Learning sciences

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The aims of the learning sciences (LS) are to understand the nature of learning from a broad range of perspectives, and to shape the ways that learning environments and resources are designed and used. LS incorporates both *systemic* and *elemental* approaches to investigating questions about learning, as a complement to the primarily elemental approach emphasized in cognitive science research. Thus, its greatest potential is in the integration of systemic and elemental perspectives. Four major themes are central. First, research in LS attempts to bridge the divide between research and practice. Second, research in LS is motivated by limitations of theories of learning and cognition for specifying instruction. Third, research in LS embraces the importance of analyzing and assessing complex interventions through both experimental and design-based research. Fourth, research in LS emphasizes the learning and behavior of the individual in interaction with the physical, social, and cultural world, as well as with semiotic and technical resources. Research in LS can be conceptualized along a continuum of time scales, from the more microscopic to the more macroscopic. The time-scale framework illustrates how disparate research traditions and research methods can function within a unifying framework for the study of learning and complex behavior. The effort to 'scale-up' from more elemental findings to more complex, authentic settings has been generative for LS, but faces serious challenges. There is an alternate route to establishing a cumulative scientific knowledge base, namely, 'scaling down' from more complex, ecologically valid levels to more elemental levels. Studies of basic learning processes, framed in the context of the larger system, are well positioned to support impact in authentic settings. *WIREs Cogn Sci*

Learning sciences (LS) is a confederation of fields of study and scholars—primarily from psychology (including cognitive, developmental, and educational psychology), education, computer science, and neuroscience, but also from other areas of social science such as anthropology, social linguistics, and sociology—whose mutual interests are to understand the nature of learning from a broad range of perspectives, and to shape the ways that learning environments and resources are designed and used. Many learning scientists engage in what could be termed ***eduneering*** because of the important focus on the design, implementation, evaluation, and redesign of innovative learning approaches and tools. In the spirit of engineering research, the evaluation of success is based in part on societal impact—measurable improvements in learning and performance, interest and motivation, instructional practices, or educational policies—and not on theory development alone. It would be inaccurate, however, to frame LS exclusively as a form of applied cognitive science. Rather, scholars in LS investigate basic research questions about learning and learners, the role of social context and culture, and the nature of the design process itself, as well as more applied questions about the implementation process and the sociological and policy issues that arise when disseminating successful interventions for widespread use.

To capture this broad and evolving agenda, research in LS is often conducted at the level of complexity for which application is ultimately intended. Impact is paramount and can drive the research questions and the methods for accumulating knowledge. We frame this as the *systemic approach* to learning research and recognize it as a complement to the *elemental approach* that has historically shaped cognitive science research. The broader LS research program ultimately seeks to incorporate both elemental and systemic perspectives in a more complete account of learning.

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As with the engineering approach in science and technology,[1] a systemic approach to learning research emphasizes the iterative design process and the complex nature of implementations in authentic settings. A systemic study of learning begins with investigations that capture the complexities of the behavior and interactions of learners in their authentic social and cultural settings, such as family interactions, classrooms, community youth and leadership groups, after-school programs, and professional workplaces as they take place across the day and lifespan.[2,3] Later in this article, we propose that inquiry commencing at larger, more macroscopic levels of study can be 'scaled down' in order to take advantage of more elemental research approaches, such as controlled laboratory experimentation and neuroscientific studies. Studies of basic learning processes that are framed in the context of the larger system are well positioned to lead to impact in authentic settings, such as improved reasoning across a broad range of cultural and socioeconomic groups, and design of sociotechnical learning environments for diverse populations of learners. Within the systemic approach, the scope of research, theoretical perspectives, and data collection and analysis methods are appropriate to the complexity of the settings of intended impact. Advancements in learning theory and research methods acknowledge the complexities of authentic contexts, thus leading to sophisticated models of behavior in authentic settings.

WHAT IS LS?

The LS reflect both Modern and Postmodern views of human behavior, as well as other intellectual influences such as constructivism and socio-cultural theory. With the emergence of 'modernism' in arts and science, 'behaviorism' came to dominate studies of human behavior, pushing forth a positivist agenda that the world—in its mental as well as physical senses—was knowable through formal analysis and experimentation. Cognitive science rejected a core assumption from 'behaviorism' about the reducibility of mental events to observed phenomena. However, cognitive science retains much of the positivist character of that earlier view, particularly the reliance on experimentation and on the operationalization of mental and behavioral constructs using mathematical and computational structures. Extending formal descriptions of behavior to mental processes through the use of computer programs and simulations had a monumental influence on the types of phenomena that could be scientifically studied.

Postmodern views argue against the existence of a knowable universe and acknowledge—even embrace, at times—skepticism and the subjective nature of knowledge. A central aspect of Postmodernism is 'critical theory', where the objective is to critique and change society, rather than explain it. As an example, Kaput's[4] critical analysis of the capstone calculus course typically reserved for the small group of high school students who take advanced placement mathematics leads to a new perspective on the discipline as the mathematical study of change, which he then shows to be a topic accessible to primary grade students. From this 'critical theory' perspective, some LS scholars examine the design of curricula and instruction with an eye to how they serve the social and economic needs of an ethnically diverse student body. For example, in language arts, Lee[5] examined assumptions regarding the standard canon of literature taught in schools from the perspective of race and social justice. When race is used to 'catalog human communities', Lee[5] [p. 158] argues this shapes what schools privilege and neglect when designing curricula. When the literature and linguistic forms of historically underserved groups are excluded, it limits their access to rich and valued forms of reasoning.[6]

In LS, postmodern influences are apparent in basic theoretical constructs: knowledge is sometimes viewed from the epistemology of social and radical constructivism (e.g., see Refs 7–9) and its situated and distributed nature is emphasized;[10–16] learning is framed as changes in discourse and participation within communities,[17–19] and as problem-based and project-based;[20,21] and transfer is recast as preparation for future learning[22] and in agent-centered terms that address the perceptual and conceptual generalizations constructed by the learner rather than from the viewpoint of the domain expert.[23]

LS also has roots in developmental learning theories, such as constructivism, put forth by Jean Piaget, and socio-cultural theory, as articulated by Lev Vygotsky. A constructivist view holds that people generate knowledge based on their experiences in and interactions with the physical world. Socio-cultural theory, in contrast, holds that social interactions are the primary means through which people generate knowledge and meaning. In LS, the legacy of these developmental approaches is apparent in the theoretical emphases on processes of knowledge change[24,25] and on nested levels of social and cultural context (such as dyads and classrooms; see Ref 26) and their roles in learning and developmental change.[27] These developmental approaches have also influenced the research methods used in LS, such as clinical interviews[28] and microgenetic studies.[29]

Because LS is the product of a wide range of intellectual influences, it wrestles with the inherent tensions among these varying philosophical perspectives. Yet this interplay is central to the nature of LS scholarship. Furthermore, there is great promise for a new synthesis of these views, especially in areas such as education and technological innovation, where research methods and epistemologies influence the design of learning environments that rest on a firm evidentiary base.[30]

Several important themes within the LS program of research are worth highlighting. The first is the attempt to bridge the divide between research and practice. The second is the limitations of theories of learning and cognition for specifying instruction. The third, an outgrowth of the first two, is the importance of, and the methodological challenges involved in, analyzing and assessing complex interventions in authentic settings. The fourth is an emphasis on the learning and behavior of the individual in interaction with the physical, social, and cultural world, as well as with semiotic and technical resources.

Bridging the Divide between Research and Practice

More than five decades after the 1956 'Symposium on Information Theory' at MIT ushered in the cognitive revolution,[31] educational practitioners and cognitive scientists continue to have little interaction over the topic of learning.[32,33] Indeed, practitioners often show little interest in what researchers have produced. Research is often too abstract and decontextualized to be readily used by practitioners. Principles are often tested in a narrow range of contexts, so practitioners are skeptical about whether they will apply or scale-up to the complexities of authentic settings.[34] In like fashion, those in the research community can be dismissive of the knowledge generated by practitioners and critical of the methods they use (however, see Ref 35,36 as examples of successful collaborations). Consequently, researchers often develop 'solutions' to educational problems with little direct input from teachers or school leaders.

The misalignment of the scientific and practitioner perspectives has deep philosophical roots, going back to the classic Hellenic era, when scientific inquiry (the 'philosophical arts') was explicitly separated from its practical use (the 'manual arts'; e.g., see Ref 37,38). Learning studies are largely still conducted from this philosophical perspective, with investigations of isolated elements of cognition and practice conducted in artificial settings, the results of which are then combined and scaled up to account for the complexity of behaviors found in authentic settings. In this view, application of research stems from the output of this scientific work; the intended application does not itself shape the science or the methods that generate knowledge.

From a LS perspective, the persistent divide between research and practice is unacceptable. It hampers efforts to develop a robust science of learning, and it also interferes with the development of educational innovations that are compatible with educational institutions, organizations, and participants.

Incompatibilities between research and practice can be framed as a mismatch between levels of granularity of the phenomena of interest.[39] Teachers can benefit from an understanding of child development and cognition. However, they also need to know what they are going to teach and how they are going to teach it. Cognitive task analyses often do not give teachers what they need to assist learners. An example comes from one of our own experiences in teacher education. In a class about cognitive development, pre-service teachers were learning about the work of Robert Siegler[40] on information processing models of children of different ages reasoning about the balance scale. The teacher education lesson emphasized the qualitatively different forms of reasoning used by younger and older children, and the notion of readiness to learn. At the lesson's end, a puzzled undergraduate who felt that she gained new insight into children's thinking wanted to know whether this meant that they all needed to be teaching the balance scale to their students. To the instructor, this lesson seemed like a transparent account of core cognitive principles with actionable information for teaching. Yet to this budding teacher (and others, as nods circulated around the room), the critical concern was identifying prescriptions for classroom instruction. Too often, educational psychology courses delve into the basic structures and processes of attention, memory, perception, cognition, and language without framing the scientific knowledge appropriately for practitioners. Educational psychologists with cognitive training attempt to share the science, but teachers—a clientele that should be ideal for cognitive science—need application-ready ideas that allow them to create and carry out classroom activities, while enriching their understanding of thinking and learning (recent examples of compendia of such ideas are[41,42]).

Limitations of Theories of Learning to Prescribe and Assess Instruction

The path from elemental to systemic research can be productive as a method of theory development and is in keeping with the philosophical roots of science.

Psychological theories of learning and competence in a domain are natural sources of principles for learning environment design, and the potential benefits of this cross-fertilization are manifold. First, theories of learning help point the way toward effective designs in a search space that is extremely large and difficult to formalize (cf. see Ref 43). Second, when the design process is tied directly to a theory of competence, the principles used in the system are likely to be drawn from a larger theoretical perspective on the workings of the mind and the complexity of the domain.[44] Third, design principles rooted in a theory have the promise of being internally consistent. Finally, systems based on principles that have been tested empirically can be expected to be reliable.[45] Following this rationale, there have been repeated calls by leaders in the field of learning environment design that the work should be rooted in some theory of learning and competence in a domain.[21,46–48] This is in contrast to an early (and continuing!) tendency to base learning environment designs primarily on intuitions of how learning proceeds, historical precedence, or novel uses of available technology.[49]

As we strive to develop a scientific approach to the design of learning environments, however, it is important to acknowledge the inherent limits of learning theories in prescribing the final implementation of learning environments. Although a specification of learning is dependent upon a theory of knowledge, a theory of knowledge vastly under-specifies how learning occurs. Similarly, any learning theory underconstrains the instructional designs that are drawn from it.[50] Put simply, theories of cognition are descriptive of learning and performance, not prescriptive of the instruction needed to foster that learning.[51,52] To fully specify an instructional approach, designers and practitioners working from such theories must make a great many decisions during planning and teaching that are not stipulated by the learning research. (Note that these approaches should be distinguished from research that specifically seeks to develop cognitively and epistemologically based theories of instruction and instructional design, e.g., see Refs 3,51,53–55) The general point is that, on its own, an elemental approach to the study of learning faces enormous challenges of scaling up when the scientific work is called upon for application to authentic settings.

Studies of successful scaling up of educational innovations point to the complex, iterative, and nonlinear nature of the process, and the 'wide-angle view' necessary to secure the needed support in a systemic manner. As noted in a recent RAND report on scaling improvements in classroom-level learning and teaching,[56] successful efforts go beyond spreading to more sites and participants; they need to provide support for the enactment of new practices, the infrastructure and local policies needed to ensure the continuance of these new practices, and the transfer of knowledge and authority (ownership) of these practices. This includes aligning with the prior knowledge and beliefs of educational leaders and students.[57] New programs that do not match leaders' prior knowledge are less likely to be implemented or tend to be altered in ways that make them more familiar.[58] Yet these systemic considerations are seldom addressed in the laboratory and efficacy studies upon which scaled up field studies are based. Furthermore, successful scale-up does not adhere to a unilateral model that envisions the transfer of knowledge from innovation provider to practitioner. Instead, it depends on interactions among teachers, providers (such as researchers), education leaders, and organizations at the school, district, and state levels. Neither is scale-up universally applied. It is subject to 'local contingencies' of the settings within which the innovations are to be situated.[59] Effective innovations, such as cognitively guided instruction,[60,61] have shown that supporting teachers to implement and sustain intended instructional practices requires change throughout the local systems in which they operate.[62] This includes working within the specific policies governing regional standards, assessments, norms for accountability, and within the supporting infrastructure, which includes factors such as teacher incentives and resource allocation. To this end, Gamoran and colleagues[63] concluded that, in addition to commitment from teachers and institutional responsiveness, successful innovations benefit from a strong research base with enhanced knowledge about student thinking. Thus, in implementing effective educational programs, it is important to 'scale down' from the policy, curriculum, and instructional levels of design and analysis to more elemental research that can advance our understanding of the impact of the intervention, while at the same time contextualizing the more basic research.

Analyzing and Assessing Interventions Using Experimental and Design-Based Approaches

A great deal of LS research seeks to analyze and assess the outcomes of educational interventions. Some research that addresses these aims uses experimental designs that include control groups and that use random assignment.[64] Such studies emphasize internal validity, and they allow for strong causal inference. As such, experimental studies yield the strongest possible evidence about the efficacy and effectiveness of educational interventions.

However, in some cases, experimental design may not be suitable for studies of learning and behavior in naturalistic settings, because the control of variables can lead to unnatural adaptations of the tasks of interest, thus compromising ecological validity.[39] Also, as noted above, the limitations of learning theories for specifying all of the components that constitute a functioning learning environment mean that many non-theoretically specified (and perhaps uncontrollable) factors may have important but undocumented effects on outcomes. Experimental approaches designed to isolate a small number of influences can be too slow to generate optimal designs for complex interventions and settings.

The division between theories of learning and prescriptions for instruction, on one hand, and the need to bridge research and practice on the other hand, has led some LS researchers to explore alternative methods for analyzing and assessing the impact of interventions. One approach is to adopt a design-oriented philosophy more commonly associated with engineering fields than with social science. The design-based influences can be traced back, in part, to the Intelligent Tutoring Systems and Artificial Intelligence and Education (AI & Ed) communities, whose work inspired early LS research on learning environment development that later spawned research in educational technology and human behavior more broadly. In LS, *design-based research* methods, 'design experiments', or 'teaching experiments' (e.g., see Refs 39,65–68) address questions of what to design in a climate of imperfect knowledge of the critical factors that will impact learning. Design experiments do not strive to 'vary one thing at a time' in order to attribute causality. Instead, they allow for a vastly expanded tool kit of data collection and analysis methods that have been developed to address questions about settings, people, and phenomena that do not lend themselves easily to classic experimental methods. Design-based research provides for flexibility of interventions and faster means of innovation—similar to what Koedinger[69] [p. 8] refers to as 'the hare of intuitive design'—which can be complementary to the incremental approach of experimental research—Koedinger's 'tortoise of cumulative science'.

We offer the term ***eduneering*** to capture this design-based ethos of research and development. Given the complexity of understanding learning in rich contexts, and the dual commitment to scientific knowledge and social impact, the designs of studies in natural settings are difficult to completely specify in advance. Although an initial set of questions and possible measures for data collection can be sketched out, the design often unfolds as the study progresses. Very often, new paths of inquiry and new data sources are pursued as new insights emerge. Under this view, evaluation is dynamic and not tied to a single conceptualization of predetermined goals or outcomes. Instead, evaluation needs to focus on the actual operation and impacts of a process, program, or intervention over time.[70] Consequently, design experiments are often conceptualized in longitudinal terms, with significant redesign occurring before the implementation of a subsequent cycle of the intervention.[71] This allows for learning at various levels of the study to influence the investigation, as researchers, designers, and practitioners continue to develop a more informed perspective of how to facilitate learning. In this way, researchers become integral parts of the systems they are investigating, and, reciprocally, teachers become collaborators in the research.[36,72]

It should be noted that design-based studies often forgo the close analyses to comparison groups characteristic of experimental studies (though comparison groups are often used to track changes against learning gains with the standard level of treatment and a partial implementation of the innovative treatment; see Ref 10). However, they do provide rich process account of changes over time during the intervention. For example, in a teaching experiment in elementary mathematics, Cobb[73] presents an ongoing analysis of classroom events, along with a retrospective analysis of all the data sources generated during the intervention.

Addressing Learning and Behavior of the Individual in Interaction

Research in LS emphasizes the importance of studying knowledge structures and learning *in interaction* with the physical, social, and cultural world. From this perspective, investigations consider: the context and setting; affordances of objects in the world (e.g., see Refs 74,75); embodied knowledge grounded in experiences in the physical world (e.g., see Refs 76,77); knowledge distributed among members of a group and tools (e.g., see Refs 14,15,78); social interactions, including shared objects and representations (e.g., see Refs 19,79,80); positioning within the participation structure (e.g., see Ref 81); shared intentionality and intersubjectivity (e.g., see Refs 82–84); and cultural, ethnic, and class influences (e.g., see Refs 6,85) among others.

Scholars who focus on learners' interactions with the physical world often take an ecological[74] or embodied cognition[86,87] perspective on learning and complex behavior. From these perspectives, some of the crucial questions that LS research addresses center on the conceptual metaphors that underlie reasoning,[88,89] the importance of body movements, including gesture and manipulations of objects, in learning and instruction,[90,91] and the importance of motor and visual imagery and mental simulations of action.[77,92–95] For example, Glenberg and Roberston[96] studied how people learned to use a compass from different types of instructions, which included combinations of text, pictures, and video of an actor's hand indicating and operating the compass. Scholars who address such questions often focus on learning outside of formal education settings, such as the workplace, where reasoning and learning depend to a great extent on the use of tools, objects, and various forms of technological media.[3,97,98] As one example, a study of civil engineers and field biologists learning on the job revealed that new terminology is learned through participation in activities that establish words' meanings.[99]

Scholars who work from a social interactional perspective have coined their work, variously, as situated cognition,[100] situativity,[11,12] socio-cultural approaches,[101] situated action,[102] and distributed cognition.[13] Building on Vygotsky's socio-cultural framework, these views consider the individual acting within the socio-cultural setting as the proper unit of analysis, including the artifacts, people, activities, and practices that contribute to that setting. Because of this emphasis on the individual within the activity setting, scholars working with this approach may find it necessary to address aspects of the personal and social identities of the participants and the histories of these individuals as members of ethnic, generational, or class-based groups that engage in culture-specific activities. For example, one's linguistic practices or methods of learning may be traced back to the family or community-based practices of a cultural community.[85,103] Heath's[104] ethnographic account of middle class and rural families showed how cultural influences in the home contribute to differences in intellectual practices that have profound implications for children's school experiences. Others[85] have used the interaction-based perspective to reframe the psychological notion of traits as behavioral manifestations of 'people's history of engagement in practices of cultural communities' (p. 21) rather than inherent to an individual or members of a group. Although the study of learning in interaction is a major break with traditional information processing views of cognition, there is a general recognition that LS needs to develop an integrated approach drawing from both perspectives in order to achieve its aims.[16,105]

This perspective also has implications for the study of online communities and computer-supported collaborative learning (CSCL). The growth of technological media for collaboration and socially constructed knowledge (e.g., email, Wikipedia) has fueled this as a rich area of study unto itself.[106] Researchers in CSCL investigate how designed media influence learning and collaborative work, including the forms that unfold in academic, workplace, entertainment, and community settings. Learning is often recast as joint activity and meaning making among distal participants. Investigators in this research area seek to develop theories that will both account for this behavior and guide the design of effective media for the future.

TIME SCALES OF HUMAN BEHAVIOR

Research in LS spans a wide range of time scales and uses a wide range of methodologies. As Newell[107] argued when delivering the 1987 William James Lectures, learning, and human behavior more generally, can be conceptualized along a continuum of time scales (see also Ref 108). A time-scale analysis of behavior shows how disparate research traditions and research methods can be conceptualized within a unifying framework for the study of learning and complex behavior. At time scales below 10^{-2} s (10 ms), intellectual behaviors are at biological (primarily neural) levels of operation. In the next band of our human time scale, from 10^{-1} s (100 ms) to 10 s, behaviors transition into the cognitive band, and include perceptual and motor processes, as well as basic and complex mental processes ranging from word and object recognition to brief communicative exchanges. The next band, from 10^{2} s (minutes) to 10^{4} (hours), addresses behavior that is more planful, interpersonal (such as dialogic exchanges), and task oriented ('rational', in Newell's terms, p. 150). Human behavior at the further reaches of the next band (10^{4} s to 10^{6} s; hours to days) is characterized primarily by social and developmental operations, such as experiences with classroom or on-the-job training over whole class periods or training units spanning several days. At 10^{7} s (months) and beyond, the focus is primarily on behaviors in organizational, developmental, generational, and cultural terms. Furthermore, there are forms of research that are *trans-scale* such as studies of systems across the time scales, and studies of the nature of the scales that may naturally partition a field of inquiry. Historical analyses of scientific research and systems-level analysis are two such examples.

At each time scale, different research methodologies and theoretical perspectives are used to forge a level-specific learning theory that must be integrated with, at a minimum, its immediately preceding and succeeding levels (see Table 1). For example, moving logarithmically through the powers of ten, the time-scale analysis highlights how cognitive functions in individuals (operating in seconds) mediate between neural (milliseconds) and rational (minutes) processes. Lemke[109] contends that coherence is established when research at a more fine-grained time scale is constrained by the processes and structures at the next highest level. Rigorous research at a given level of temporal resolution, and the integration across these levels, will promote advanced theory building that will ultimately explain the manifold ways that learning occurs, and contribute to effective designs for future learning environments.

A time-scale analysis also highlights some of the barriers to an integrated and interdisciplinary science of learning. The boundaries between each of these levels of analysis tend to define distinct research traditions, each with their own professional societies, journals, and modes of scholarly discourse. The forms of research at the finer-grained scales (lower portion of Table 1) emphasize the study of relatively elemental structures and processes, such as brain structures, basic components of cognitive architectures, and sensory, motor, and cognitive processing. Methodologically, studies at this level tend to be conducted in isolated, highly constrained settings that support rigorous, quantitative conclusions. In contrast, modes of research that emphasize the study of learning over longer time scales (upper portion of Table 1) tend to occur in complex, authentic settings, often involving multiple agents and multiple modalities for encoding and expressing actions, perceptions, and ideas. Research at these levels lends itself to more narrative and qualitative research methods intended to address macroscopic processes and structures. Thus, research methodologies form another series of contrasts that correspond *roughly* with the time-scale continuum (see column 4 of Table 1). Finally, there are approaches to research on learning and behavior that naturally span time.[107,109]

Representative Research

Research programs aimed at substantive problems of learning in authentic contexts often form 'boundary crossings' that allow learning scientists to operate across elemental and systemic traditions, and ultimately to transcend them. We briefly review two programs of research to illustrate the nature and utility of the time-scale framework, and the integration of elemental and systemic approaches. Both address mathematical learning and instruction, though one focuses primarily on classroom experiences and the other on community-based experiences. Our selective review should not be interpreted as an indication that other learning domains are not conducive to this framework. Other programs of research demonstrate many of the qualities we seek to illustrate. We selected mathematics as a common element across these examples partly because it aligns most closely with our own focal areas, and partly because mathematics learning has been well studied.

Cognitive Tutors: From Science and Technology to Classrooms and Neural Systems

We first illustrate these various time scales with research on 'cognitive tutors', a well-integrated program of research that incorporates theoretical and methodological approaches across many of the time bands of this framework. At the center of this research and development program is a type of software-based *intelligent tutoring system* for mathematics learning.[110] To address the complex nature of classroom learning and instruction, the program of research and development has taken a systemic perspective, including considerations at the macroscopic range of the time scale—such as teacher participant design, teacher training, and classroom social interaction—as well as an elemental perspective, focusing on cognitive and neural processes at the more microscopic range of the continuum.

As a form of instructional software, 'cognitive tutors' provide learners a rich problem-solving environment that incorporates a variety of representational tools, and that provides tutorial guidance in several forms, such as feedback about steps taken in problem solving, messages in response to common errors, and hints about next steps. The specifics depend on the particular version of the 'cognitive tutor' under consideration. At their core, 'cognitive tutors' are based on a cognitive theory of learning and problem solving called adaptive control of thought—rational (ACT-R),[44] and they were created in part to test aspects of the theory. Within ACT-R, cognition is modeled as a system of *productions*, which are condition-action (or if-then) pairs that link actions to higher-level goals and features of context [e.g., **If** the goal is to solve $a(bx + c) = d$, **then** rewrite as $abx + ac = d$]. Each 'cognitive tutor' contains a production system model of the competencies the tutor is intended to help students acquire. Using the model, the tutor

TABLE 1 | Time Scales of Human Behavior and the Corresponding Areas of Study and Research Methods (Adapted from Ref 107)

	Time scale (S)	Level of study	Scope of research	Representative methodologies
Spans time scales	Trans-scale	• System	• Design • Interactions among levels • Multidisciplinary	• Ecology • Systems science • Modeling • Historical analyses • Economics
	10^7 s (months) & beyond	• Organizational	• Generational changes • Legislation • Economics • Equity and social justice • Leadership decisions • Standards • Personal development • Professional development • Program evaluation	• Policy analysis • Program evaluation (quantitative & qualitative), • Longitudinal studies • Experimentation • Modeling • Ethnography
← Decreasing • Time Scales • Increasing →	10^4 s (hours) to 10^6 s (days)	• Social-cultural-historical	• Teaching practices • Curricular studies • Socially mediated learning • Learning environments • Context of learning • Robust learning • Cognitive development	• Discourse • Field observation • Design-based research • *In vivo* experimentation • Ethnography • Microgenetic studies • Longitudinal studies
	10^2 s (minutes) to 10^4 s (hours)	• Rational	• Individual achievement • Teacher and student behavior • Beliefs • Identity	• Interviews • Psychometrics • Experimentation • Cross-sectional studies • Conversation Analysis • Survey • Journaling • Case study • Modeling
	10^{-1} to 10 s	• Cognitive	• Symbolic processes and structures • Situated cognition • Embodied cognition	• Experimentation • Cognitive modeling • Think-aloud reports • Gesture analysis
	10^{-2} s down	• Biological	• Neural processes • Perception • Motor processes • Cognitive processes • Emotion • Imitation • Empathy	• Neuro-imaging • Single-cell recording • Eye tracking • Modeling

interprets each student's actions and uses this information to estimate how well the student has acquired each of the relevant productions. The tutor uses these interpretations to provide students with feedback about correctness, to individualize instruction based on students' solution steps, to select problems appropriate to individual students' needs, and to determine when students have mastered the target concepts and skills.

We focus here on recent work on 'cognitive tutors' for geometry and algebra instruction. Much of the work leading up to the construction of 'cognitive tutors' in any given domain is situated at the cognitive-symbolic level (i.e., a time scale of 10^{-1} to 10 s, or tenths of seconds to tens of seconds, see Table 1). The tutors focus on specific skill development, as reflected by the condition-action rules, as the unit of analysis for amassing a large and sophisticated body of mathematical knowledge. For example, Koedinger and Anderson's[111] early work on expertise in constructing proofs in geometry involved collecting and analyzing think-aloud reports of experts as they planned proofs. This work revealed that experts did not plan in a step-by-step fashion; instead, they planned proofs at a more abstract level. Koedinger and Anderson simulated this planning process using a process that relied on parsing problems into perceptual chunks that cue relevant schematic knowledge. The 'cognitive tutor' for geometry builds on this knowledge in its model of expert proof construction. As a second example, several studies have documented the range of strategies that competent algebra problem solvers use in solving linear equations.[112,113] The 'cognitive tutor' for algebra builds on this knowledge of alternative solution strategies in its model of expert knowledge of algebraic reasoning.

Research on 'cognitive tutors' has subsequently proceeded in multiple directions, both toward larger, more macroscopic time scales, and toward smaller, more microscopic time scales. Research on the *efficacy* of 'cognitive tutors' on individual skill learning in classroom settings extends to the more macroscopic time scales, including the rational, the social-cultural-historical, and organizational levels (see Table 1). A number of studies of both 'geometry and algebra tutors' have documented large learning gains in classrooms that use the tutors over extended time periods, compared with classrooms that do not use the tutors. For example, one evaluation of the 'geometry tutor' showed that students who worked with the tutors over an academic year scored about one standard deviation better on a final test of proof skills than students who did not work with the tutor, even though both groups were taught by the same human teacher.[114] Similarly, an evaluation comparing a 'cognitive tutor algebra' course with a traditional algebra course over one academic year (the organizational time scale of 10^7 s and beyond) found that students in the 'cognitive tutor' course performed 15–25% higher on standardized test items, and 50–100% higher on items assessing problem solving and use of representations.[35]

Studies of *classroom functioning* in classrooms that use 'cognitive tutors'[115] work at a social-cultural-historical time scale (hours to days, see Table 1). A qualitative study of the use of 'geometry tutors' in an urban high school documented substantial changes in classroom functioning in classrooms that used the tutors, relative to comparison classrooms that did not use the tutors.[116] Students in tutor classrooms started their work more promptly at the beginning of the period, and were more likely to work until the end of the period, than students in comparison classrooms. Students in tutor classrooms also appeared to be more engrossed in their work. The tutor also wrought changes in the social environment of the classrooms. Teachers' assistance to students was more individualized in tutor classrooms, because teachers' behavior was less constrained by the needs of the class as a whole. Teachers in tutor classrooms knew that students working on the tutors were involved in productive activities, so they could devote assistance to individual students without worrying that other students were floundering or getting off-task. Teachers in tutor classrooms were also less likely to 'hover' or to offer unsolicited help to students, as they knew that students could access help from the tutor at any time. In turn, the students became more active in seeking help when they needed it. Students in tutor classrooms were able to receive help in a more private, one-on-one manner (rather than receiving it publicly), and this also led to changes in patterns of help seeking. There was also considerably more peer interaction in these classes, an element that the researchers report was 'key' to its success.[114] Finally, in tutor classrooms, there was an increase in 'friendly' competition among the students, because student progress in tutor classrooms varied more than student progress in comparison classes. This was because student progress through the tutor was self-paced, whereas student progress in the comparison classrooms was less variable and more constrained, with the group as a whole moving on to new material together.

Other research on 'cognitive tutors' has extended to more microscopic time scales, typical of perceptual and neuroscientific investigations (seconds to milliseconds, see Table 1). Gluck[117] and Anderson & Gluck[118] investigated the eye movements students produced when using a simplified version of a 'cognitive tutor' for algebra to better understand the processes that mediated its success, and to inform future designs. One surprising finding was that approximately 40% of the tutor messages to students were not read. In many such cases, students immediately corrected their behavior, suggesting that the specific content of the tutor message was not actually needed. However, in some cases, students did not immediately self-correct, and they were then likely to make an error. Another compelling finding was that eye movements sometimes revealed differences in strategy use among students whose behavior appeared identical at the behavioral level. For example, in solving word problems where students first produced a symbolic expression, some students answered subsequent questions by fixating on the symbolic expression, whereas others fixated back on the verbal problem statement and ignored the symbolic expression they had produced.

Other research has begun to use functional magnetic resonance imaging (fMRI) brain imaging to study learning from 'cognitive tutors'. Anderson et al.[119] scanned adults solving algebra problems in a simplified 'cognitive tutor' that was designed to enable use in the scanner. Participants were scanned on two separate occasions, before and after instruction about the material, so that changes due to learning could also be evaluated. Patterns of neural activation were largely in line with predictions drawn from past fMRI studies of algebra problem solving,[120] and with predictions based on the ACT-R cognitive model that underpins the 'cognitive tutors'. One unexpected finding suggested that learning involved increased efficiency in perceptual processing (manifested in reduced activation in the fusiform gyrus region of the temporal lobe). Thus, the imaging data helped to identify specific changes that occur with learning (both predicted and unpredicted). These findings can then feed back to inform the cognitive model that provides the knowledge engine of the 'cognitive tutors'. Furthermore, this knowledge can also be used to generate recommendations for improving educational practice—both recommendations about how to build better 'cognitive tutors', and recommendations about how to structure more ordinary learning situations for optimal success.

A Socio-Cultural Approach to the Study of Math Instruction and Learning

A second illustration of research across time scales is Nasir's program of research on learning mathematics through game playing, and its relationship to learners' goals and social identities. The focus is on young African-American males learning to play dominoes. The studies (e.g., see Refs 121,122) use ethnographic and observational methods, as well as structured interviews and surveys.

As with any well-structured game, dominoes has a clear set of goals, an initial state, and operators that define the legal moves through the search space. There are also strategies that identify advantageous moves and that reduce the cognitive demands for selecting them. Thus, there is a familiar structure to the domain that lends itself to a fairly standard information processing account.[123] In this way, the research addresses goal-based problem-solving behaviors at the level of cognitive processes and structures (10^{-1} s to 10^{1} s). Yet the cognitive account is a performance-oriented one, and therefore omits other notable phenomena that Nasir identifies in studying how young learners are initiated into the practice of effective domino play and how that play and the players develop over time.

In dominoes and many other activities (such as determining basketball statistics)[124] players' mathematical goals are tied to broader *practice-linked goals*.[124] In dominoes, learners at the elementary school level first strive simply to make legitimate moves. This entails basic pattern matching methods so that one's own pieces are properly placed at openings on the board. Later, typically by middle school, learners try to optimize the number of points each move will tally. This involves systematically comparing the options available based on the board configuration and the dominoes available to the player. Then the player must perform the mental calculations for the points accrued with each option, and select accordingly. By high school, Nasir observed players using sophisticated probabilistic thinking and counterfactual (if-then) reasoning to make reasonable judgments about what plays an opponent may make on later turns, and striving to block one's opponent from making higher scoring moves, as well as optimizing one's own position.

To more fully understand the strategies used by learners, Nasir[124] set up mock boards with configurations that made varied strategic demands. These situated interviews revealed that advanced players were managing a great deal of information about their opponents' pieces and those that were left unplayed, as well as board openings that would allow them to make multiple plays over the course of the game. More sophisticated play was not simply the result of players adopting more and more powerful strategies. Rather, players were adopting new goals for game playing that were inextricably linked with their advancement in their levels of play as well as changes in their identities as participants in the competitive community of players.

In Nasir's view, the process of adopting strategies for complex game play, typically framed as *learning* from a cognitive perspective, is alternatively framed as changes in the learner's identity to a more engaged and able social participant.[17,124] In this way, the research addresses individual achievement and performance (10^2 s to 10^4 s) and socio-cultural-historical influences (10^4 s to 10^6 s). Influences on players' identities were most evident in the flexibility of their interactions during play. Neophytes maintained their roles within school and neighborhood relationships during the games, such that friends were given to generous and affable interactions with one another, while a bully was accorded the same respect in a game as elsewhere. Among more advanced players, particularly at the high school level, one's positive or negative reputation for play temporarily altered the nature of the interactions, and this was evident in differences in shared laughter or teasing.

Changes in players' performance of both the game playing task and the mathematical forms of reasoning that made advances in play possible were accompanied by changes in the players' goals and identities. Both longitudinal changes of individual players and cross-sectional differences between ages and levels of experience were reflected in shifts in cognitive processes, as evidenced by changes in declarative knowledge and game playing strategies, as well as changes in social practices, methods of interaction, and values. Players shifted from basic pattern matching and addition at the elementary school level to complex inferences about probability and logical thinking at the high school level. This shows the broad developmental aspects of this program of research, which spans the time scales of 10^7 s and beyond, down to cognitive strategies and operations (10^{-1} s to 10^1 s). Far from a linear account, the influences appear to be bidirectional and mutually constitutive. Thus, as players became more engaged, they acquired new skills and knowledge that supported greater involvement. Increased opportunities for participation, along with increased competence, contributed to more identification with the practices and the practice communities at social and personal levels, which, in turn, fostered greater motivation to learn the mathematics as well as the games. These mutual influences reveal a systemic structure (top row of Table 1) that could be overlooked by a solely elemental approach to learning research.

Another way that this program of research illustrates the broad LS perspective is its particular recommendations for the education of African-American children. Traditionally, cognitive science has shied away from issues of inequity within schools and other learning settings, focusing instead on the articulation of mental processes and structures with respect to a certain task. Yet African-American students, as well as individuals from other minority groups, can come to disidentify with formal education.[125] Dominoes and basketball are seen as racially stereotyped activities by both in-group and out-group members,[126] yet they also are highly demanding and engaging activities that can provide an effective locus for the development of mathematical knowledge. By identifying situated practices in out-of-school settings that foster the type of learning valued by educational institutions, LS contributes to new visions of both learning and learning environment design.

PROPOSAL FOR A UNIFIED FRAMEWORK FOR THE LS

The Value of Integrating Systemic and Elemental Perspectives

We contend that LS research stands to gain from integrating the systemic and elemental views of learning research. To contribute substantively to learning theory, a research program must have all the elements of any rigorous science, particularly 'accumulation of . . . coherent, disciplined, and rigorous knowledge and explanation; the conduct of focused and disciplined scholarly inquiry and discovery; and the resulting informed and improved action that ensues from the application of the outcomes of the first two elements in practice',[127] [p. 228]. The character of the elemental approach to science is to derive the laws of nature from examination of all available data. This approach is most appropriate when there are a small number of patterns to be found among a relatively small number of variables. The emphasis of elemental research in cognitive science, for example, is to isolate cognitive mechanisms and form an explanatory account of behavior.[52]

Research conducted from the elemental perspective is indeed informative for education, as noted by several collections of research in the area of cognition and instruction.[128–130] Controlled studies of elemental processes are essential for understanding how isolated processes and stimuli influence learning without the complexities of the classroom or other authentic settings.[131] However, when authentic interventions are driven exclusively by elemental research, the instructional design is frequently an adaptation of the laboratory approach. It is learning-oriented, at times student-oriented, but seldom classroom-oriented, and must 'fill in' aspects of instructional design that are unspecified by the research.[50]

Many LS scholars believe that a science of learning and of learning environments must be prescriptive as well as descriptive.[51,52,132] The analytic accounts of behavior that emerge from scientific study must inform these scholars about ways to influence learning by modifying the world and the ways learners interact with teachers and other students, as well as forms of technology and visual media. From this perspective, the study of learning can be cast as a 'design science'.[1] When framed in this way, the progress and maturity of a science of learning are naturally measured by its impact on society, in addition to how well the terrain of learning processes and structures are mapped out.

For aspects of learning research where impact is as important as theory building, and where the systemic nature of the phenomena is paramount and isolated effects of individual factors are generally indeterminable, the eduneering approach is warranted. Design issues and the interaction among system components and resources come to the fore, and quantitative methods are most powerful when used in concert with design methods, qualitative forms of analysis, and interpretive frameworks.

'Scaling Down' as a Method for Establishing a Cumulative Knowledge Base

The effort to 'scale-up' from more elemental findings to more complex, authentic settings has been quite generative for the LS in terms of questions and findings. We believe that including the systemic approach conveys an additional route to establishing a cumulative scientific knowledge base, namely 'scaling down' from more complex and ecologically valid levels to those elemental levels that contribute to it.

From an elemental perspective, *scale-up* of research involves a shift to a broader sample and to new settings and tasks. Many of the contextual, social, practice-based and design-based complexities that were originally excluded from the scope of the research now must be introduced. Yet the very methods and models that drove the research successes are often incommensurate with the new environs. Consequently, the path from successful elemental research to wide dissemination is disjoint and often unsuccessful.

Scale down uses the findings from longer time scales of analysis to generate targeted research questions at finer-grained levels. In this approach, learning and practice are studied first in the complex settings within which they naturally occur: the settings of the organizational system (such as districts and schools), places of professional practice (such as a field, shop floor, or office), learning environments (such as a classroom, workplace, or multi-user gaming environment), and the individual (addressing issues such as identity, goals, and pre-existing knowledge structures). Research at a higher time scale or level of aggregation then constrains research at lower levels, providing it a target phenomenon that needs further explication.[109] For example, in the 'cognitive tutors' program, data from the year-long program evaluation served to constrain research at various finer-grained levels, such as the work on classroom interactions among peers and the teacher,[133] on visual processes used in attending to hints from the tutor,[117,118] and on neural processes involved in encoding information.[119] This integrated research then informs theories of learning that constrain the design of future learning environments.

CONCLUSION

In this article, we have argued that the LS are poised to make great strides in understanding complex human behavior by integrating a *systemic approach* to investigating questions about learning with the *elemental approach* that has historically been emphasized in cognitive science research. We presented four major themes that we see as central to LS: connecting research to practice; developing evidence-based prescriptions for instruction and learning environment design; analyzing and assessing educational interventions using both experimental and design-based approaches; and framing learning and behavior of the individual in terms of interactions with the physical, social, and cultural world. From the LS perspective, impact is paramount and motivates the research questions and methods.

We have further argued that research in the LS can be conceptualized along a continuum of time scales.[107,109] We illustrated this time-scale framework with examples drawn from research on 'cognitive tutors' and on socially situated game playing, two very different programs of research in which mathematics learning can be observed. These two examples span levels of human behavior from the more microscopic to the more macroscopic. As a unified framework for understanding learning, the time-scale framework illustrates how disparate research traditions and research methods can inform one another and ultimately contribute to an integrated research program.

Finally, we note that the effort to 'scale-up' from more elemental findings to more complex, authentic settings has been quite generative, in terms of questions and findings, for the LS. However, we suggest an additional route to establishing a cumulative scientific knowledge base, namely 'scaling down' from more complex, ecologically valid levels to those elemental levels that contribute to it. For a comprehensive science of learning, we need not only to scale-up, but also to scale down.

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