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A Mind with a Mind of Its Own: How Complexity Theory Can Inform Early Science Pedagogy

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Abstract

In the current paper, we develop an approach to early science pedagogy that is based on insights about how complex adaptive systems function. Complexity approaches have an important advantage over traditional information-processing approaches: They anticipate the proverbial 'mind with a mind of its own' without having to postulate exclusively mental constructs. They also offer insights about key determinants of learning and effective pedagogy, again without postulating exclusively mental constructs. For complex adaptive systems, learning depends on the presence of sufficiently salient novelty (i.e., variability), and it depends on the presence of sufficiently salient repetitions or ordered patterns (i.e., stability). Science learning, therefore, requires science-relevant novelty and science-relevant patterns of order. Equipped with these insights, we address two challenges of early science pedagogy: (1) how to combine children's self-guided explorations with teachers' strategic interventions, and (2) how to minimize the chances of generating misconceptions about science. The answer lies in creating a learning context that maximizes science-relevant variability and science-relevant stability. If both aspects are abundantly available, a child's self-guided explorations are effective. Conversely, if either aspect is missing, efforts must be made to add them strategically

Highlights

- A new approach to early science learning is offered, motivated by insights about the mind as a complex adaptive system.
- Complexity theory, unlike information-processing theory, anticipates the often-lamented tendency for the mind to behave as if having a mind of its own.
- Two key determinants of learning are identified: (1) the amount of variability in the surrounding, and (2) the amount of stability from one experience to the next.
- Science topics can be organized systematically by whether the variability and stability available in the surrounding are relevant to the chosen science topic.
- Science topics with sufficient variability and stability (i.e., *basic-level science content*) are best learned via mere explorations, without needing teacher intervention.
- Science topics that lack either variability or stability (i.e., *sub-ordinate* and *super-ordinate level science content*, respectively) require teacher intervention to support learning.

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to a child's experience. Adding science-relevant stability is particularly challenging, yet crucial to avoid science misconceptions.

Keywords Complex adaptive systems · Science taxonomy · Preschool science learning · Early childhood education

> "When data of any sort are placed in storage, they are filed, and information is found by tracing it down. The human mind does not work that way. With one item in its grasp, it snaps instantly to the next that is suggested by the association of thoughts, in accordance with some intricate web of trails."
> —Bush 1945

Recent decades have seen a strong push for science learning at the preschool level (Kloos et al. 2012; National Research Council 2001). Yet, challenges remain. For example, details are still unclear about how to combine children's self-guided explorations with a teacher's strategic interventions (e.g., Ashiabi 2007; Fullan 1994; Golbeck 2001; Hadley 2002; Kagan 1990; Lazonder and Harmsen 2016; Mayer 2004). Similarly, there are still questions about how to avoid misconceptions about science phenomena (cf. Carey 2000; Shtulman and Valcarcel 2012; Vosniadou 2007). In the current paper, we offer solutions to these challenges, using insights about complex adaptive systems.

Complex adaptive systems consist of elements that are affected by outside forces, as well as by each other (Holland 2006). One familiar example is the system that produces the weather: Molecules of water and air are affected by the sun's heat, as well as by each other (e.g., when air is caught in a tornado). Other examples include cells, organs, bodies, and animal groups (e.g., ant colonies, bird flocks, schools of fish, families). Complex adaptive systems are also found in social organizations, the world wide web, and the economy (Caldarelli and Catanzaro 2012; Davis and Sumara 2006; Davis et al. 2009; Gargiulo and Benassi 2000; Hilpert and Marchand 2018; Mendes and Dorogovtsev 2003; Whitchurch and Constantine 2009). Even the mind operates like a complex adaptive system, whether the emphasis is on perception, problem-solving, or reasoning (Chow et al. 2011; Clarke and Collins 2007; Colunga and Smith 2008; Fenwick 2003, 2008; Jacobson and Wilensky 2006; Kello et al. 2007; Mason 2008; Sporns and Zwi 2004). In each case, elements organize themselves into structures that persist over time, all without a fixed blueprint or an external controller.

In the current paper, we build upon these ideas to derive explicit recommendations for early science education (see also Barab et al. 1999; Davis and Simmt 2003). Our paper is organized as follows. First, we describe what a complexity approach can offer, vis-à-vis the traditional information-processing approach to children's cognition. We then develop a complexity-based learning theory, derived from the working of an iconic complex adaptive system: the ecosystem. Next, we apply the complexity theory of learning to the working of the mind. In extending these insights to children's science learning, we offer a taxonomy of science content that considers complexity-based key determinants of learning. Finally, we use the proposed taxonomy of science content to address current challenges in early science education.

What Do Complexity Accounts Offer That Traditional Accounts Cannot?

The mind's ability to make sense of its surroundings is typically addressed with information-processing accounts (e.g., Miller 1956). These accounts attribute mental activities to an underlying flow-chart architecture of processes (e.g., Anderson 1996, 2015; Weisberg and Reeves 2013). The input to such a flow chart is the child's surrounding, and the output is the meaning that the mind computes (e.g., Fodor 1981; Gazzaniga 2004). In this view, identifiable units guide the processing of information from input to output. For example, attention is thought to stem from a unit responsible for executive function; memory is said to involve the mind's storage system; and reasoning is said to stem from the unit that manipulates symbols (e.g., Halford et al. 1998; Kurby and Zacks 2008). These accounts are hugely popular, so much so that information-processing terms have become part of everyday language (e.g., 'selective attention, 'long-term memory', 'representation').

Despite their popularity, there are concerns about the underlying assumptions of information-processing accounts (e.g., Barsalou 2008; Lakoff 2008; Van Orden et al. 2003). For example, information-processing accounts imply a reflexive and scripted mind: Information impinges on the senses and triggers the formation of knowledge in a computationally fixed way (cf. Ohlsson 2011). In reality, numerous examples suggest the opposite to be true. The mind is actively filtering and selecting—as if having a mind of its own (Carey 2014; Fine 2008; Flavell et al. 1998; Piaget and Inhelder 1969). Everyday observations of children illustrate this point: Children can oscillate from being highly focused to absent-minded, all without obvious changes in the surrounding. And children will sometimes remember seemingly irrelevant details, while forgetting what appears to be exceedingly obvious. They might even make up new content and reject experiences that do not fit with their expectations (Kelemen 1999; Kuhn 1989; Shtulman 2017; Simons and Keil 1995).

In order to accommodate the apparent willfulness of mental activity, information-processing accounts must put forth additional theoretical constructs, on top of the assumed architecture. For example, to explain unexpected behavior, postulated processes include interference, inhibition, and implicit memory (e.g., Diamond 1985, 1990; Posner and DiGirolamo 1998). And, to explain unexpected learning or forgetting effects, individual differences have been invoked, for example in cognitive readiness, working-memory capacity, accessibility, or developmental stage (Jonassen and Grabowski 2012; Ormrod 2011). Such theoretical maneuvering has allowed information-processing accounts to remain relevant in cognition. However, the framework has not succeeded in univocally addressing questions about learning.

In contrast to information-processing accounts, complexity approaches can capture the aliveness of systems without needing additional theoretical constructs (e.g., Holland 2000; Iberall and McCulloch 1969; Kauffmann 1993). Whether the new structure is a cold front, an ant hill, a pattern of brain activation, or social interactions, no domain-specific machinery is needed to explain why a behavior persists. Instead, the only requirement is a large number of elements, connected to the outside and to each other, and placed under certain thermodynamic constraints (Deacon 2011; Jacobson et al. 2016; Michaelian 2005). More specifically, the general laws of thermodynamics push for elements to settle into organizational structures that speed up the process of increasing randomness (Gross and Blasius 2008; Nicolis and Prigogine 1989). The mind's working follows the same principle: Meaning emerges from pressures to abide by the laws of thermodynamics (Swenson 2000; Turvey and Carello 2012).

In sum, while both complexity and information-processing accounts can explain stable patterns of human behavior, only complexity accounts anticipate the apparent willfulness of mental activity. They do so by capitalizing on the general principles of dissipating thermodynamic gradients. These principles, when applied to interacting elements of a medium, push for structures to emerge and persist against perturbations, as if having a mind of their own. Thus, what looks like a willful agent is instead an emergent pattern resulting from the universal tendency to maximize randomness. In the next section, we describe selected features of complex adaptive systems to derive a general theory of learning.

How Do Complex Adaptive Systems Learn?

So far, we have given a justification for why complexity accounts provide a useful framework to capture mental activity. The next step is to address the question of learning. Here, we turn to ecosystems, a type of complex adaptive system that has been linked to the working of the mind before (Castillo et al. 2015; La Cerra and Bingham 2002; Ulanowicz 2009, 2012; Weber 2010). Like all complex adaptive systems, ecosystems consist of elements that are affected by outside forces and by each other: Species are affected by the surrounding, and they feed on each other. Furthermore, ecosystems are subject to the same thermodynamic laws that push for the self-organization seen in all complex adaptive systems: The exchange of calories contributes to the overall dissipation of calories, increasing randomness. However, ecosystems differ from the generic complex adaptive system in their maturity. Over centuries of calorie exchange, species have changed each other in a lasting way. This makes it possible to identify key determinants of learning more readily than in a more transient complex adaptive system.

Figure 1 shows an example ecosystem: a schematic of the real-life Cone Spring ecosystem (Allesina and Bondavalli 2003). The elements of this system are bacteria, detritivores (e.g., worms), carnivores (e.g., birds), and organic material. Importantly, each element of the ecosystem is a complex adaptive system in itself (e.g., species are composed of animals

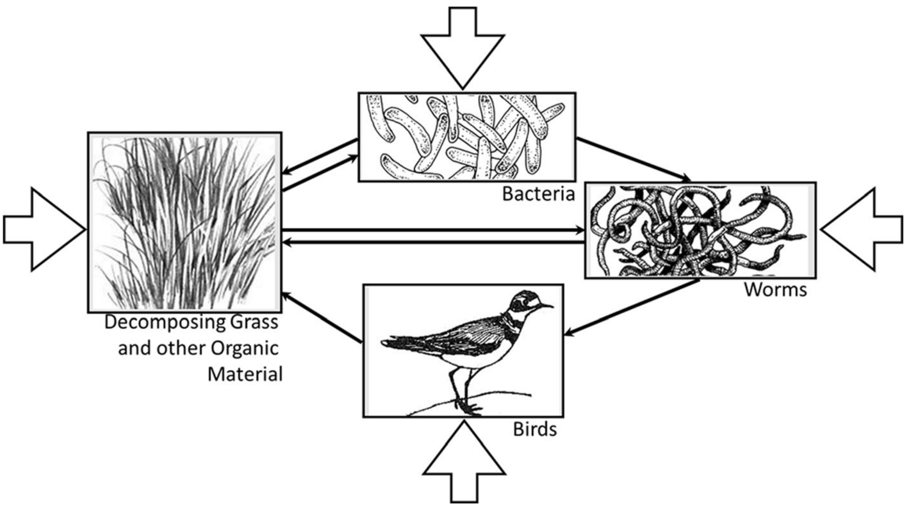

Fig. 1 Schematic of the Cone Spring ecosystem. The wide arrows reflect the network's sensitivity, and the line arrows reflect the cohesion between species

organized into families, herds, swarms, etc.). Even a single animal is not a fixed entity: Though seemingly distinct from other animals and entities around it, an animal is actually composed of many smaller systems that are in constant exchange with the outside and each other (cf. Barabási and Albert 1999).

The two types of arrows in Fig. 1 reflect the ways in which an ecosystem can learn (i.e., adapt). The wide arrows show the *sensitivity* of the elements. Sensitivity pertains to the degree to which elements can change in response to something new or different (e.g., a new sound, a different temperature, a shift in chemical concentration, etc.). Thus, sensitivity captures the elements' ability to change in response to outside *variability* (i.e., a change that is observable against a static background). Species differ in what they are sensitive to. For example, whereas most birds can easily detect changes in sounds, worms may be less sensitive to acoustic variability. Regardless of a species' particular sensitivities, the same principle applies: Larger variability will affect elements the most.

The narrow line arrows in Fig. 1 show the *cohesion* among elements, also referred to as dynamic coordination, coupling, or synchronization (Kelso et al. 2013; Pantaleone 2002; Strogatz 2004). Cohesion pertains to the degree to which elements can change each other. In the case of ecosystems, cohesion is manifested in the exchange of calories: Bacteria eat organic material, worms eat bacteria, birds eat worms, and so on. The more that birds prey on worms, the more their hunting skills and digestive systems align with what worms have to offer. This, in turn, increases the tendency for birds to prey on worms in the future, which gives the system its persistence. Thus, cohesion operates in a circular way: Birds can only prey on worms if their hunting skills and digestive systems align with the worms' characteristics. Once initiated, this alignment becomes amplified over time.

How does the outside affect cohesion? There is no external controller strategically arranging birds and worms in such a way that they can affect each other. Instead, the connection among species stems from an outside order that has become amplified over time. Birds can only prey on worms if they encounter worms regularly. This, in turn, depends on birds and worms having adapted to the surrounding that repeats itself over time. Put differently, cohesion is a function of outside *stability*: the patterns of order that repeat themselves against a noisy background. Once coordination emerges in response to predictable outside patterns, these patterns can become further amplified, changing the animals to the point that they no longer reflect the patterns that gave rise to the initial coordination.

In sum, ecosystems provide important insights about how complex adaptive systems change over time. It comes down to the two characteristics of sensitivity and cohesion, which illustrates the key outside features that affect complex adaptive systems: outside variability (e.g., a drastic change in temperature during a forest fire) and outside stability (e.g., a predictable repetition of the four seasons). Variability affects elements via their sensitivity, and stability affects the elements via their cohesion. In the next section, we apply these insights to the working of the mind.

How Does the Mental Complex Adaptive System Work?

Picture a sunny butterfly garden, complete with plants and insects, as well as pathways, soil, and loose parts. When visiting the butterfly garden, a child's mental activity will turn the busy surrounding of colors, shapes, and smells into lasting meaning. It will also allow the child to ignore and forget some aspects of the surrounding, namely to fulfill the thermodynamic law of increasing randomness. Central to these activities are the same aspects that characterize all complex adaptive systems: Mental activity involves a large number of elements that are characterized by sensitivity and cohesion, changed by outside variability and outside stability.[1] Here, we present the details of these aspects, namely to derive the ideal pedagogy for science learning (see Table 1 for a summary of the working of complex adaptive systems, applied to ecosystems and the mind).

Elements In information-processing terms, the units of mental activity are known as "sensations," "percepts," "representations," "symbols," or the like. To avoid the theoretical overlap, we will use the more general term of *impressions* to define the elements of the mind's complex adaptive system. For a child watching a butterfly, impressions could pertain to the butterfly sitting perched upon a leaf, the butterfly flapping its wings, or the butterfly landing on a flower. Importantly, impressions are not mere snapshots of an experience. Rather, they are themselves networks of elements, the same way a species consists of individual creatures embedded within a system. The nested hierarchy of complex adaptive systems that makes up an impression allows the impression to last a moment longer than the experience that gave rise to it. A child can close her eyes momentarily and will still be able to picture the butterfly sitting perched upon a leaf.

Sensitivity The same way species in ecosystems are affected by outside changes, the impressions of a mental network are affected by novel events. It is the child's sensitivity to a new shape, a new sound, or a new behavior. Thus, sensitivity is the way by which impressions are enriched by something novel, different, or unexpected. Note that information-processing approaches generally portray mental elements, once formed, as being cut off from the outside. There are, however, theoretical precursors to the idea that impressions remain continuously connected to the outside. Piaget, for example, coined the term 'assimilation' to describe how schemata, after having been formed, nevertheless get changed by new experiences (Piaget 1954). A similar notion is echoed in situated-cognition approaches: the idea that cognition, rather than being the product of symbol manipulation encapsulated within information-processing machinery, is continuously affected by the outside context (e.g., Gibbs 2005). Table 2 provides more details on how the complexity approach compares with other developmental theories.

Cohesion In addition to being affected by outside change, impressions are affected by each other. This is because impressions coordinate with each other, analogous to the coordination between species. Cohesion between two impressions stems from the match between them (cf. Bush 1945). This match could come from two impressions having something in common—for example, when a child looks at the same butterfly in two different positions (the match being in the overall shape of the butterfly's wings in relation to other parts of its body). Or it could come from two impressions being associated with each other—for example, when a teacher points out a butterfly and tells a story about it (the match being in the idea of the butterfly that connects the different impressions of the story). It could even come from correlational or causal links, such as the link between butterflies and summer, or the link between butterflies

[1] The idea of elements being changed is broadly conceived to include not only genuine change but also the idea of elements being created. Incidentally, education typically focuses the process of creating something (e.g., knowledge), while ecology typically focuses on the process of change (e.g., adaptation of species). However, the distinction between creating and changing is likely to be artificial. In reality, elements of complex adaptive systems are neither fully new, nor fully old.

Table 1 Characteristics of complex adaptive systems, exemplified in ecosystems and the mind

Characteristic of complex adaptive systems	Applied to ecosystems	Applied to mental activity
They consist of elements that are themselves complex adaptive systems	Species are made up of interacting creatures that are complex adaptive systems in their own right	Multiple impressions make up a mental network, each consisting of its own network of impressions
Elements are sensitive to outside variability	Creatures are sensitive to changes in the surrounding	Impressions are enriched by something new
The largest variability (against a static background) affects the system the most	Large changes are likely to affect the ecosystem the most	Obvious changes and differences affect mental networks the most
Elements are cohesively coupled to each other	Creatures feed off each other	Impressions couple with each other
Cohesion reflects a match between elements	There is an alignment between predator and prey	The basis for the coupling is a match between impressions
Cohesion stems from outside stability	Alignment stems from an adaptation to what remains the same over time	Coupling stems from a common thread or repeating patterns
The most obvious stability (against noisy background) affects the system the most	Creatures adapt to whatever they encounter most frequently	Obvious common thread (against noisy background) is preferred

and caterpillars. Importantly, the match that gave rise to the initial coordination of impressions will increase over time, the same way predators adapt to their prey over time.

Table 2 Side-by-side comparison between complexity theory (CT) and other prominent theories

Existing learning theory	Main claims	Alignment with CT	Discrepancy with CT
Situated-Cognition Theory (cf. Embodied Cognition; Embedded Cognition)	Cognition, rather than being defined as a brain -based manipulation of symbols, is defined by actions in richly structured situations.	CT emphasizes the mind's continuous connection to the outside and rejects the idea of computational processes and symbol manipulation.	CT defines the connection to the outside more precisely (variability and stability) and specifies internal processes to the mind.
Piaget's Theory of Developmental Stages	Knowledge, rather than being transmitted directly, emerges as an adaptation to the child's experiences and follows a stage-like development (from con crete to abstract).	CT highlights emergence and anticipates differences in learning difficulty. Sensitivity and cohesion map onto the processes of assimilation and accommodation.	CT goes beyond the concrete-abstract divide and captures learning difficulty systematical-ly. It also explains how stage-like behavior can emerge from complex interactions.
Vygotsky's Social-Learning Theory	Learning is best when the task matches competence (zone of proximal development). Adults need to help find this balance to minimize the learner's frustration or boredom.	CT rejects the idea that learning is a fully internal process that proceeds on predictable trajectory. It anticipates the role of social interactions to maximize learning.	CT provides additional details about the circumstances in which an intervention from a knowledgeable adult is needed and how exactly the adult can support learning.

Note that information-processing approaches treat mental elements as fixed entities, to be stored in long-term memory like a book in a library. However, the idea that mental entities affect each other is again not entirely new. Piaget, for example, introduced the notion of 'accommodation', the process by which an existing schema can change a newly acquired schema. More pointedly, Karmiloff-Smith described the process of 'representational re-description,' asserting that children's ideas change retrospectively, in the direction of a common abstraction (Karmiloff-Smith 1992). Further expansions and mathematical grounding came from connectionist models, with complexity approaches adding to the theoretical foundation (e.g., Spencer et al. 2009).

Outside Variability Outside variability pertains to changes against a static background—everything that is new or different in the surrounding. Examples include different modalities (e.g., sound vs. light), different features (e.g., color vs. texture), and differences in feature magnitude (e.g., short vs. tall). The more variability in a particular feature, the more those impressions get enriched. Indeed, preschool settings are often loaded with variability: Walls feature primary colors and sharply delineated shapes, new props feature never-before-seen functions, and teachers exaggerate their behavior to express their excitement or concern. The more obvious the outside variability (against a static background), the more likely it will be to enrich an impression. In contrast, if a change or difference is too small (e.g., subtle changes in a toy's shading), it will remain unnoticed and be treated as background.

Outside Stability Outside stability pertains to re-occurring patterns against a noisy background—regularities that repeat themselves from one experience to the next. Examples include the broad shapes of objects or living things, the consistent arrangement of objects, stable routines, and predictable sequences of events. Outside stability contributes to the match between impressions, which is needed for impressions to coordinate with each other. Thus, the more obvious the outside stability, the more likely it is that impressions will coordinate with each other. It is no surprise then that preschool settings are rich in stability. The teachers remain the same over a period of time, they arrange their classrooms in ways that are stable, and they often follow the same routines and rules from one day to the next. If a repeating pattern of order or a common thread across experiences is hidden, say because there is too much change in a child's experience, individual impressions cannot synchronize on the basis of that thread. Instead, the hidden pattern of order becomes part of the background.

The fact that sensitivity and cohesion are based on opposite aspects of the outside provides the mind with an effective decision-making tool about what is relevant and what is not (i.e., what to pay attention to, what to ignore, what to remember, and what to forget). Specifically, variability can only be attended to if it is more obvious than what remains stable. Otherwise, the stability would have priority, and the variability would be ignored as noise. Vice versa, stability can only be remembered if it is more obvious than what changes. Otherwise, the variability would have priority, and the stability would be ignored as static background. Thus, outside variability and outside stability are weighed against one another as the mind seeks to make sense of the surrounding.

In sum, outside variability and stability are fundamental to an account of learning (Rączaszek-Leonardi 2016; Riley and Turvey 2002; Tumer and Brainard 2007). This is because both variability and stability affect the mental network, whether by enriching impressions (via sensitivity) or by increasing the strength by which impressions are coupled to each other (via cohesion). Thus, for learning to happen, one must consider (1) the amount of variability in the surrounding (i.e., change, difference, novelty) and (2) the amount of stability in the surrounding (i.e., patterns of order, symmetry, common threads from one experience to the next). In the remaining two sections, we apply these insights to science learning and effective pedagogy.

How Does Outside Variability and Stability Matter for Science Learning?

Science content is typically defined to include two broad areas: *science inquiry* (i.e., the generation of scientific knowledge), and *scientific truisms* (i.e., science facts). Science inquiry ranges from making observations to testing predictions and drawing causal inferences. Science truisms, on the other hand, pertain to facts in domains such as life science (e.g., comparison of living things, growth of organisms), physical science (e.g., states of matter, energy), and earth/space science (e.g., weather, day/night cycle, seasons). Although this traditional taxonomy is widespread (Kloos et al. 2018; Zimmerman 2000), it fails to consider how the mind learns (or fails to learn). In this section, we propose a new taxonomy of science content, one that builds upon the idea that variability and stability are the key determinants of learning.

Central to the proposed taxonomy is the degree to which (1) obvious variability is relevant to science (vs. distracting and irrelevant), and (2) obvious stability is relevant to science (vs. distracting and irrelevant). To illustrate, consider again the butterfly garden. An example of science-relevant variability (i.e., SR variability) is the difference between animals and plants. Another example of SR variability, less salient perhaps, is the difference in butterfly wings between different types of butterflies. In contrast, an example of science-relevant stability (i.e., SR stability) is the broad shape of the butterfly wings, repeated across impressions. Another example of SR stability, difficult to detect spontaneously, but nevertheless present, is the predictable way in which plants turn sunlight into nutrition (i.e., photosynthesis).

Combining SR variability and SR stability, we distinguish between three types of science content: (1) science content for which SR variability and SR stability is exceedingly obvious in a child's typical surrounding, (2) science content for which only SR stability is obvious (while SR variability is hidden), and (3) science content for which only SR variability is obvious (while SR stability is hidden). For ease of description, we use nomenclature proposed by Rosch (1975, 1978) and distinguish between (1) *basic-level* science content, (2) *sub-ordinate level* science content, and (3) *super-ordinate level* science content.[2]

Basic-Level Science Content Basic-level science content has obvious SR variability and obvious SR stability, both available abundantly to young children. The concept of a butterfly as an animal category is a good example of basic-level content. Regarding SR variability, butterflies differ starkly from other animals—more so than the irrelevant differences among individual butterflies (e.g., the difference in detailed wing shapes). And regarding SR stability, the features that are characteristic of butterflies (e.g., their broad shape) are stable from one moment to the next—more so than irrelevant characteristics of the butterflies' position or behavior. Table 3 lists this and two more examples of basic-level content (states of matter and

[2] In order to explain why some words are learned much faster than others, Rosch (1975) focused on a word's level of specificity. Basic-level concepts were said to be neither too specific nor too abstract. Sub-ordinate level concepts, on the other hand, were said to be more specific than basic-level categories; and super-ordinate level categories were said to be less specific (i.e., more abstract) than basic-level categories. The complexity view is in line with this taxonomy but adds detail to what is meant with specificity.

Table 3 Examples of basic-level science content

Variability (novelty, difference)		Stability (patterns, common thread)
Animals (e.g., butterflies)		
Relevant	Stark differences between butterflies and other animals (e.g., shape, behavior)	Characteristic butterfly features (e.g., overall shape) are stable over time
Irrelevant	–	–
States of matter (e.g., ice)		
Relevant	There are many differences between ice and water (e.g., temperature, texture, behavior)	Characteristic features of ice (e.g., temperature) are stable from moment to moment
Irrelevant	–	–
Seasons (e.g., winter)		
Relevant	There are many differences between winter and summer (e.g., temperature, precipitation)	Characteristic winter features (e.g., leafless trees) are stable from moment to moment
Irrelevant	–	–

seasons). For each of these concepts, SR variability and SR stability are far more pronounced than irrelevant variability and stability.

Sub-Ordinate Level Science Content For sub-ordinate level science content, naturally occurring SR variability is absent or difficult to detect (vis-à-vis variability that is irrelevant to science). Consider, for example, the concept of Monarch butterflies. They differ from other butterflies in only small details (e.g., the color pattern of wings)—hidden from the many other features that vary in a butterfly garden. On the other hand, SR stability is obvious: The detailed color patterns of the Monarch wings are stable from one moment to the next, allowing impressions to couple on the basis of wing patterns (once the difference in wing pattern is detected). Table 4 lists other examples of sub-ordinate level science content. In each case, there are many irrelevant changes and differences that can distract the child (resulting in hidden SR variability). Once relevant aspects are discovered, they are available reliably over time (resulting in obvious SR stability).

Super-Ordinate Level Science Content Finally, for super-ordinate level science content, naturally occurring SR stability is hidden, compared to stability that is irrelevant to the science content. This is content that gives rise to strikingly novel but rare events. One example is the concept of a butterfly's life cycle: SR variability lies in the caterpillar turning into a cocoon, and the cocoon turning into a butterfly. Both of these transformations are clearly distinct and rather surprising, making for obvious SR variability. However, these transformations are rare, happening only once in an animal's life. Many irrelevant events take place between one transformation and the next, making for a heavily interrupted common thread (i.e., hidden SR stability). Table 5 lists this and other examples of super-ordinate level science content.

In sum, the complexity-based determinants of learning offer a taxonomy of science content that cuts across domains. Central to this taxonomy is the degree to which (1) the most obvious outside variability is science-relevant, and (2) the most obvious outside stability is science-

Table 4 Examples of sub-ordinate level science content

Variability (novelty, difference)		Stability (patterns, common thread)
Types of butterflies (e.g., Monarch butterfly)		
Relevant	Minimal differences between Monarch and Swallowtail (e.g., wing colors)	Defining features of Monarch butterflies are stable across time
Irrelevant	Stark differences between butterflies and other animals (e.g., shape, behavior)	–
Measurements of objects (e.g., mass)		
Relevant	Difficult to isolate differences in mass	Defining feature of mass (perceived heaviness) is stable over time
Irrelevant	Stark differences among objects (e.g., color, shape, size, function)	–
Measurement of weather (e.g., temperature)		
Relevant	Difficult to isolate differences in temperature	Defining feature of temperature (perceived warmth) is stable over time
Irrelevant	Stark differences in weather (e.g., sky cover, precipitation)	–

Table 5 Example super-ordinate level science content

Variability (novelty, difference)		Stability (patterns, common thread)
Life cycle of butterflies		
Relevant	Change of a cocoon into a butterfly is highly salient	Change of a cocoon into a butterfly is rare; link between cocoon and butterfly (DNA) is hidden
Irrelevant	–	Features characteristic of cocoons (vs. butterflies) are stable over time (e.g., shape)
Mammals		
Relevant	Giving birth to live young is highly salient	Live birth is rare; characteristic features of mammals are hidden (e.g., uterus)
Irrelevant	–	Many similarities between mammals and non-mammals (e.g., bats and birds fly).
Measurements of materials (e.g., buoyancy)		
Relevant	Objects that differ in buoyancy behave differently in water	Informative contrast in sinking behavior is rare, and causal feature is hidden (e.g., density)
Irrelevant	–	Many features remain stable over time (e.g., shape, color, size)
Water cycle		
Relevant	Transformation from one body of water to another is highly salient	Cycle of transformations is hidden (from rain to river to clouds).
Irrelevant	–	Bodies of water remain stable over time

relevant. Science content for which both of these requirements are met fits into the category of basic-level science content. Science content that lacks salient SR variability fits into the category of sub-ordinate level science content. And science content that lacks salient SR stability fits into the category of super-ordinate level science content. This taxonomy anticipates learning difficulty and thus allows for inferences about ideal pedagogy, as discussed in the next section.

Which Early Science Pedagogy Is Best?

Despite a strong push for early science education, the ideal pedagogy remains unclear. Some claim that preschoolers are innate scientists, capable of discovering scientific facts merely from exploring surroundings on their own (Cook et al. 2011; Gopnik 1996, 2012). In contrast, others claim that typical preschool environments require the implementation of strategic interventions to promote science learning (e.g., Fisher et al. 2013; Kirschner et al. 2006). These disagreements do not help with the difficulties of addressing children's naïve beliefs and science misconceptions. The complexity-based taxonomy of science content can bridge these discrepant views and shed light on the ideal pedagogy. The crucial insight is that different types of science content require different types of pedagogy.

Table 6 provides a guiding overview of the ideal pedagogy for each type of science content. Basic-level science content is the easiest to learn. Given that both SR variability and SR stability for this type of content are exceedingly obvious in children's surroundings, nothing more is needed than a child's self-guided explorations of the surrounding. The teacher simply has to provide a setting in which children can freely explore. Incidentally, nature can be an ideal setting for this to occur (Kloos et al. 2018). More generally, basic-level science content pertains to instances in which the mind seems innately eager to learn (cf. Kuhn 1989; Schulz 2012).

Learning sub-ordinate level science content, by contrast, can be more problematic. Given that this type of content lacks SR variability, relevant differences have to be detected first. Consider again the example of types of butterflies. The difference between Monarch butterflies and Swallowtails has to be detected amid a busy pattern of colors, shapes, sizes, and behaviors of animals in the butterfly garden. To help, efforts need to be made to add SR variability strategically. For example, teachers could ask children to draw the butterflies they observe and then stimulate a discussion about differences in wing colors. Strategies of documenting and discussing observations along these lines have been found to be highly effective (e.g., Brenneman and Louro 2008; Fleer 1991; Fleer and Beasley 1991).

Table 6 Example pedagogy for science content at each level

	Basic level	Sub-ordinate level	Super-ordinate level
Ideal pedagogy	Mere exposure	Guided exposure	Top-down intervention
Potential risks	None	Missed information	Mistaken beliefs
Example activities:			
Life Science	Exposure to nature	Prompts to capture and talk about natural events	Prompts to link life-cycle schema with nature
Physical Science	Exposure to states of matter	Prompts to measure and talk about object properties	Prompts to link density schema with object buoyancy
Earth/Space Science	Exposure to seasons	Prompts to measure and talk about the weather	Prompts to link water-cycle schema with weather

Most challenging is the learning of super-ordinate level science content. Given that this type of content lacks SR stability, it would be utterly insufficient to merely expose children to the natural, physical, or celestial world. The salient SR variability, without salient SR stability, will inadvertently highlight misleading stability, and thus lead to misconceptions. Even pointing out a surprising event would be insufficient for learning. For example, pointing out that the earth is round, not flat, might yield a mental network of a flat-shaped circular, rather than spherical, planet (e.g., Vosniadou and Brewer 1992).

In spite of the evident challenges, learning super-ordinate level science content is not entirely off-limits for young children. It would require a dedicated teacher with a firm understanding of the relevant science, willing to modify the learning context strategically to establish a common thread between relevant experiences. Schematic representations are potentially useful here (also referred to as concept maps or conceptual models; e.g., Hunter et al. 2008; Gobert and Buckley 2000; Kenyon et al. 2008; Novak 2010; Wiser and Smith 2008). Schematic models give teachers the ability to highlight how events are stably connected to each other, while omitting superficial patterns of order (e.g., irrelevant stability in colors, shapes, and sizes).

In sum, the complexity-based taxonomy of science content highlights the fact that different learning goals require different types of pedagogy. If the goal is to merely learn basic-level science content, children's self-guided explorations are sufficient to promote early science learning. In contrast, if the goal is to learn sub-ordinate level science content, the teacher's active involvement is needed, namely to strategically add the missing SR variability. Finally, if the goal is to learn super-ordinate level science content, caution is advised. This is because children's self-guided explorations can lead to misconceptions. Carefully controlled instructional activities are needed to add the missing SR stability, for example by incorporating conceptual maps. Though not impossible, this can be difficult to accomplish in a typical preschool classroom.

Conclusion and Limitations

We sought to contribute to the discussion on early science education by using complexity theory as a guide to how the mind works. Under this framework, the mind forms networks of impressions that are sensitive to outside variability and that couple with other impressions on the basis of outside stability. This minimalistic model of the mind is specific enough to provide guidelines about the key determinants of learning: A successful learning context provides sufficient outside variability and sufficient outside stability. Applied to early science learning, this means that successful learning requires two conditions to be met: (1) the most readily available outside variability needs to be science-relevant, and (2) the most readily available outside stability needs to be science-relevant. Based on these considerations, we derived a taxonomy of science content that cuts across science domains and focuses instead on whether these two key determinants are met in a young child's everyday surrounding.

Notwithstanding the potential of the proposed account of learning, there are limitations that need to be considered carefully. On practical grounds, teachers must be able to correctly sort the science topics in their lesson plans to fit the identified taxonomy. Although we have provided a cursory guide towards this end, we simplified various aspects, including children's individual differences. What seems novel for one child might be boring to another child, and what seems obviously ordered to one child might appear random to another child (cf. Tanaka and Taylor 1991). Thus, while the complexity approach can be useful to derive insights about early science pedagogy, it cannot replace a teacher's close supervision of children's learning.

On theoretical grounds, the limitations pertain to existing gaps in understanding the working of complex adaptive systems. For example, while thermodynamics has been univocally identified as a driver of complex adaptive systems, little is known about how thermodynamic pressure affects the sensitivity and cohesion of emergent networks. Relatedly, while learning has been established as an adaptation to outside variability and stability, little is known about how sensitivity and cohesion interface. Without clear answers to these questions, additional details about children's learning remain speculative, including details about the attractors and control parameters of learning (for interesting speculations, see Deacon 2011; Ulanowicz 2012).

Taken together, we have argued for the usefulness of applying the lens of complex adaptive systems to questions about learning and pedagogy. Research on early science education is divided on questions of best pedagogy, which often leaves educators to go by their own intuitions about how to meet the recommended science standards and address children's science misconceptions. The complexity lens offers insights that can address these challenges. For example, it presents an argument against a 'one-size-fits-all' approach to early science pedagogy. It also cautions against a pedagogy that relies on engaging but disjointed demonstrations, on the grounds that unorganized experiences foster the development of misconceptions. Finally, it offers a way to organize the curriculum in a way that supports pedagogical decision-making, ultimately allowing for an integrated conversation about how to promote early science learning.

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