light on the hand as well as at the end of the stick. The bimodal neuron now fired for light flashes near the hand as well as at the end of the stick, showing that the peripersonal space (the area of possible activity coded for by the neuron) had been extended to include the area covered by the stick (bottom panels, Fig. 1). The intentional action led to the stick being incorporated into the body, and the monkey's peripersonal space (possible activity space) now extended to the entire area, and objects, reachable by the stick. I will term this "active" incorporation, as the extension occurs only through intentional action. This extension of peripersonal space is important, as it shows that such incorporation is not just about adding an external entity to the body schema. Incorporation expands the range of possible activities the monkey can do—in terms of location of activity, other entities involved, nature of activity, the number of activities, and the permutations and combinations of activities. This expanded range also extends the monkey's understanding/knowledge of the stick, as well as the space around it, which is now understood in relation to the stick. The monkey's cognitive capacities are thereby expanded. Similar incorporation of external entities into the body schema has been shown with humans as well (Farne et al. 2005).

An interesting variation of this incorporation effect (which I term "passive" incorporation) is the rubber hand illusion (Botvinick and Cohen 1998). In this experiment, one hand of the participant is placed on a tabletop, and is visible to the participant. The other hand is placed on the participant's knee, under the table, and is not visible to the participant. The experimenter then places a rubber hand on the tabletop, above and parallel to the unseen hand, and next to the seen hand. The wrist end of this rubber hand is covered with a cloth. The experimenter then touches the unseen hand (under the table) and the seen rubber hand, synchronously, using a brush. After some time, the participant feels the rubber hand as part of his body, and he feels physically threatened if a knife is brought near the rubber hand. This feeling of threat is indicated by a raised galvanic skin response. When the stroking of the unseen hand and the rubber hand is asynchronous, the participant does not report feeling the illusion, and the heightened skin response does not occur. The RHI has recently been extended to induce the feeling of having three arms (Guterstam et al. 2011), and also an "invisible hand effect" when a hand is felt when empty space in front of the participant is stroked in synchrony (Guterstam et al. 2013).

The incorporation of the rubber hand into the body is similar to the incorporation of the tool by the monkey. But it is also different, as the incorporation occurs not through intentional action, but through a dissociation of visual and tactile inputs. One way to understand the relation between passive and active incorporation is to consider the passive as a faint case of the active, where the perceptual effect appears similar to the effect of using a tool, even though no intentional action is executed. In the tool case, the tactile input is seen and felt in a distant manner, but it occurs in synchrony with the visual input of the tool moving. This synchrony could be one of the factors that lead to the tool being incorporated as part of the body schema. In the passive case, a similar synchrony is detected, with no tool present. The brain then "fills-in" the missing tool, by incorporating the locus of the synchrony (the external entity) into the body schema, even though there is no intentional action executed with the entity. Recent results show that such passive incorporation also has cognitive effects. For instance, when asked to bisect a horizontal line midway, most people show a leftward bias (pseudoneglect), which is attributed to the dominance of the right brain hemisphere. This bias is reduced after the rubber hand illusion. This compensatory effect is specific to individuals who report having vividly experienced the illusion (high responders) as opposed to individuals who do not (low responders). Also, pseudoneglect was eliminated only after RHI application to the left hand (Ocklenburg et al. 2012). This suggests that passive incorporation changes the nature of actions that follow, and the cognitive events related to such actions. The extension of the peripersonal space after such incorporation has not been investigated, though the following study seems to suggest that such a change could occur following passive incorporation.

In a further variation of the RHI effect, a remarkable new study has shown that a similar synchronous splitting of the visual and tactile inputs can lead to the feeling of being out of one's body, and owning another body of a different size (van der Hoort et al. 2011). In this experiment, participants lie down, with their head looking toward their feet, while wearing a virtual reality headset that shows the legs of a mannequin lying next to them. An experimenter then simultaneously strokes the participant's legs, as well as the legs of the mannequin, with a rod. This simple manipulation creates a sensory dissociation similar to the RHI: the stroking is felt in one's own leg, but it is seen as happening synchronously in the mannequin's leg. Similar to the RHI, the synchronous dissociation creates the feeling that the feet of the mannequin are the participant's own. Interestingly, the participants then feel like they themselves are the size of the mannequin, and they feel threatened if the mannequin is attacked. This 'out-of-body' experience has remarkable cognitive effects. If the incorporated mannequin is small, the subjects feel short, and when asked to use their hands to judge the size of small boxes shown to them, participants judge the boxes as quite big. Conversely, if the incorporated mannequin is huge, participants feel they themselves are huge, and thus judge really large boxes as small.

Extending this effect further, a similar synchronous dissociation has been shown to create the feeling of being out of one's own body, and being in a point of space outside. This happens when the participant feels the tactile input in her chest, but sees the visual input in a point in space behind her, an illusion achieved using virtual reality goggles. This leads to the incorporation of this (empty) space into the body schema, and the shifting of the visual perspective to that point in space. This effect is quite remarkable, as it shows that the perceptual synchrony can lead to a form of idealized incorporation, where empty space is incorporated into the body (similar to the invisible hand illusion), by shifting the visual perspective to that point in space. This incorporation also has cognitive effects, such as a different judgment of the distance one needs to walk to reach a target (Ehrsson 2007; Lenggenhager et al. 2007). This experiment shows passive incorporation at the level of the whole body, and this type of incorporation seems to alter the nature of cognitive activities performed by the subject, and the space and perspective associated with these cognitive activities. How this global-level incorporation affects possible actions/activities and extension of peripersonal space is not clear, as this has not been explored yet.

These experiments indicate that: (1) Objects are incorporated into the body schema when used as tools, (2) Objects resembling body parts are easily incorporated into the body schema through a synchronous dissociation mechanism, and such incorporation has cognitive effects, (3) Space outside the body can easily be incorporated into the body schema, and this leads to cognitive effects. These results show the possibility of extending your body schema to incorporate external entities and perspectives (and thus knowing them by participation), and how such incorporation can lead to cognitive changes. These are early and indicative results, but taken together with the tool-use case, and the ease with which incorporation occurs, they suggest that such incorporation is possible, and it is very common. The cognitive effects illustrated by these experiments also suggest that such incorporation of external entities and space into the body schema could be a mechanism through which we understand/know external objects—via the new activities, perspectives, or the different ways of doing/examining old activities, which the objects and their features make possible.

The incorporation account provides a new way of understanding how model-based reasoning based on computational models lead to discovery, particularly discovery based on games such as Foldit. Essentially, scientific discovery games work by re-representing conceptual knowledge as a control interface, where global knowledge of the system can be gained through actions on models and feedback from these actions. The above account of how the body schema is extended to incorporate external tools and artifacts suggests the underlying mechanism in the case of Foldit and similar games could be a similar gradual integration of the internal imagination process and the external model, and the implicit understanding of the system's behavior that emerges from this incorporation.

Further, this account could be extended to model-based-learning, where conceptual knowledge is gained through similar actions and feedback, via the manipulation of models and physical artifacts. In mathematics and science education, manipulatives and models are commonly used to improve learning of abstract concepts, such as fraction concepts and area concepts, and unperceivable patterns, such as DNA structure and stereochemistry. More broadly, there are standard approaches to learning based on actions and feedback, such as learning-by-doing and activity-based-learning, and software platforms that promote action-based learning, such as Geogebra, Netlogo (Wilensky and Reisman 2006), and Kill Math, which seeks to promote learning of math and science concepts through manipulations of objects and numbers on screen. The incorporation account of model-based learning allows understanding learning situations involving manipulable models and novel digital media (Landy et al. 2014; Landy and Goldstone 2009; Majumdar et al. 2014; Marghetis and Nunez 2013; Ottmar et al. 2012), and also extend learning frameworks based on modeling (such as Modeling Theory, Hestenes 2006).

6 Beyond Telling

Computational models are complex, opaque and highly dynamic entities that embed experimental data and theoretical concepts. The two cases discussed above suggests that discoveries made by novices using such models significantly exploit *implicit* knowledge, of patterns (case 1) and visuo-spatial structure (case 2). Understanding model-based reasoning using computational models thus require an account where implicit knowledge plays a significant role. The incorporation account (Chandrasekharan 2009; Chandrasekharan and Nersessian, 2015), proposes such a theoretical model, where discoveries based on computational models are based on the gradual development of a coupling between the internal imagination system and the external model. This coupling emerges through the process of building the model and running thousands of simulations and variations. I propose here that the cognitive mechanism underlying incorporation is a reuse/extension of the mechanism involved in the incorporation of tools into the body schema (also see Chandrasekharan 2014).

Since computational models and media are here to stay, what broader implications for science practice and science education are offered by these case studies and the incorporation account? I explore four implications below:

1. From a cognition perspective, a key implication is the wide acceptance of implicit knowledge as a critical component of model-based reasoning and discovery. Computational modelers, in combination with their models, know more than they can tell (Polanyi 1958). Related to this is a focus on the process of building the model, and how building contributes to incorporation, and thereby, discoveries. The building process is poorly understood, and most studies of modeling ignore this critical component, particularly when building is done by communities of modelers, as in the case of *Foldit*. This three-fold combination, of implicit processes, building, and incorporation, could eventually lead to an embodied cognition account of MBR.
2. This shift in scientific practice will be reflected in science education, with the two dominant modes of training in science, apprenticeship and classroom training (which Bruner calls "showing" and "telling" modes), augmented by a modeling-based training. This new "enactive" mode is more social, participatory (as systems such as *Foldit* allow students to work with real problems) and decentralized than the currently dominant "telling" mode practiced in classrooms. While less embodied than the "showing" mode of learning in research laboratories, the enactive mode is more powerful in terms of exploration. The currently dominant telling mode is both enabled by and built around static media such as text and diagrams, and the dynamic nature of new computational media, particularly simulations and visualisations, is already disrupting science education based on this mode.
3. Computational models are constantly revised and expanded, through the embedding of experimental data and theoretical developments. Coupled with their role as generators of counterfactual scenarios and innovations,

computational models develop a complex and constantly changing relationship with the external world. Their correspondence with the real world is achieved, contingent, and constantly evolving. The central role played by computational models in contemporary practice suggests that this nature—achieved, contingent, and constantly evolving—will reshape our understanding of the nature of scientific knowledge, towards science-as-engineered-artifact that becomes part of reality and changes it, rather than (just) the view that science accurately captures pre-existing reality.
4. A central feature of computational models is their extreme ability to generate counterfactual scenarios and mechanisms. This feature makes them ideal for developing new technologies and mechanisms, and this makes computational models one of the key structures supporting the ongoing blending of science and engineering into engineering sciences, particularly in biology. The acceleration of this blending, and the blending of the related distinction between discovery and innovation, is a key practice implication of the shift to computational models and media.

7 Conclusion

The shift from the traditional static media such as text and graphics to computational modeling is set to change the practices of science and science education, particularly model-based reasoning based on external models. I examined two instances of the use of computational modeling to make key discoveries, and proposed an incorporation account of how building these models lead to scientific discovery. This incorporation account was extended further to propose an underlying cognitive mechanism, based on the way the body schema is extended during tool use. I then examined some of the major implications of this account. This account just begins the process of understanding the systemic shift to computational media and its implications for science and science education. A lot more needs to done before we can get a good grasp of the nature of this shift, particularly to design institutional structures around computational media.

References

Banzhaf, W. (1994). Self-organization in a system of binary strings. In R. Brooks & P. Maes (Eds.), *Artificial life IV* (pp. 109–119). Cambridge, MA: MIT Press.
Bohannon, J. (2009). Gamers unravel the secret life of protein. *Wired* Magazine, *17*(05), 17–05.
Botvinick, M., & Cohen, J. (1998). Rubber hands 'feel' touch that eyes see. *Nature, 391*, 756.
Chandrasekharan, S. (2009). Building to discover: A common coding model. *Cognitive Science, 33*(6), 1059–1086.

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Chandrasekharan, S. (2014). Becoming knowledge: Cognitive and neural mechanisms that support scientific intuition. In L. M. Osbeck & B. S. Held (Eds.), *Rational intuition: Philosophical roots, scientific investigations* (pp. 307–337). New York: Cambridge University Press.

Chandrasekharan, S., & Nersessian, N. J. (2015). Building cognition: The construction of computational representations for scientific discovery. *Cognitive Science, 39*(8), 1727–1763.

Chandrasekharan, S., Nersessian, N., & Subramanian, V. (2012). Computational modeling: Is this the end of thought experiments in science? *Thought Experiments in Philosophy, Science, and the Arts, 11*, 239.

Cooper, S., Khatib, F., Treuille, A., Barbero, J., Lee, J., Beenen, M., & Popović, Z. (2010). Predicting protein structures with a multiplayer online game. *Nature, 466*(7307), 756–760.

Di Paolo, E. A., Noble, J., & Bullock, S. (2000). Simulation models as opaque thought experiments. In *artificial life VII: The Seventh International Conference on the Simulation and Synthesis of Living Systems* (pp. 497–506).

Dunn, J., & Clark, M. (1999). Life music: The sonification of proteins. *Leonardo, 32*(1), 25–32.

Edwards, L., Peng, Y., & Reggia, J. (1998). Computational models for the formation of protocell structure. *Artificial Life, 4*(1), 61–77.

Ehrsson, H. H. (2007). The experimental induction of out-of-body experiences. *Science, 317*, 1048.

Farne, A., Iriki, A., & Ladavas, E. (2005). Shaping multisensory action-space with tools: Evidence from patients with cross-modal extinction. *Neuropsychologia, 43*, 238–248.

Guterstam, A., Gentile, G., & Ehrsson, H. H. (2013). The invisible hand illusion: Multisensory integration leads to the embodiment of a discrete volume of empty space. *Journal of Cognitive Neuroscience, 25*(7), 1078–1099.

Guterstam, A., Petkova, V. I., & Ehrsson, H. H. (2011). The illusion of owning a third arm. *PLoS One, 6*(2), e1720.

Hestenes, D. (2006). Notes for a modeling theory. In E. van den Berg, T. Ellermeijer & O. Slooten (Eds.), *Proceedings of the 2006 GIREP conference: Modeling in physics and physics education* (Vol. 31, p. 27). Amsterdam: University of Amsterdam.

Hestenes, D. (2011). Notes for a modeling theory. In *Proceedings of the 2006 GIREP Conference: Modeling in Physics and Physics Education*. (Vol. 31).

Hestenes, D. (2013). Remodeling science education. *European Journal of Science and Mathematics Education, 1*(1), 2013.

Iriki, A., Tanaka, M., & Iwamura, Y. (1996). Coding of modified body schema during tool use by macaque postcentral neurons. *NeuroReport, 7*, 2325–2330.

Khatib, F., DiMaio, F., Foldit Contenders Group, Foldit Void Crushers Group, Cooper, S., Kazmierczyk, M., Gilski, M., Krzywda, S., Zabranska, H., Pichova, I., Thompson, J., Popovic, Z., Jaskolski, M., Baker, D. (2011). Crystal structure of a monomeric retroviral protease solved by protein folding game players. *Nature Structural and Molecular Biology, 18*, 1175–1177.

Kim, J. S., Greene, M. J., Zlateski, A., Lee, K., Richardson, M., Turaga, S. C., et al. (2014). Space-time wiring specificity supports direction selectivity in the retina. *Nature*, *509*(7500), 331–336.

Kirsh, D. (2010). Thinking with external representations. *AI and Society, 25*(4), 441–454.

Koerner, B. I. (2012). New videogame lets amateur researchers mess with RNA. *Wired Science*.

Landy, D. H., & Goldstone, R. L. (2009). How much of symbolic manipulation is just symbol pushing? In *Proceedings of the Thirty-First Annual Conference of the Cognitive Science Society*, (pp. 1072–1077). Amsterdam, Netherlands: Cognitive Science Society.

Landy, D., Allen, C., & Zednik, C. (2014). A perceptual account of symbolic reasoning. *Frontiers in Psychology*, *5*.

Langton, C. (1990). Computation at the edge of chaos: Phase transitions and emergent computation. *Physica D: Nonlinear Phenomena, 42*, 12–37.

Langton, C. G. (1984). Self-reproduction in cellular automata. *Physica D: Nonlinear Phenomena, 10*, 135–144.

Lee, J., Kladwang, W., Lee, M., Cantu, D., Azizyan, M., Kim, H., et al. (2014). RNA design rules from a massive open laboratory. *Proceedings of the National Academy of Sciences, 111*(6), 2122–2127.

Lehrer, R., Horvath, J., Schauble, L. (1994). Developing model-based reasoning, *Interactive Learning Environments*, *4*(3), 218–232.

Lehrer, R., Schauble, L. (2006). Cultivating model-based reasoning in science education. In Sawyer, R. Keith (Eds.), *The Cambridge handbook of the learning sciences*, (pp. 371–387). NY, US: Cambridge University Press, xix, 627 pp.

Lenggenhager, B., Tadi, T., Metzinger, T., & Blanke, O. (2007). Video ergo sum: Manipulating bodily self-consciouness. *Science, 317*, 1096–1099.

Lenhard, J. (2004). Surprised by a nanowire: Simulation, control, and understanding. *Philosophy of Science, 73*, 605–616.

Lenhard, J. (2006). Surprised by a nanowire: Simulation, control, and understanding. *Philosophy of Science, 73*(5), 605–616.

Majumdar, R., Kothiyal, A., Pande, P., Agarwal, H., Ranka, A., Murthy, S., et al. (2014). The enactive equation: Exploring how multiple external representations are integrated, using a fully controllable interface and eye-tracking. In *Proceedings of the Sixth International Conference on Technology for Education* (T4E), IEEE.

Maravita, A., & Iriki, A. (2004). Tools for the body (schema). *Trends in Cognitive Sciences, 8*(2), 79–86.

Marghetis, T., & Núnez, R. (2013). The motion behind the symbols: A vital role for dynamism in the conceptualization of limits and continuity in expert mathematics. *Topics in cognitive science, 5*(2), 299–316.

Nersessian, N. J. (1999). Model-based reasoning in conceptual change. In *Model-based reasoning in scientific discovery* (pp. 5–22). US: Springer.

Nersessian, N. J. (2010). *Creating scientific concepts*. MIT press.

Ocklenburg, S., Peterburs, J., Rüther, N., & Güntürkün, O. (2012). The rubber hand illusion modulates pseudoneglect. *Neuroscience Letters, 523*(2), 158–161.

Ong, W. J. (2013). *Orality and literacy*. Routledge.

Ottmar, E., Landy, D., & Goldstone, R. L. (2012). Teaching the perceptual structure of algebraic expressions: Preliminary findings from the pushing symbols intervention. In *The Proceedings of the Thirty-Fourth Annual Conference of the Cognitive Science Society* (pp. 2156–2161).

Polanyi, M. (1958). *Personal knowledge: Towards a post-critical philosophy*. Chicago: University of Chicago Press.

Polanyi, M. (1966). *The tacit dimension*. London: Routledge.

Prusinkiewicz, P., Lindenmayer, A., & Hanan, J. (1988). Developmental models of herbaceous plants for computer imagery purposes. *Computer Graphics, 22*(4), 141–150.

Reynolds, C. (1987). Flocks, herds, and schools: A distributed behavioral model. *Computer Graphics, 21*(4), 25–34.

Rotman, B. (2008). *Becoming beside ourselves: The alphabet, ghosts, and distributed human being*. Duke University Press.

Runions, A., Fuhrer, M., Lane, B., Federl, P., Rollang-Lagan, A., & Prusinkiewicz, P. (2005). Modeling and visualization of leaf venation patterns. *ACM Transactions on Graphics, 24*(3), 702–711.

Schneider, B. (2012). Climate model simulation visualization from a visual studies perspective. *Wiley Interdisciplinary Reviews: Climate change, 3*(2), 185–193.

Sims, K. (1994). Evolving virtual creatures. *Computer Graphics, 8*, 15–22.

Sincell, M. (2000). NanoManipulator lets chemists go mano a mano with molecules. *Science, 290*, 1530.

van der Hoort, B., Guterstam, A., & Ehrsson, H. (2011). Being barbie: The size of one's own body determines the perceived size of the world. *PLoS One, 6*(5), e20195.

Von Neumann, J. (1951). The general and logical theory of automata. *Cerebral mechanisms in behavior, 1*, 41.

Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—An embodied modeling approach. *Cognition and instruction, 24*(2), 171–209.

Winsberg, E. (2006). Models of success versus the success of models: Reliability without truth. *Synthese, 152*(1), 1–19.