A Multi-Epistemological Mapping of Knowing, Learning, and Analytics in Materials Science and Engineering

Mr. Petr Johanes, Stanford University

Petr Johanes is currently a PhD candidate in Learning Sciences and Technology Design (LSTD) at the Stanford University Graduate School of Education. He holds a B.S. and M.S. from the Department of Materials Science at Stanford University and has experience teaching in Engineering as well as Education. Petr's main research interest is in building data-driven digital environments to investigate the role of epistemology in the experience, design, and research of learning.

A Multi-Epistemological Mapping of Knowing, Learning, and Analytics in Materials Science and Engineering

Science, technology, engineering, and mathematics (STEM) disciplines are cross-pollinating in increasingly varied ways to give rise to fields such as robotics, systems biology, or materials science and engineering. These fields require pulling together from a variety of disciplines not only content knowledge, but also pedagogical strategies, assessment methodologies, and learning theories. After all, when teaching how to design a robot and assessing a resulting design, the methods and standards from a single discipline would not suffice. Furthermore, as research into increasingly complex phenomena requires more complex combinations of these disciplines, preparing STEM students for navigating these collaborations becomes an important learning objective. Facilitating and researching this kind of preparation requires novel technological as well as philosophical tools.

To simplify the exploration of this kind of learning, this paper focuses on materials science and engineering as an illustrative example. The reasons for this become clear once the paper introduces integrative pluralism, the philosophical framework to help navigate how to work with the knowledge standards and practices of multiple disciplines. To provide an appropriate theoretical and instructional design context for integrative pluralism, the paper sets the stage with the knowledge-learning-instruction (KLI) framework as a lens through which to view current trends in instructional research and design. In the second half, the paper proposes assessments and computer-based learning environments (CBLEs) to deliver on the promise offered by this exploration. The ultimate purpose of this paper is to make the case that instructional design that early and explicitly takes epistemology into account is not only necessary to advance learning design and research in multi-disciplinary field, but also complementary to current frameworks.

Materials Science and Engineering

Materials science and engineering is an inherently multidisciplinary endeavor. Researchers, practitioners, and students study the fundamental properties of materials and the processes used to create and control those properties [1]. The discipline has its roots in metallurgy, but today it includes the study of nanomaterials in a wide variety of applications, including energy technology, biotechnology, and many others. In short, materials science does not only deal with metals anymore.

As such, materials science and engineering encounters and investigates phenomena that can be complicated and complex. Here, complicated refers to phenomena that require a non-trivial series of causal links to explain. Complex, however, refers to phenomena that require a systems framework to explain. Specifically, complex systems share the following aspects: (1) they involve multiple related processes; (2) their processes tend to operate at different levels of analysis; (3) they are sensitive to initial conditions, and (4) they show emergent properties [2]. This last aspect has been of particular interest to scientists and philosophers of science. One clear example of emergent behavior is that the taking out of a gene sequence that codes for a life-sustaining protein does not always lead to the death of a cell [3]. The cell can, under certain conditions, re-purpose other gene sequences or other proteins to create a makeshift solution and survive. In short, the behavior of complex systems is not completely predictable or explicable by a priori knowledge about the initial state of the system.

Materials scientists and engineers almost by default work with multiple levels of analysis. Subatomic behaviors give rise to atomic behaviors, which give rise to molecular/grain behaviors, and so on until the processes give rise to macroscopic behavior [4]. Different disciplines inform the study of these different levels. Physics might have the most robust models for subatomic and atomic behaviors, whereas biology might have the most robust models for cellular behaviors. This is not to say that physicists do not study cells and that biologists do not study atoms. This is to say that different disciplines have uniquely focused on and uniquely structured themselves to investigate behaviors at specific levels of analysis.[1] More on this later. For now, what is important is that materials scientists and engineers contribute and leverage insights from other disciplines to better explain and engineer for phenomena that involve multiple levels of analysis.

One example that this kind of thinking applies to is the study of topological insulators [5]. Topological insulators are materials that are only a few atomic layers thick but long, resulting in atoms-thick nano-ribbons. The synthesis of these materials required significant innovation, including figuring out how to override the thermodynamics related to their growth [6], [7]. Once synthesized, the materials displayed electron transport behaviors that were initially either not reliably predictable or reliably explicable by existing models [8]–[10]. The study and subsequent application of these materials requires knowledge from subatomic and particle physics and surface chemistry to create models that reliably account for the electronic and other behaviors. Identifying which assembly of insights from which disciplines to address specific aspects of these materials requires a principled and productive method for making those assemblies.

Current Mappings of Knowing, Learning, and Analytics

What might a current mapping of knowing, learning, and analytics look like for materials science and engineering? This is an incredibly complex question to answer, but prevalent curriculum construction and instructional design frameworks today somehow link a view of knowledge (or, an epistemology), a view of learning, and a view of assessment [11]–[14]. For instance, if one considers learning to be the construction of mental representations of knowledge that transfer from one context to another (as in the cognitivist tradition of learning), then knowledge might be defined as units of encodable and retrievable information [15], [16]. The assessments of one's learning (defined in this way) might then center on demonstrating the appropriate encoding, retrieval, and transfer of that information beyond the conditions of initial learning [17]. However, if one re-defines learning from constructing a stable knowledge structure to acquiring and activating a task-appropriate set of cognitive and epistemological resources, then transfer across contexts is no longer the most relevant way to view learning and assessment [18]. The resources can include, in physics for instance, resources such as 'force as mover' (that forces are responsible for the motion of objects) or 'dynamic balance' (that there is conflict between opposing forces) [19]. The idea

[1] Here and throughout the paper, I wish to make clear that when I refer to a field such as biology, those fields do not have monolithic epistemologies or methodologies. The fields are useful to capture a wide range of mini-communities that together share some but mainly not all viewpoints and standards. Cellular biologists might investigate a different scale of matter than an environmental biologist, but they both share epistemological membership in an academic field called biology.

here is that learners acquire these resources usually through experience in the world (as push against an object, you might perceive the force as the mover) and then instruction is a matter of activating the right set of resources to any particular situation. One could have all of the prior knowledge necessary to solve a particular physics problem, but if one activates resources that frame the problem in a manner that does not render it amenable to be solved using the prior knowledge, then the prior knowledge might as well not have been there. Learning here is recognizing the demands of the task and activating the right resources – it is more about knowing as an event (to be experienced) rather than about knowing as a structure (to be constructed) [18]. These two examples from the transfer literature demonstrate the linkages between knowing, learning, and analytics, and that knowing is not an objectively defined or agreed-upon term [14].

Since the main thrust of this paper is about designing navigating and planning instructional and assessment activities, the knowledge-learning-instruction (KLI) framework [12] developed out of the knowledge tracing literature [13] serves as a productive starting point. The KLI framework differentiates between observable events (instructional events and assessment events) and unobservable events (learning events). Therefore, moves by an instructor (instructional events) aimed at producing learning (learning events) set up moments during which the learner demonstrates knowing (assessment events). The learning that occurs as a result of an instructional event can only be inferred from the learner demonstration in an assessment event. The learning events (changes in cognitive and brain states) acquire and modify knowledge components (KCs), acquired units of cognitive function or structure that can be inferred from performance on a set of related tasks. While the presentation of a complete taxonomy of KCs is outside of the scope of this paper (see Ref. [12] for a full review), their prominence in the KLI framework is important. KCs are directly linked to performance, and so assessment activities need to enable the observation of skills (knowing how to do something, or procedural knowledge) or use of knowledge (knowing what something is, or declarative knowledge). The assessments therefore tend to revolve around specific learner tasks, each of which requires certain KCs (skills or knowledge). This means that when planning instruction, instructors create demonstration-based learning objectives (e.g., students will be able to calculate the tensile strength of a material), which relate to knowledge components (e.g., state what tensile strength is, use tensile strength equation), from which they then design the necessary instructional and assessment activities. This focus on demonstrable learning objectives and aligning the learning objectives with assessment activities is a major contribution of the knowledge modeling and knowledge tracing literature to curriculum design [11], [20], [21].

This mapping brings with it various trade-offs, and they are extremely attractive from a design perspective. First, by relating decomposable and concrete knowledge components to demonstrable assessment activities, designers can create highly structured objectives that lend themselves to clear exam/test creation. The designers might however be missing out on designing learning experiences beyond purely conceptual structures, such as relating to participatory trajectories [22] or wider sociocultural identity formation [23]. In other words, the curriculum might be focused on the knowledge structure aspect of learning, and only on the knowledge structure aspect of learning. Second, designers can rusk the risk of seeing the knowledge components and skills as independent of the evolution of the field from which they originate. For instance, calculating the yield of a chemical reaction might require the same KCs in chemistry as it does in biology, but that does not mean that the skill fulfills the same function or holds the same level of importance in both fields. In this sense, the designers can miss out on the epistemological origins and disciplinary-based differentiations of the KCs (especially when designing instruction in environments with multiple epistemologies at play). Third, while the KLI framework includes different levels of KCs and different levels of theory, there is nothing in the framework to nudge instructional designers toward thinking in terms of multiple levels of analysis. This helps focus instructional designers on working in a specific range of KCs and theory (to bridge the gap between theory and practice [12]). However, it can also constrain thinking about instruction and assessment to only one level of analysis. In summary, mapping demonstrable assessments to decomposable knowledge components to infer cognitive learning events provides ways to constrain the complexity of instruction [12], [24].

The constraining of that complexity, however, specifically misses out on the complexity that can enrich learning in a multi-disciplinary (multi-epistemological, really) field such as materials science and engineering. To explore this claim, let us now re-visit the question that started this section: What might a current mapping of knowing, learning, and analytics look like for materials science and engineering? Materials science and engineering draws from various epistemologies (e.g., physics, chemistry, biology), and so a single knowledge component (e.g., calculating the yield of a chemical reaction) can have multiple origins and functions based on the nature of the task. Calculating the yield of a chemical reaction to find out if the reaction might significantly change the thermodynamics of the system requires different standards of evaluation (probably from physics) than to find out if the reaction might kill the cells operating in the system (probably from biology). Knowing how to differentiate between these different epistemologies, operate across them, and also be able to combine techniques and insights from them might become learning events to explicitly design for. The mapping for instructional design, therefore, might want to capture more of the instructional complexity. To be clear: the KLI framework could most probably be revised with enough research to eventually uncover these kinds of skills and knowledge components. Over the next several sections, this paper aims to investigate how (1) using philosophical frameworks specifically built to capture epistemological complexity can influence instructional design and (2) designing computer-based learning environments and assessments can promote learning in epistemologically-complex ways. By the end, this paper demonstrates the usefulness of this approach as a way to complement the knowing, learning, and assessment/analytics mapping from existing frameworks.

Integrative Pluralism

Looking for ways to allow scientists to more productively study emergent complexity in cellular operations (such as the makeshift solutions to missing gene sequences mentioned earlier), a philosopher of science, Sandra Mitchell created the integrative pluralism framework. The critical insight for this framework arose from the reality that the epistemological standards of one discipline might not productively map onto another, but that both disciplines need to work together to investigate this class of phenomena. For example, looking for universal, irreducible equations (an approach favored in certain fields of physics) might not be the most productive way to investigate biological research questions (especially when the phenomena might resist such reduction). The four main propositions of integrative pluralism are: (1) that many theories and models can compatibly (and not only competitively) co-exist; (2) that we can connect findings across levels of analysis; (3) that we can be pragmatic about which theories and models we choose to integrate (we do not need to do so for all theories and models at the same time); and (4) that we need to continuously update scientific practice with philosophical frameworks and vice versa [2]. With this framework, scientists do not need to resort to epistemological anarchism (all approaches are equally valid, so evaluating them is meaningless) or isolationist pluralism (each level of analysis works as a self-contained unit) [3]. This last point is extremely important because integrative pluralism is itself a response to anarchic, reductionist, and isolationist epistemologies to be more inclusive, more productive, and more aligned with how scientists actually work.

The mapping of this framework onto materials science and engineering now becomes readily apparent, especially since Mitchell herself uses physics, chemistry, and biology as the main example in her explanation of the framework [2]. Materials science and engineering is a discipline whose practitioners integrate other disciplines to bring them to bear on specific research and engineering problems [1]. After all, a materials scientist investigating the behaviors of folding proteins requires a different integration than a materials scientist investigating electron transport in topological insulators. This claim that materials scientists and engineers integrate other disciplines – and that this is a core skill in this community – is the lynchpin of this paper and the launching point for the upcoming sections.

Integration-based Assessment

If integrating diverse sciences to explore, explain, and engineer complex phenomena is a core skill – and really the core – of the discipline, then how do we prepare students for it? Consequently, how do we assess for this skill?

At a high (read: curriculum) level, recognizing and teaching with the awareness of the diverse epistemologies at play in materials science and engineering can already be a major step in this direction. Pointing out explicitly in classes that various disciplines pursue different forms of knowledge and evaluate knowledge with different standards can most likely help prepare students for navigating the communities and publications associated with those epistemologies. This also communicates to students what they will need to do as professionals within the discipline [25], [26]. Such a recognition also paves the way for a course whose explicit task is to give students practice with strategically and mindfully integrating diverse disciplines. This does not necessarily mean a capstone course that brings together students from different parts of materials science and engineering. This could be a course even halfway through a curriculum that presents students with research and/or engineering problems that lend themselves to integration. Then, the task of the students is to assemble the insights and techniques they believe to be the most pertinent and find ways to verify their attempt with their peers. This is by no means an easy task, but one that materials scientists and engineers routinely engage in.

What kinds of assessments can we craft for evaluating students' integration capability? This remains an open question. Nonetheless, below are some ideas:

- Recognizing diverse epistemologies
    - What kind of questions about *[phenomenon]* would be interesting to *[community]*?
    - When publishing a paper with a brand-new finding, what do you think are the standards that *[community]* would use to evaluate the validity of that finding?
- Recognizing levels of analysis
    - Describe the main processes and the models we currently use to predict and understand them, that explain *[phenomenon]*. Please, separate the processes into

different levels, where the behavior from one level influences the behavior in the next level.
    - Starting at the atomic level and progressing upward (in scale to the macroscopic), explain *[phenomenon]*. Use as many levels as you see fit.
- Practicing integration
    - When researchers investigated *[phenomenon]*, what disciplines did they pull knowledge and evidence from? Why?
    - If you were to investigate *[phenomenon]*, what disciplines would you draw from? Why?

As these assessments illustrate, they would work best after the students had been introduced to enough diversity of knowledge about materials. For the assessments in the "Practicing Integration" section especially, one could imagine giving students a list of several standard perspectives (e.g., equilibrium thermodynamics, molecular kinetics, crystallography, surface chemistry). The assessments effectively ask students the question: which analytical approaches matter for explaining what phenomena?

Computer-Based Learning Environments

To realize the potential of this shift in perspective, we need computer-based learning environments (CBLEs) that allow us to plan integratively pluralistic instruction and collect data on it. As will become clear throughout this section, there are several reasons why CBLEs are necessary for assessments and analytics designed in line with integrative pluralism. For one, the many-to-many mappings of epistemologies, assessment activities, and learner responses could possibly be done on paper, but becomes user-friendly and real-time only in CBLE. Also, CBLEs enable collecting data that reveal trends in learning and instructional design based on the sequence, content, and timing of what learners and instructors do, not what they claim to do [27]–[29]. Collecting process data of this kind is difficult with non-computer-based methods. Finally, learning designers can also design interfaces that embody the principles of the knowing, learning, and analytics mapping, nudging learners as well as instructors into accepting and using the mapping responsibly [30], [31].

The point of the integrative pluralism-infused labeling/mapping is that it allows us to ask three important learning-centered questions. First, is the current epistemological arrangement facilitating the learning we want? Second, are there adequate supports for students to learn and opportunities for them to practice how to navigate the epistemological structure of the learning environment? Third, when looking at the wider program (of a course sequence, department, or school), is the program as a whole developing the epistemology it wants? These questions demonstrate that integrative pluralism is valuable not only in helping us structure learning, but also productively recognize epistemology in learning.

With these questions in mind, we can now discuss how this mapping manifests in software form. On the instructor/researcher side, the main feature is being able to label content with epistemological features. Current learning management software (e.g., Canvas[2], Blackboard[3]) and

---

[2] For more information, please, visit: https://www.canvaslms.com/

[3] For more information, please, visit: http://blackboard.com

online learning platforms (e.g., Open EdX[4], Coursera[5]) allow for some labeling of material, generally based on instructional function or medium (e.g., quiz, textbook, video). For us to actualize the integrative pluralism framework, we need to be able to label content with various epistemological features, namely: level of analysis (or, epistemological location); representation of knowledge (or, epistemological form); class of explanatory models that benefit from this knowledge (or, epistemological utility); and ways of evaluating this knowledge (or, epistemological standards). In essence, these four features respectively answer these questions: *Where* does the knowledge come from? (Physics, Biology, Chemistry) *What* is the knowledge? (Text, Empirical Data, Visuals) *When* is it most valuable/appropriate to use the knowledge? (Atomic Behavior with Equilibrium Thermodynamics Constraints, Crystalline Grain Defect Behavior, Particle Transport in Low-Dimensional Materials) *How* do you evaluate the knowledge? (Analytical Proof, Empirical Evidence, Observation) Below in **Figure 1**, is a possible design of software that would allow for this functionality.

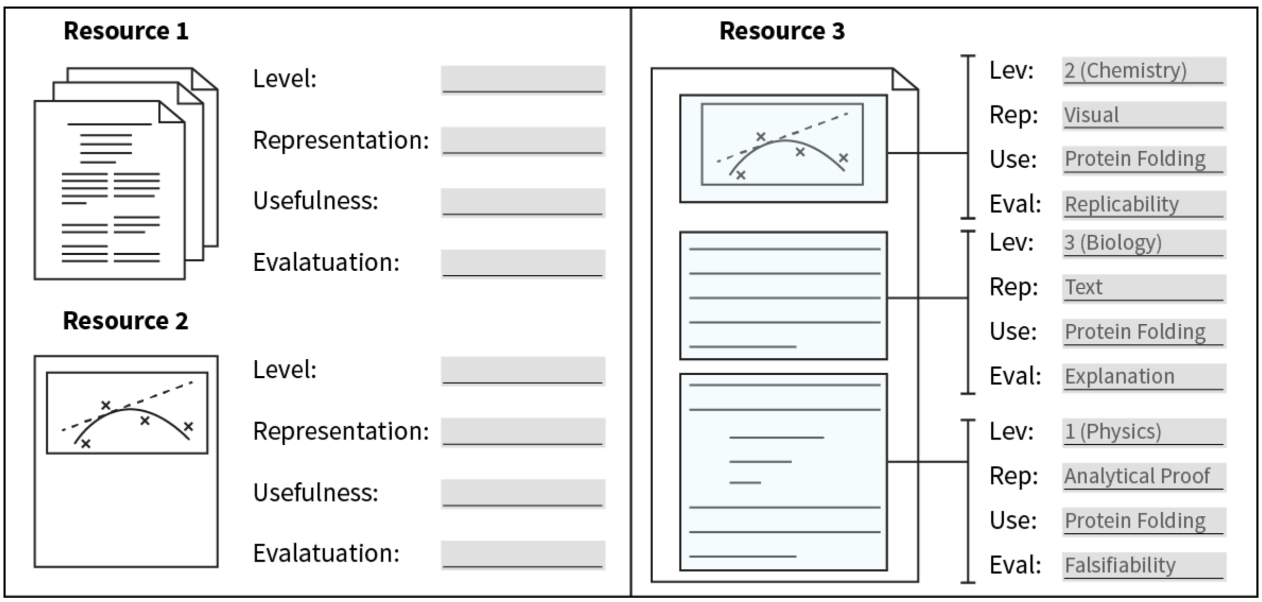

Figure 1. Shows software that allows users to label content with various epistemological features inspired by the integrative pluralism framework. The input options on the right are filled out with the case of all of these pieces of knowledge being useful for a specific integration around protein folding. The same knowledge could also be used for other integrations into other phenomena.

[4] For more information, please, visit: https://open.edx.org
[5] For more information, please, visit: https://coursera.org

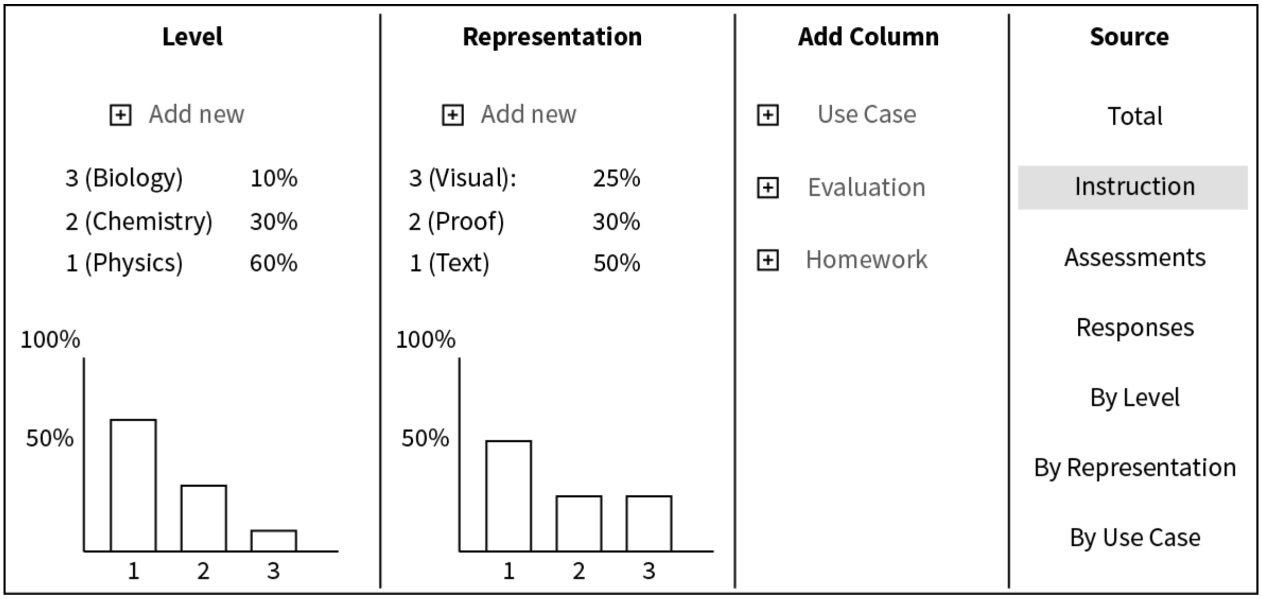

Figure 2. Shows a dashboard with possible statistics regarding the epistemological features of a learning environment. Above, the statistics relate to all of the instructional material (as indicated by the selection in the "Source" column). The interface also shows the ability to add columns.

As **Figure 2** illustrates, the statistics resulting from this kind of labeling can be especially powerful when applied to the content, assessments, and responses, not just averaged across the overall course. What if we find out that the content epistemologically leans in one direction and the assessments lean in another? This is not to say that this is necessarily undesirable. Content involving quantum chemistry, for instance, might involve a significant amount and alignment with physics, not just chemistry. Analytical proofs and some logic operations might be required to fully characterize some of the phenomena of study.

Much of the labeling in this system does not overtly show up in the learner experience. However, learners can interact with assessments designed with integrative pluralism at their core. **Figure 3** shows what such an assessment might look like with a text input and drag-and-drop interface. Below is an outline of a possible learner experience with the software:

- The learner reads about a particular phenomenon that the learner needs to explain.
- The learner then chooses to start at and name a level of analysis.
- Within that level of analysis, the learner selects from a menu the main source of information or insight about the process occurring at that level.
- The learner then writes in the equations or evidence for the process at that level and also cites them from the most relevant place in the learning environment.
- The learner explains how this process informs and/or constrains the process at the next level.

We can imagine expanding this interface by one column that would have learners state a research question or two that researchers at that level might be interested in. However, as a basic flow, this set of columns and activities works.

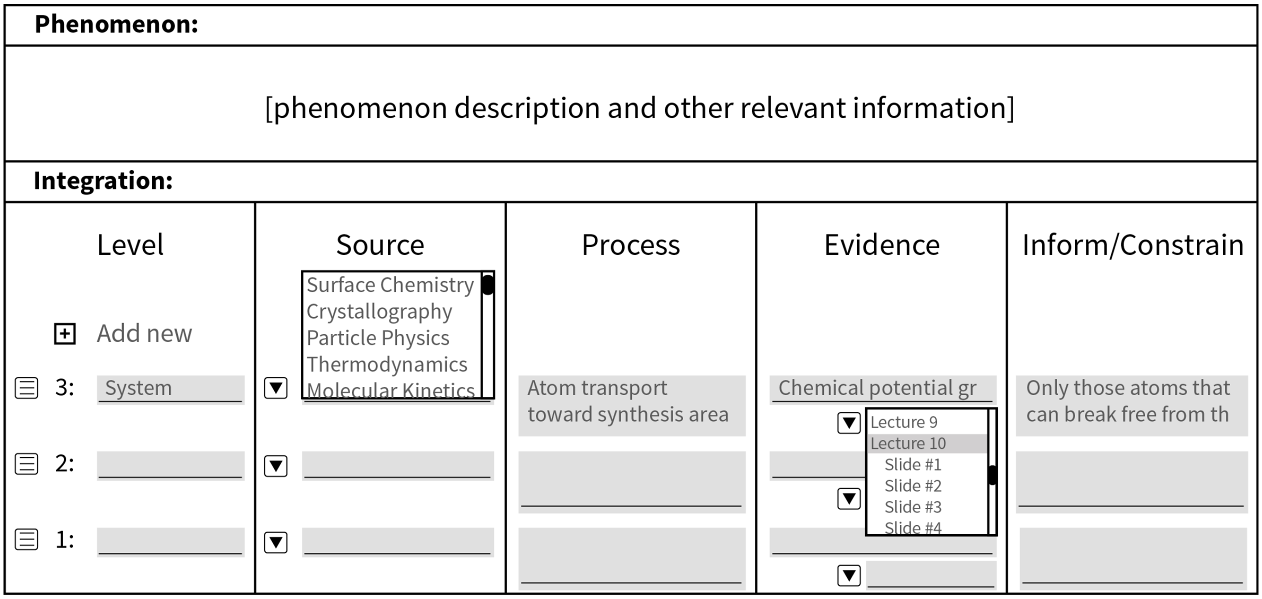

Figure 3. This figure shows a possible assessment environment in the manner that a learner would experience it. The "Level" column allows learners to add as well as re-arrange levels of analysis that they themselves name. The "Source" and "Evidence" columns show examples of open drop-down menus the learners can use. The choices in the "Source" drop-down menu can be input by the instructor.

An interesting application for these digitally-crafted integrations is that learners could save them and test them with examples beyond their original use. Creating a knowledge structure that generalizes (with the correct formalism) to many more scenarios than the ones that inspired it is a critical learning step, especially in STEM disciplines. Saving integrations and testing them on an expanding range of scenarios could become a vehicle for this kind of learning. More importantly, the learning environment could track the changes learners make as they attempt to re-arrange an existing integration or as they arrange a new one. Do learners construct them in a bottom-up or a top-down or a hybrid approach? Do they target certain levels or epistemologies earlier than others? What if some homework assignments build up to an integration, which then becomes a reference for future assignments? In this sense, the integrations can become tools not only for assessment, but also for future learning.

Conclusion

The purpose of this paper is not to present final software designs or tested instructional practices based on integrative pluralism. The framework, although introduced to the learning sciences, is not yet that explored through implementation via instructional design. The purpose of this paper is to use integrative pluralism to (1) re-define a core skill of certain STEM disciplines, (2) draft new kinds of assessments based on that re-definition, and (3) imagine what software might support such assessments. Ultimately, this exploration allows us to ask as educators and researchers: What does the integrative pluralism framework add to our toolkit? The answer this paper argues for is: a new and productive lens with which to plan, facilitate, and research learning that complements well existing standards/trends in instructional design. Crafting assessments and organizing them to conscientiously build up to a specific epistemological view and skill set seems to be an equally challenging and necessary task in modern STEM disciplines. It is not the paper's intention to position integrative pluralism as inherently better than the KLI framework, for instance, but to position it as a necessary and useful framework to balance constraining more of complexity with capturing more of it. Furthermore, giving students practice with exploring and capturing complex phenomena is becoming ever more important in a world of increasing collaboration and increasingly complex phenomena. All instruction molds more than just *what* knowledge we hold in our minds. Integrative pluralism might be a framework to help us attend to that "more" productively and consciously.

References

[1] S. Lane, A. Karatsolis, and D. R. Sadoway, "Materials Science and Engineering Reasoning: A New Tool for Helping Students See the Big Picture," presented at the ASEE Annual Conference & Exposition, New Orleans, Louisiana, 2016.

[2] S. D. Mitchell, *Unsimple truths: Science, complexity, and policy*. University of Chicago Press, 2009.

[3] S. D. Mitchell, *Biological complexity and integrative pluralism*. University of Chicago Press, 2003.

[4] J. Cesonis, "An Introductory Teaching Resource for Materials Science and Engineering," *age*, vol. 26, p. 1.

[5] X.-L. Qi and S.-C. Zhang, "Topological insulators and superconductors," *Rev. Mod. Phys.*, vol. 83, no. 4, pp. 1057–1110, Oct. 2011.

[6] H. Wang *et al.*, "$MoSe_2$ and WSe_2 Nanofilms with Vertically Aligned Molecular Layers on Curved and Rough Surfaces," *Nano Lett.*, vol. 13, no. 7, pp. 3426–3433, Jul. 2013.

[7] D. Kong *et al.*, "Synthesis of MoS_2 and $MoSe_2$ Films with Vertically Aligned Layers," *Nano Lett.*, vol. 13, no. 3, pp. 1341–1347, Mar. 2013.

[8] C.-Z. Chang *et al.*, "Experimental Observation of the Quantum Anomalous Hall Effect in a Magnetic Topological Insulator," *Science*, vol. 340, no. 6129, pp. 167–170, Apr. 2013.

[9] D. Hsieh *et al.*, "A tunable topological insulator in the spin helical Dirac transport regime," *Nature*, vol. 460, no. 7259, pp. 1101–1105, Aug. 2009.

[10] Y. L. Chen *et al.*, "Massive Dirac fermion on the surface of a magnetically doped topological insulator," *Science*, vol. 329, no. 5992, pp. 659–662, 2010.

[11] G. P. Wiggins and J. McTighe, *Understanding by design*. Ascd, 2005.

[12] K. R. Koedinger, A. T. Corbett, and C. Perfetti, "The Knowledge-Learning-Instruction Framework: Bridging the Science-Practice Chasm to Enhance Robust Student Learning," *Cogn. Sci.*, vol. 36, no. 5, pp. 757–798, Jul. 2012.

[13] A. T. Corbett and J. R. Anderson, "Knowledge tracing: Modeling the acquisition of procedural knowledge," *User Model. User-Adapt. Interact.*, vol. 4, no. 4, pp. 253–278, 1994.

[14] J. G. Greeno, "Response: On Claims That Answer the Wrong Questions," *Educ. Res.*, vol. 26, no. 1, p. 5, Jan. 1997.

[15] H. A. Simon, *The Sciences of the Artificial*. MIT Press, 1996.

[16] A. Newell, *Unified theories of cognition*. Harvard University Press, 1994.

[17] J. D. Bransford and D. L. Schwartz, "Chapter 3: Rethinking Transfer: A Simple Proposal With Multiple Implications," *Rev. Res. Educ.*, vol. 24, no. 1, pp. 61–100, Jan. 1999.

[18] D. Hammer, A. Elby, R. E. Scherr, and E. F. Redish, “Resources, framing, and transfer,” in *Transfer of Learning from a Modern Multidisciplinary Perspective*, J. P. Mestre, Ed. Greenwich, CT: Information Age Publishing, 2005, pp. 89–120.
[19] A. A. DiSessa, “Knowledge in Pieces,” in *Constructivism in the Computer Age*, G. Forman and P. B. Pufall, Eds. New Jersey: Lawrence Erlbaum Publishers, 1988, pp. 49–70.
[20] S. A. Ambrose, M. W. Bridges, M. DiPietro, M. C. Lovett, and M. K. Norman, *How learning works: Seven research-based principles for smart teaching*, 1st ed. John Wiley & Sons, 2010.
[21] E. J. Hansen, *Idea-based learning: A course design process to promote conceptual understanding*. Stylus Publishing, LLC., 2012.
[22] B. Rogoff, J. Baker-Sennett, P. Lacasa, and D. Goldsmith, “Development through participation in sociocultural activity,” *New Dir. Child Adolesc. Dev.*, vol. 1995, no. 67, pp. 45–65, 1995.
[23] J. G. Greeno, “The situativity of knowing, learning, and research.,” *Am. Psychol.*, vol. 53, no. 1, p. 5, 1998.
[24] K. R. Koedinger, J. L. Booth, and D. Klahr, “Instructional complexity and the science to constrain it,” *Science*, vol. 342, no. 6161, pp. 935–937, 2013.
[25] R. Heard, “AC 2010-172: INSTRUCTION OF PROFESSIONAL SKILLS TO MATERIAL SCIENCE AND ENGINEERING STUDENTS USING A MULTI-YEAR MODULE APPROACH,” *age*, vol. 15, p. 1, 2010.
[26] L. Vanasupa, B. London, K. C. Chen, and R. Savage, “Curricula to Educate the 2020 MSE Engineering Professional: Simple but Powerful Changes in the way that MSE is Taught,” *Mater. Eng.*, p. 31, 2006.
[27] C. Thille, E. Schneider, R. F. Kizilcec, C. Piech, S. A. Halawa, and D. K. Greene, “The future of data-enriched assessment,” *Res. Pract. Assess.*, vol. 9, 2014.
[28] C. Piech *et al.*, “Deep knowledge tracing,” in *Advances in Neural Information Processing Systems*, 2015, pp. 505–513.
[29] P. Johanes, “Epistemic cognition: A promising and necessary construct for enriching large-scale online learning analysis,” in *Proceedings of the Fourth ACM Conference on Learning at Scale, L@S 2017*, Cambridge, MA, 2017.
[30] A. Israni and J. F. Pane, “Mastery Learning in Practice: A (Mostly) Descriptive Analysis of Log Data from the Cognitive Tutor Algebra I Effective- ness Trial,” p. 28.
[31] A. C. Sales and J. F. Pane, “The Role of Mastery Learning in Intelligent Tutoring Systems: Principal Stratification on a Latent Variable,” p. 22.