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What happened to the interdisciplinary study of learning in humans and machines?

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ABSTRACT

When the Learning Sciences emerged in 1991, there was an ethos of studying learning in humans and machines in conjunction with one another. This ethos reflected three decades of prior work on the interdisciplinary study of learning; however, in the three decades since the emergence of the Learning Sciences, it seems to have largely disappeared. I begin by describing the ethos that was prevalent in 1991 using quotations from the inaugural editorial of the *Journal of the Learning Sciences*. I then describe how this ethos was prevalent decades before the Learning Sciences in four distinct approaches to cognitive science research, which I call the "Four C's"—cognitivism, constructivism, cybernetics, and connectionism. I suggest three reasons why the Learning Sciences moved away from the use of artificial intelligence as a central tool for thinking about learning, noting that these reasons do not suggest a fundamental incompatibility between the two. I end by discussing how Learning Scientists might once again embrace artificial intelligence and computational modeling and use them as tools for gaining insight into the constructivist, situated, and socio-cultural nature of learning.

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Introduction

When the Learning Sciences (LS) officially formed in 1991—the year that the field obtained both a journal and a conference—there was an ethos in the air of studying big-picture interdisciplinary questions around the nature of learning in both humans and machines. In fact, this ethos was present long before the official formation of LS, reflecting three decades of work on the interdisciplinary study of learning. Since the early days of artificial

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intelligence (AI), researchers were using AI to theorize about human intelligence and learning, and they were using insights from how people think and learn to develop AI. As part of this process, computational models were used to formally describe learning theories and simulate how people learn. However, in the three decades since the formation of LS, the field distanced itself from its roots in AI and computational modeling, such that they are no longer core concerns of the field. Why did these shifts occur? Are AI and computational modeling irrelevant to the study of how people learn *in vivo*—or do the Learning Sciences still have something to gain from the interdisciplinary study of learning in humans and machines?

In this paper, I first give a sketch of the ethos that connected research on AI and human learning that prevailed when the Learning Sciences formed.[1] I then briefly describe four different approaches to studying cognition and learning that informed this ethos and were prevalent before 1991: cognitivism, constructivism, cybernetics, and connectionism. I will refer to these as the "Four C's." I then discuss why the Learning Sciences have moved away from the ethos that united the Four C's despite their differences. I postulate three reasons for why this is the case, noting that these reasons do not suggest a fundamental incompatibility between AI approaches and the Learning Sciences. I end by discussing why AI and computational modeling may still be relevant to LS today and give some illustrative examples of how such methods might be used to better understand the constructivist, situated, and socio-cultural nature of learning. Whether or not the Learning Sciences find value in returning to an interdisciplinary study of learning in humans and machines is ultimately a question that the LS community needs to contemplate and answer; this essay provides a starting point for such a discussion.

The science of human and machine learning in 1991

I claim that the Learning Sciences formed, at least in part, out of an interest in understanding learning in humans and machines. While the community was primarily interested in our understanding of human learning, especially as relevant to educational contexts, the study of artificial intelligence was seen by many as a clearly important piece. We can see this by briefly examining some of the individuals who were responsible for the formation of the Learning Sciences. Roger Schank was a prominent AI researcher who shifted his career from focusing on AI and natural language processing to educational issues when he established the Institute for the Learning Sciences (ILS) at Northwestern University in 1989, thereby picking a name for what would

[1]In an earlier paper (Doroudi, 2022), I provided a much more detailed historical examination of how research on AI and education were intertwined throughout history; the conclusions of the present paper were largely a result of that historical investigation.

soon become a field. In 1991, he chaired the first International Conference of the Learning Sciences and his student, Janet Kolodner, who was also studying AI before this time, became the inaugural editor of the *Journal of the Learning Sciences* (JLS) at Schank's suggestion. Moreover, the editorial board of the journal included other well-known AI researchers who were also interested in education, including Marvin Minsky, Seymour Papert, Douglas Lenat, William Clancey, Elliot Soloway, as well as some of Schank's former students. It is important to note that these researchers had made foundational contributions to AI, not just applying AI to education. Some of them pivoted their research to education (e.g., Schank, Papert, and Soloway); others remained as primarily AI researchers (e.g., Minsky, Lenat, and Clancey). Of course, there were also many many others on the editorial board (and in the broader burgeoning Learning Sciences community) who were not AI researchers, but even then, many of these researchers were cognitive scientists who were familiar with computational modeling and AI, even if they did not use these methods themselves.

Moreover, by taking a look at the inaugural editorial of the *Journal of the Learning Sciences*, we find that an emphasis on AI and machine learning—not merely as applied tools, but as tools for understanding learning—was prevalent. As Kolodner (1991) states when describing existing strands of research that fed into LS, "Artificial intelligence (AI) researchers are using computer programs to study learning processes and are evolving plausible models of learning that can be tested on the computer" (p. 3). Moreover, when describing the kinds of studies that they would publish, Kolodner (1991) stated that

> Also welcome are articles about machine learning, especially when machines are put in realistic learning situations. Sometimes the experiments we do on machines help us make predictions about people, impact the way we can use machines for teaching, and impact the way we can use machines in industry.
>
> Of particular interest are computational models, content theories, and theories combining both. A computational model is a model of the processes by which reasoning happens, rather than just being an exposé of what is known before and what is known after. Some computational models are implemented on machines, and others have that potential (p. 4).

Again, these emphases all reflect the use of AI as a tool for understanding human thinking and learning. They came out of an ethos where studying human learning and studying artificial intelligence were naturally intertwined.

The Four C's before 1991

For three decades prior to the emergence of the Learning Sciences, such an interdisciplinary ethos was present in research on learning. In this section, I briefly outline four different approaches to cognitive science research, broadly conceived, that reflected the interdiscplinary ethos of studying learning in humans and machines: cognitivism, constructivism, cybernetics, and connectionism. Moreover, I show that different approaches to studying learning that had different epistemological and methodological approaches were all motivated by studying human learning and AI in tandem. This in turn suggests that the Learning Sciences' shift away from computational modeling is perhaps not simply due to a change in how the community viewed the nature of learning, which I discuss in the subsequent section.

Cognitivism

Cognitivism (or information-processing psychology) views the mind as being an information processor, much in the same way as a computer. The cognitivist approach to studying cognition and learning was highly influential in the early days of cognitive science. Indeed, it emerged when Herbert Simon and Allen Newell presented one of the first AI programs in 1956, the year that many claim that both the field of AI in particular and the broader field of cognitive science formed (Gardner, 1987). In AI, their work helped establish the symbolic AI paradigm that was mainstream for years. In psychology and education, cognitivism replaced behaviorism as the dominant learning theory for decades (at least in the United States).

Simon and Newell's approach was to study how humans solve problems and then build computer programs that could solve those problems. Therefore, to them AI was largely a tool for reifying and extending psychological theories; investigations on human problem-solving and machine problem-solving were undertaken in juxtaposition with one another. Simon and Newell would go on to make direct contributions to education research themselves (Doroudi, 2022), but their legacy in LS is best seen through the work of their intellectual descendants and colleagues (e.g., John R. Anderson, Kenneth Koedinger, Albert Corbett) and the development of intelligent tutoring systems (especially cognitive tutors). Indeed, Anderson et al. (1995) published an early paper in the *Journal of the Learning Sciences* called "Cognitive Tutors: Lessons Learned." Therefore in the early days of the field, the Learning Sciences still acknowledged the contributions of the cognitivist approach, although it was also trying to shift away from a purely cognitive perspective.

Constructivism

In parallel with the development of the cognitivist approach, constructivism was being developed to make sense of both human and machine learning. The constructivist approach is rooted in the theories of Jean Piaget and it views the mind as actively and gradually constructing knowledge in ways that build upon and extend one's prior understandings. Specifically, Piaget posited that the mind uses two processes to construct knowledge: *assimilation*, whereby new information is incorporated into existing knowledge structures, and *accommodation*, whereby existing knowledge structures are substantially modified to account for new information.

Constructivism as applied to both AI and education is best seen in the work of Seymour Papert and Marvin Minsky, both of whom were AI researchers at the Massachusetts Institute of Technology (MIT) interested in how children learn. Papert had also worked with Piaget for a few years before coming to MIT. While the cognitivist approach in both AI and education emphasized intelligence as exhibited by expert's problem-solving ability, constructivists emphasized how children or machines gradually learn and develop over time. Moreover, while cognitivism tends to use a top-down reductionistic method by breaking down a problem-solving task or a topic that needs to be learned into component parts, constructivism tends to model the mind in a more bottom-up fashion, where the different pieces interact, resulting in emergent behavior. This is exemplified by Minsky's (1988) Society of Mind theory in AI and diSessa's (1993) Knowledge in Pieces theory in LS. Another major difference between constructivism and cognitivism was in epistemology. This is especially seen in the writings of Ernst von Glasersfeld, whose radical constructivism interpreted Piaget's thought as suggesting that the mind cannot be merely a reflection of an external reality—that we each construct our own realities and our goal should be to develop mental structures that are useful in making sense of the world around us (von Glasersfeld, 1984).

Cybernetics

Cybernetics is not typically considered a part of cognitive science, because it emerged independently; in fact, it formed in the 1940s, predating Cognitive Science proper (as represented by the Cognitive Science Society). Many definitions have been offered for what cybernetics really is, but for our purposes, it can be viewed broadly as a transdisciplinary field that studies goal-directed behavior, regardless of what entity is carrying out the behavior (whether humans, machines, animals, biological cells, societies, etc.). Since learning is a prime example of a goal-driven behavior, cyberneticians exhibited an interdisciplinary approach to studying learning in humans and machines. Moreover, Clancey (2008) has identified systems theory, a close relative of cybernetics, as a scientific antecedent of situated cognition (which has been widely influential in LS). In the 1970s, cyberneticians largely embraced a constructivist epistemology; Ernst von Glasersfeld, the founder of radical constructivism, was a cybernetician. Even Papert and Piaget have been regarded as affiliated with cybernetics (Hof, 2021). Thus cybernetics is intertwined with constructivism in many ways. However, cyberneticians approach problems from a distinct perspective that would likely not be familiar to many education researchers and educators who adopt a constructivist approach.

Perhaps more than anyone, Gordon Pask was a cybernetician who was interested in simultaneously understanding learning in humans and machines. In 1955, Pask created EUCRATES, a teacher machine that would teach a student machine, each of which was governed by a neural network with certain tunable parameters (Pask, 1961, 1965). Pask would subsequently build many sophisticated analog computer machines over his career, most of which interacted with human learners. These machines helped him develop his own theory of learning called "conversation theory," which provided a very formal exposition of the nature of conversations, whether they take place within a mind, between people, between a person and a machine, between two machines, or between distributed minds (Pask, 1975). As such, conversation theory has been regarded as a constructivist theory (Scott, 2001b) that preempted distributed cognition (Scott, 2001a).

Connectionism

Motivated by biology, connectionism is the approach to cognitive science that models learning using artificial neural networks. Like constructivism and cybernetics, connectionism focuses on learning as a gradual process, rather than emphasizing expert performance. Cybernetics actually laid down some of the foundations for connectionism. Cyberneticians McCulloch and Pitts (1943) first proposed a neural network model for computation. As mentioned earlier, Pask also created machines to simulate teaching and learning using neural networks in the 1950s. However, connectionism lost popularity in the 1970s, and only reemerged in the late 1980s as a viable alternative to other approaches in AI. While connectionism relies on neural networks, its goal was not to simply produce an effective tool for machine learning, which is how it is seen today after being rebranded into "deep learning." Rather, the researchers who advocated for it were cognitive scientists who wanted to give a more accurate model of human cognition (McClelland et al., 1986).

However, unlike the other three C's, connectionism has been largely uninfluential in education. This is likely because it models learning at a very granular scale (i.e., at the level of individual neurons), which is difficult to connect to educational practice. Nonetheless, connectionist models have been proposed to model constructivist phenomena, like Knowledge in Pieces (diSessa, 1993) and phenomena under the lens of distributed cognition (Hutchins & Hazlehurst, 1991, 1995).

What happened after 1991?

I have shown that for several decades before the Learning Sciences emerged, there was a general tendency to investigate human and machine learning simultaneously (even if this manifested in several different approaches). I also showed that even when LS first emerged, this ethos was still present. However, I claim that both Learning Scientists and AI researchers today have largely moved away from this interdisciplinary mode of thinking about learning in humans and machines. Why? I suggest three reasons below.

A change in focus

The Learning Sciences were committed to viewing learning as a complex phenomenon grounded in real socio-cultural contexts. The formation of LS coincided with the emergence of theories that viewed learning as situated (Lave & Wenger, 1991), distributed (Hutchins, 1990; Salomon, 1993), and embodied (Johnson, 1989). In fact, many of these theories emerged in reaction to the limitations of symbolic AI and the cognitivist approach. Computational models of cognition that did not consider the complexities of the socio-cultural context and learning that took place outside of the confines of an individual head were seen as too limited. As such, Learning Scientists gravitated toward qualitative methods and design experiments. As qualitative methods become more popular, subsequent generations of Learning Scientists were more likely to be trained in these methods as opposed to computational modeling and AI.

Nonetheless, the early Learning Scientists that were making this shift were still cognitive scientists who were trained in the ethos of thinking about human and machine cognition in conjunction with one another. Some of the very pioneers of the newly emerging distributed theories of learning in the 1990s advocated for using computational models (Greeno & Moore, 1993; Hutchins & Hazlehurst, 1991). Moreover, as Baker (2000) argued to the AIED community, "criticism of the view of human beings as symbolic information processors is not the same as criticizing (computational or other) modeling as such, but rather a specific type of computational model of human capacities" (p. 127). However, the Learning Sciences never again had a critical mass of members embracing such methods.

Moreover, in recent years the Learning Sciences have shifted toward giving more attention to the political context of learning (Booker et al., 2014) and being attuned to racial inequities and injustice (Nasir et al., 2021). Computational modeling therefore might seem even less useful to the focus of LS, as (1) current LS approaches are even further removed from computational modeling, and (2) increasing concern around algorithmic bias makes researchers even more skeptical about applying computational models to social and educational problems. However, the use of computational models as tools for thinking about learning may not be as susceptible to algorithmic bias as the use of computational models as tools that directly intervene on the practice of teaching and learning. In fact, studying algorithmic bias could potentially help us learn more about human biases and inequity, as discussed in the next section.

Distancing itself from AIED

The First International Conference of the Learning Sciences was actually designed to replace what would have been the Fifth International Conference of Artificial Intelligence and Education. Roger Schank and his colleagues were attempting to re-brand an existing community. However, the concerns of the newly formed Learning Sciences were not exactly the same as that of the burgeoning AIED community. In part, LS was not solely concerned with learning environments that use AI. The AIED community decided they wanted to continue their own conference that was independent of ICLS, beginning with AIED 93 (Self, 2016) The ICLS community also saw themselves as distinct from the AIED community. As Sawyer (2005) recounts what happened after the first ICLS:

> But the newly formed learning sciences community and the AI and Education community found that they had somewhat different interests. AI and Education researchers continued to design tutoring systems and other educational tools based on AI technologies, while the learning sciences community was more interested in studying learning in real-world learning environments, and in designing software that focused on learners' needs, whether or not AI technology was needed. After the 1991 conference, the AI community and the learning sciences community parted ways (p. 14).

Thus, researchers who were interested in applications of AI in education would gravitate toward AIED, while researchers interested in understanding and designing learning environments through the lens of constructivist and socio-cultural perspectives would gravitate toward ICLS. Perhaps in branding their identities as distinct research communities, AIED and ICLS lost an approach to research that could have acted as a bridge between them.

AI moved on

The above two arguments attempt to explain why LS moved away from using AI. But AI also moved away from studying human learning and cognition (Forbus, 2010). From the mid-1980s to the 1990s, AI was going through an "AI winter," a period of decreased excitement and funding (Nilsson, 2009). When funding for AI increased again, the techniques had changed with growing emphasis on machine learning (studied independent of human cognition) among other new areas (Nilsson, 2009). Indeed, if one looks at AI research today, connectionism has become increasingly popular in the form of deep learning, with the other three C's largely on the decline, if not entirely absent from the field (Martınez-Plumed et al., 2018; Synced, 2018). Moreover, deep learning today is primarily motivated by increasing the accuracy of machine learning models, not fundamental considerations around how people learn (Perconti & Plebe, 2020).

It is true that cognitive science still brings together researchers interested in artificial and human cognition (including educational concerns), but it is rare for individual cognitive scientists to (a) simultaneously explore both sides and (b) explore them in educational contexts. Indeed, recent surveys of cognitive science have shown that psychology has become more dominant in the field over the years, and the role of artificial intelligence has declined (Cooper, 2019; Gentner, 2019). For example, Cooper (2019), showed that in recent years fewer papers have been submitted to *Cognitive Science* on topics such as "Computer Simulation," "Knowledge Representation," "Neural Networks," and "Symbolic Computational Modeling." This is despite the growing popularity of AI in general, and neural networks in particular. As suggested by Gentner (2019), "Many AI researchers now work in industry on projects that do not require thinking about the nature of cognition." (p. 890). Moreover, cognitive scientists who do study the interplay between human and machine cognition are typically not studying this in the context of authentic educational settings.

What lies ahead

The three reasons I articulated for why the Learning Sciences moved away from AI collectively suggest that the separation of LS from AI is not so much due to the fact that the Learning Sciences conceptualized learning in a way that made AI irrelevant, but rather, that the fields evolved in ways that made the relevance of AI to the study of learning no longer obvious. Below I argue for several different ways in which AI may still be relevant to LS today and how future research in LS could once again embrace an interdisciplinary approach to studying learning in humans and machines.

Complex systems

It is true that complex theories of learning that are attuned to socio-cultural contexts, politics, and equity are more difficult to model computationally. For this reason, I contend it is worth looking at a fifth C: complex systems. In doing so, I echo the call of Learning Scientists who have also recently advocated for adopting complex systems in LS (Jacobson et al., 2016; Jacobson & Wilensky, 2006). Complex systems draw upon the constructivist, connectionist, and cybernetic approaches described earlier. Complex systems approaches can complement existing quantitative and qualitative methods in LS and offer several distinct advantages (Abrahamson & Wilensky, 2005; Jacobson & Wilensky, 2006) First, they can force us to formally and precisely convey our theoretical claims and they can be used to refine those claims by comparing the results of simulations with empirical data. Second, they can be used to quickly run simulations of "longitudinal studies," which would be difficult or impossible to run in the real world. Third, they can be used to simulate many "what-if" scenarios in a risk-free environment by manipulating parameters in the models, which again could be difficult or impossible to run in the real world. In what follows, I discuss two approaches to complex systems computational modeling—agent-based models (ABMs) and dynamical systems—focusing on concrete examples that are of relevance to the Learning Sciences.

Agent-based models

Agent-based modeling is a particular approach to computational modeling that might be useful to LS as it can be used to model both the distributed nature of learning in an individual mind (diSessa, 1993; Minsky, 1988; Papert, 1980) as well as the distributed nature of learning across different people and tools (Carley, 1986; Hutchins & Hazlehurst, 1991). ABMs are compatible with the constructivist perspective, and in some cases, the connectionist approach to computational modeling; all of these approaches tend to model learning in a bottom-up fashion.

ABMs can be used to examine constructivist phenomena in learning. For example, diSessa (1993) proposed a computational model for his highly influential Knowledge in Pieces framework, but such a model has never really been implemented and tested to my knowledge; it has primarily been studied using deep qualitative inquiry. The Knowledge in Pieces framework has two different conceptual models for describing intuitive conceptions (i.e., p-prims) and more robust mature understandings (i.e., coordination classes; diSessa, 2018). According to the model described by diSessa (2018) each p-prim could be represented as a node in a connectionist network (or analogously, as an agent in an ABM). The hypothesis is that changes to the connections in the network, which change the dynamics of which nodes get activated in different situations, would result in conceptual change that results in coordination classes. Simulating such a formal connectionist model could therefore give new insights into how conceptual change can lead from a network of loosely coupled p-prims to a robust coordination class over a long period of time.

ABMs can also be used to examine socio-cultural phenomena. For example, in an article in *Instructional Science*, Carley (1986) conceptually described an ABM that would model "knowledge acquisition as a social phenomenon." In this model, each agent has a knowledge representation inspired by AI formalisms of the time (developed under the cognitivist and constructivist AI perspectives), but unlike most work in AI, these knowledge representations change as a result of social interaction, which depends on both the degree of shared knowledge and the structure of the social network. Moreover, the knowledge representation formalism inherently allows for different individuals having different interpretations of shared concepts. As such, this model seems quite compatible with theories in the Learning Sciences that view knowledge construction as (a) dependent on social context and (b) constructed both individually and socially. While this model has been implemented and studied in sociology (Carley, 1991; Carley et al., 2009), it has seemingly been ignored in LS despite its relevance.

Dynamical systems

Recently, cognitive scientists have striven to develop modeling frameworks that could account for embodied cognition and grounded cognition (Pezzulo et al., 2013; Schöner, 2008). One such approach involves the use of dynamical systems, an alternative approach to ABM for modeling complex systems. Dynamical systems are closely aligned with the cybernetic perspective. According to Schöner (2008), there are two ways of using dynamical systems for modeling cognition. One is to view dynamical systems as a metaphor for how complex properties of cognition emerge over time; the other is to actually model cognition with a mathematical dynamical systems model.

The former approach has been used in the Learning Sciences. Barab et al. (1999) articulated a situated theory of learning that describes the learner-environment system as a dynamic self-organizing system. Abrahamson and Sánchez-García (2016) articulated a theory of embodied interaction for mathematics learning that draws upon dynamical systems theory and ecological psychology. As a mathematical modeling theory, dynamical systems have been used to describe embodied cognition (Schöner, 2008), but these models have seemingly not yet been extended to embodied learning. This could be an area of further inquiry in LS.

The epistemological status of computational models

The above analysis has hopefully shown that certain kinds of computational models may be compatible with learning theories used in LS, but some Learning Scientists may remain skeptical that computational modeling is epistemologically compatible with current approaches in LS. However, as mentioned above, the constructivist and cybernetic approaches to AI align with a constructivist epistemology that is common in LS. Moreover, regardless of the *kind of computational model* employed, epistemology says more about the *kind of inference* that can be made from such models.

To this point, Greeno and Moore (1993) have argued for the use of computational models to describe situated theories of learning, but in a way that is different from traditional cognitivist modeling. They mention how their work too depends on "symbolic computational models," but their "use of computational simulations involves a different metatheory from the one commonly used in information-processing psychology" (p. 56). They claim that while information-processing psychology focuses on " *demonstrative* simulations" that try to explain the exact mechanisms behind cognition, their work relies on " *descriptive* simulations" that take the more modest goal of trying to describe some of the properties of cognition.

Similarly, McClelland (2009), one of the pioneers of the connectionist tradition, described his view of the status of computational models in cognitive science more generally:

> I argue that we should think of models as tools for exploring the implications of ideas. They can teach us things about the consequences of particular ways of construing the processes that take place when humans engage in particular kinds of cognitive tasks, with sometimes surprising consequences. … A good fit never means that a model can be declared to provide the true explanation for the observed data; a poor fit likewise does not necessarily show that the core principles embodied in a model are necessarily the source of the misfit (p. 12).

Hennig (2003, 2010) puts forth an explicitly constructivist epistemology for statistical and mathematical modeling (which can also be applied to computational modeling). In fact, he cites constructivist cyberneticians, such as von Glasersfeld and von Foerster as inspiration. In this view, models are tools for making sense of the phenomena being modeled, but they are not mirrors (or even approximations) of reality. Instead, Hennig (2003) argues that

> The benefits and dangers of modeling are closely connected: Models enable understanding, clarification and communication of the researchers' perceptions and concepts, but this comes to the price that these perceptions must be adapted and reduced to the formal language (p. 239).

McClelland and Hennig remind us of the limitations of models, echoing Box's (1979) famous maxim: "all models are wrong but some are useful." However, I contend that while the LS community has acknowledged that all computational models are wrong, perhaps it has done so at the expense of ignoring the possibility that some may be useful.

The continued relevance of cognitivism

Although many Learning Scientists have moved away from cognitivism, it is important to acknowledge that just because information-processing is not sufficient to account for the complexity of learning in real world contexts, that does not mean it is not necessary or useful. For example, according to Greeno and Moore (1993), in their defense of situated theories,

> We believe that fundamental insights about mind and intelligence have been achieved by adopting and developing the symbolic processing view, and these insights must be built upon in whatever we move toward now. At the same time, we believe that the symbolic processing framework should be subsumed by a theory in which symbolic processes are considered as a kind of cognitive activity, with the goal of explaining symbolic activity in terms of more general individual and social cognitive principles (p. 57).

For decades, some researchers in AI have been interested in how to combine the advantages of symbolic systems and connectionist systems to attain more robust AI and to better understand human cognition (Marcus, 2020; Minsky, 1991; Sun & Alexandre, 1997). However, to my knowledge, such hybrid models have not been explored in LS. How can we devise models that simultaneously capture the precision of rule-based learning (e.g., as seen in intelligent tutoring systems) but also deal with the complexities and ambiguities of real world learning? Perhaps combinations of the Four C's are needed.

Beyond computational models

Throughout this paper, the discussion of the relevance of AI to the Learning Sciences has mostly been about the relevance of computational models. However, I suggest that AI has more to offer than just models; AI can offer a different way of thinking about problems in the Learning Sciences. This was seen earlier when discussing the use of dynamical systems as a metaphor. More broadly, cybernetics can also be viewed as a metaphor for understanding learning; "cybernetics is a way of thinking, not a collection of facts" (von Glasersfeld, 1992). Viewing cybernetics as being about more than just machines, von Glasersfeld (1992) claims "Its concepts of self-regulation, autonomy, and interactive adaptation provide, for the first time in the history of Western civilization, a rigorous theoretical basis for the achievement of dynamic equilibrium between human individuals, groups, and societies." This way of thinking seems absent from LS today, but an examination of the first few issues of the journal *Instructional Science* shows various ways in which a cybernetic approach was applied to the study of learning and teaching.

Pask's conversation theory is an illustrative example of a precise and formal cybernetic theory of how people (and machines) learn in different contexts. Conversation theory uses a kind of mathematical formalism that is rare in LS, yet it was articulated to account for the constructivist, distributed, and social nature of learning. Conversation theory and its associated form of knowledge representation (entailment meshes) have a number of features that might make them relevant to LS [e.g., knowing something is in terms of mutual agreement, not objective truth; knowledge is represented heterarchically, rather than hierarchically; analogies across disparate topics are emphasized and represented; the learner can add new topics to the existing knowledge representation (Pask & Kopstein, 1977).

Moving toward more recent examples of how AI can be applied to, I have shown how the bias-variance tradeoff (a theoretical concept in machine learning) can be formally applied to educational debates, such as the debate between cognitive and situative theories and the debate between direct instruction and discovery learning (Doroudi, 2020). By doing so, formal analogies can be applied between ideas or techniques in machine learning and different ways of approaching these debates in the Learning Sciences. Moreover, we have shown that the bias-variance tradeoff can also be used to interpret research on how people learn, including individual differences in learning (i.e., memorization vs. rule abstraction) and the interplay between assimilation and accommodation in constructivism (Doroudi & Rastegar, 2023).

Moreover, a recent area of focus in machine learning is the study of algorithmic bias. While the prevalence of algorithmic bias may raise questions about applying machine learning in educational contexts, studying the *concept* of algorithmic bias can actually serve as a tool for reflecting on human biases. Indeed, recent work has outlined structural similarities between algorithmic bias and cognitive biases (Johnson, 2021). LS could build on this with a focus on biases that influence and are influenced by learning. This is but one example of how studying learning in machines might serve (rather than go against) the equity-centered goals of the Learning Sciences.

Finally, the recent emergence of large language models (LLMs; like ChatGPT) suggests new possibilities for probing into the nature of human and machine learning. Researchers can potentially study how LLMs can learn through language to gain insights into how people learn (while also noting important differences). From a practical perspective, researchers could potentially quickly simulate different curricula and pedagogies using LLM learners to inform the design process and experiments done with actual students.

Reinvigorating a science of learning in humans and machines

All of the examples above are meant to illustrate how the study of intelligence and learning in machines may have something to offer the Learning Sciences. But a true "science of learning in humans and machines" would involve a bidirectional relationship whereby the Learning Sciences could help advance AI as well. For example, as Goel (2022) has recently argued, "neither symbolic nor connectionist AI have much to say about socially situated intelligence." Goel (2022) claims herein lies an opportunity for AI researchers to

> develop new computational theories of socially situated intelligence (as well as embodied intelligence, physically situated intelligence, distributed intelligence, and social and cultural intelligence) that place significant parts of a machine's "mind" outside its "head." As just one example, there is much to be done in the space of designing intelligent agents that can learn from and teach other intelligent agents including humans, that can use interactions with humans to develop a mutual theory of mind, and that can foster better human-human communication and collaboration (p. 85).

It seems to me that a learning sciences community that is also concerned with AI would be in a unique position to aid in the development of such theories.

Ultimately, the LS community must decide whether it wants to return to an ethos of studying learning in humans and machines and which of the directions outlined above should be pursued. But these decisions should be guided by a thoughtful reflection on the past of the field. My hope is that this paper offers such a reflection.

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