A Typology of Models for Integrating Computational Thinking in Science (CT+S)

Ari Krakowski
Lawrence Hall of Science
University of California, Berkeley
Berkeley, CA, USA
akrakowski@berkeley.edu

Eric Greenwald
Lawrence Hall of Science
University of California, Berkeley
Berkeley, CA, USA
eric.greenwald@berkeley.edu

Meghan Comstock
Graduate School of Education
University of Pennsylvania
Philadelphia, PA, USA
mccom@gse.upenn.edu

Natalie Roman
Lawrence Hall of Science
University of California, Berkeley
Berkeley, CA, USA
nroman@berkeley.edu

Jacob Duke
Lake Washington School District
Redmond, WA, USA
jacduke@lwsd.org

***Abstract*—In order to expand opportunities to learn computer science (CS), there is a growing push for inclusion of CS concepts and practices, such as computational thinking (CT), in required subjects like science. Integrated, transdisciplinary (CS/CT+X) approaches have shown promise for broadening access to CS and CT learning opportunities, addressing potential self-selection bias associated with elective CS coursework and afterschool programs, and promoting a more expansive and authentic contextualization of CS work. Emerging research also points to pedagogical strategies that can transcend simply broadening access, by also working to confront barriers to equitable and inclusive engagement in CS. Yet, approaches to integration vary widely, and there is little consensus on whether and how different models for CS and CT integration contribute to desired outcomes. There has also been little theory development that can ground systematic examination of the affordances and tradeoffs of different models. Toward that end, we propose a typology through which to examine CT integration in science (CT+S). The purpose of delineating a typology of CT+S integration is to encourage instantiation, implementation, and inspection of different models for integration, and to promote shared understanding among learning designers, researchers, and practitioners working at the intersection of CT and science. For each model in the typology, we characterize how CT+S integration is accomplished, the ways in which CT learning supports science learning, and the affordances and tensions for equity and inclusion that may arise upon implementation in science classrooms.**

Keywords—Equity and inclusion in computing, Computational thinking, Transdisciplinary (CT+X) curriculum models.

I. Introduction

Computation has become critical to an ever-broadening list of disciplines, from science to social studies. However, the growing role of computing in academic and workforce pathways risks further deepening persistent inequities in participation: female-identifying, Black, Latinx, and Native American individuals remain markedly underrepresented in CS pathways [1]. In an effort to broaden participation and address the self-selection bias associated with elective CS coursework and afterschool programs [2], there is a growing push for inclusion of CS concepts and practices in required subjects like science [3, 4, 5]. This integrated approach not only holds promise for broadening access to instruction, but it also better reflects the transdisciplinary nature of the contemporary and computationally-enabled STEM profession [6] and can promote learning in integrated disciplines [7, 8, 9, 10, 11, 12, 13].

While there is broad support for and notable exemplars of transdisciplinary integration of CT learning in core academic courses—including in formal science courses—approaches to integration vary widely, and there is little consensus on whether and how different models for CT integration in science (CT+S) contribute to desired outcomes. Progress requires attention to two key concerns. First, CT+S learning experiences cannot accomplish broader participation in CS pathways if they are not successfully taken up at scale; therefore, a comparison of different CT+S models must attend to factors that promote broad implementation. Second, there is an emerging consensus in STEM education that to inspire a broader array of students toward CS, educators, curriculum designers, and researchers must not only expand access, but must also confront barriers to more inclusive student engagement.

II. A Typology for CT+S Integration

We propose a typology of CT+S instructional models (Fig. 1) that helps to reveal affordances and challenges of particular models for cultivating desired outcomes, and to promote continued discussion about how CT+S models may be implemented in practice. Our typology emerges from ongoing work by the authors across multiple studies examining the design, implementation, and outcomes of CT+S curricula and pedagogical approaches, including two NSF-funded projects (see DRL#s 1657002 and 1838992). Thus, the typology is informed by interviews with dozens of science teachers and school district administrators, ongoing partnerships with districts at the vanguard of implementing CS/CT+X curricula, as well as collaborations with colleagues similarly working at the intersection of CS and science. Finally, because the typology can describe instruction at different grain sizes (e.g., complete instructional units as well as individual learning experiences), models within the typology are not mutually exclusive and can often occur in combination. Insofar as they represent approaches that can confront distinct barriers to equitable and inclusive CS education, it may be advantageous to draw on multiple models within the typology to design CT+S curricula.

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CT+S Integration Model	Synergistic	Alternating	Practice-forward	Issue-forward
Defining characteristic	CT learning and disciplinary science learning occur in service of one another in real time.	CT learning and disciplinary science learning alternate with respect to instructional focus and time.	CT learning is integrated with science and engineering practices (SEPs) recognized as core epistemic practices.	CT learning is positioned in service of addressing compelling, real-world problems of significance outside the classroom.
Recognizable features	Science concepts are needed to engage in CT learning, and CT learning promotes development of science understanding.	Science learning and CT learning can be accomplished separately through independent engagement with each domain in turn.	CT learning supports deep engagement with SEPs, particularly those in which science teachers have deep pedagogical expertise.	Learning is driven by a socioscientific issue that serves as the anchoring phenomenon to motivate inquiry and knowledge construction.

Fig. 1. *Summary: Typology of Models for Computational Thinking in Science (CT+S) Integration*

A. *Synergistic Integration*

This model of CT+S integration refers to instructional sequences in which CT learning and science learning occur simultaneously and synergistically—that is, students build CT understanding alongside disciplinary science understanding such that their intellectual work requires engagement with both domains. As such, learning experiences mirror the work of STEM professionals, such as computational biologists, who investigate phenomena salient to their discipline not simply by using computational tools, but by translating those phenomena in ways that are amenable to such tools, and/or developing and refining computational tools to better serve investigation of disciplinary phenomena.

An emphasis on disciplinary understanding is a defining characteristic of the synergistic model of CT+S integration. Moreover, with synergistic CT+S approaches, CT learning and disciplinary science learning occur reciprocally [6], in service of one another in real time. Thus, as students learn to use, modify, or create computational artifacts, science concept(s) are necessary to create, evaluate, or make sense of the code (or the rules of the computational tool). Put another way, you need the science to make sense of the code, and you need the code to advance understanding of the science. As such, the CT learning helps support students in building, deepening, or consolidating their understanding of standards-aligned science concepts [7, 8, 9, 10, 11, 12, 13]. For example, in one learning sequence we are investigating, students code a dynamic computational model that accurately represents the effects of different environmental factors (e.g. temperature increase, ocean acidification, etc.) on populations in a coral reef ecosystem. In the lesson sequence, students' implement control structures in a block-based coding language such that the conditions that must be met for a specific output to occur in the computational model emerge directly from the biological relationships among coral, predators, competitors, and abiotic environmental threats to the ecosystem.

B. *Alternating Integration*

The alternating model of CT+S integration refers to instructional sequences in which CT learning and science learning take turns in time and instructional focus: student learning is focused on science concepts, and then on CT practices. In collaborative learning contexts, alternating integration may be characterized by a divide and conquer approach wherein some students focus primarily on the CT aspects of the problem space while others focus on the science aspects. The STEM workplace analogue to alternating integration may be seen in interdisciplinary projects in which the tasks can be distributed according to expertise, and the expertise remains with the disciplinary representative on the team—the programmer programs and the scientist investigates.

As with synergistic integration, alternating integration is characterized by accountability to the disciplinary science concepts that a teacher at that grade is expected to address, and also includes meaningful CT learning experiences. That is to say, in both synergistic and alternating integration there are extended learning opportunities with both content areas. The distinction between synergistic and alternating models rests in the nature of the cognitive work in which students are engaged. To what extent is the CT and science disciplinary learning in service of one another in a given activity? To what extent are students building understanding of disciplinary science content and CT practices in concert? For alternating integration, while students' intellectual work in the two domains may be related or of the same topic (e.g., space, or ecosystems), the work can be accomplished by engaging with each domain independently, or in turn. In contrast with synergistic integration, however, the science learning does not explicitly engage computational thinking, and the programming requires little science understanding to successfully accomplish. As an example, a student may apply science knowledge to determine the criteria for a robotic bee that can pollinate flowers (e.g., how much pollen to collect, from which plants, and how much to distribute, and to which plants); that student (or another student) then applies knowledge of a programming language to program the bee bot according to the criteria.

C. *Practice-forward Integration*

Practice-forward CT+S integration aims to integrate CT in science courses through connections between CT and other science and engineering practices (SEPs), such as scientific modeling and data analysis, long-recognized as core epistemic practices in science, and emphasized in science standards [14, 15]—and accordingly, in science classrooms. In fact, there is growing recognition that these science practices afford facile and authentic integration with CT learning [12, 16, 6].

With a practice-forward approach, students may have extended opportunities to engage with CT alongside deep engagement with a disciplinary practice. As a result, practice-forward CT+S learning experiences focus on developing facility with the SEPs and less so on building conceptual understanding of the phenomenon underlying the investigation. For example, in a practice-forward learning sequence we are studying, students interact with a national air quality dataset using code to query, filter, explore, and create visualizations of the data. Over the course of the lesson sequence, students gain exposure to data science practices and experience with the underlying computation involved in analyzing and creating visualizations from large datasets. Students are not expected, however, to develop a mechanistic account of the sources of pollution or the science of how it impacts living things.

D. *Issue-forward Integration*

The issue-forward approach to CT+S integration makes use of compelling socioscientific issues to motivate CT+S learning. This model often involves situating the CT and science ideas inside a problem context in which those ideas matter to students, as well as to scientists and science practitioners. The focus on a driving problem for inquiry aligns with recent calls for phenomena-centered learning [17]. It also draws on problem-based science approaches to student engagement in science classrooms [18, 19, 20, 21], in which compelling, real-world problems provide the context for inquiry, knowledge construction, and application. Importantly, positioning coding in service of addressing real-word problems also reflects research-based strategies [e.g., 22, 23, 24, 25, 26] aimed at confronting barriers to broader participation in CS, for example, through confronting perceptions that coding is of limited value or relevance to solving real-world problems [27, 28, 29].

In this model of integration, the socioscientific issue is integral to student engagement with (both CT and S) content. In other words, the issue drives student learning. For example, disease transmission represents a current and pressing socioscientific issue that could ground issue-forward integration. Students can build and apply CT knowledge to manipulate relevant variables (e.g. infection rate, vaccination rate), with less explicit attention to the biology of host-virus interactions (e.g., viral replication mechanisms inside host cells). This model stands in contrast to approaches in which students learn domain content in school-bound ways, and are then presented with real-world connections at the periphery.

III. Discussion: Considerations for Equity

A core impetus driving integration of CT into required academic courses such as science is to broaden participation in CS pathways by expanding access to CT learning opportunities for students underrepresented in CS. A growing body of research also makes clear that inspiring a broader array of students toward CS will also require explicit attention to designing more inclusive learning environments. In the following section, we discuss the different models' affordances and challenges for centering equity at the intersection of CT and science learning (Fig. 2).

A. *Affordances for equitable CT+S integration*

The synergistic and alternating models both hold promise for expanding access to CT+S learning beyond self-selected students: at a minimum, these models squarely attend to disciplinary science content standards, a critical criterion for scalable uptake in science classrooms. The synergistic model, in particular, foregrounds the reciprocal, transdisciplinary learning of science and CT [6]. This can serve, in turn, to promote a more expansive and authentic contextualization of CS and support system-level efforts aimed at better preparing youth for 21st century academic and career pathways [30, 31].

Within the CT+S typology, both practice-forward and issue-forward models offer clear pathways for drawing on students' lived experiences and cultural and community funds of knowledge. Learning experiences that connect to and build from students' interests, cultural knowledge, and lived experiences can enable students to bring their own voices into the learning environment [31, 32, 33, 34, 35, 36]. Further, positioning learning in service of addressing meaningful real-world problems can confront negative perceptions that CS work is of limited social value [22, 23, 24, 25]. This is readily apparent for the issue-forward model in that it fits within a broader paradigm of socioscientific issue-driven approaches that specifically seek to address the personal dimensions of learning, "placing scientific knowledge and its uses squarely within our and our students' social, political, and cultural lives [38]." Similarly, because the practice-forward integration model is relatively agnostic about the concepts and phenomena with which students engage, it may also create opportunities for positioning coding as a tool that can be applied to contexts that are responsive to students' ideas, experiences, and interests. For example, in the practice-forward learning sequence on air quality described above (section IIC), the national scope of the massive dataset enables place-based customization of instruction as students investigate air quality in their community and compare it to other areas of the United States. Throughout the lesson sequence, students also freely explore datasets about high-interest topics that are more familiar to students (e.g., music, sports), and build or apply their developing facility with data practices to make sense of the attributes and patterns in the dataset(s) they chose to analyze.

Depending on how they are designed, integrative approaches may therefore enable students to move beyond receptive knowledge 'for school' (I know something important in science class) to productive knowledge (I can explain something of significance in the broader world). Moving beyond the traditional "science for school" stance permits a more expansive and inclusive epistemic and discursive repertoire that can promote broader, more equitable participation in STEM [39, 40, 41, 42]. Similarly, these models may support multiple entry points for learners with different wells of expertise and interest, and the potential to leverage their respective expertise along the way to advancing understanding of less familiar domains.

B. *Challenges for equitable CT+S integration*

Engaging students in socioscientific issues often requires explicit attention to the underlying science concepts that enable youth to meaningfully engage with the broader social problem: a social issue may be readily understandable on the surface, yet engaging with the science of it may require extensive, beyond-grade-level content. Thus, we have found it critical to select issues with this concern in mind, and support the learning of underlying science concepts where that background knowledge cannot be assumed. A related difficulty for both synergistic and alternating integration models is that each domain introduces its own unique challenges for accessing instructional material. While learning may be reciprocally supportive [6], it can also present impediments for students who have not had positive

	Synergistic	Alternating	Practice-forward	Issue-forward
Affordances for centering equity in CT+S integration	**Addresses disciplinary content** standards alongside science practices, facilitating uptake at **scale**		Readily **affords connections to students' lived experiences** & **funds of knowledge**	
	Promotes **reciprocal learning** of CT+S **authentic** to contemporary science		Addresses **core practices** in science, supporting uptake at **scale**	Positions CT in service of **impactful** real-world problems
Challenges for centering equity in CT+S integration		Additional **instructional time** and **cognitive demand** may be needed to support: - sensemaking/synthesis across domains	- engagement with CT- enabled core practices	- understanding of issue at grade level
	May limit time available for connections **to students' lived experiences & funds of knowledge**		**Backgrounds disciplinary content** standards, which can limit uptake at **scale**	
		Can **magnify subject area silos** of expertise		

Fig. 2. *Affordances and Challenges of Integrated CT+S Models for Centering Equity in Science Classrooms*

experiences with one or both domains. Alternating models, in particular, can magnify divisions of expertise (real and perceived) such that "science kids" gravitate toward the science content and "tech kids" gravitate toward the computational work. Thus, without explicit attention to this possibility, the integrated instruction may do little to support students to reach beyond their comfort zones and engage with the less familiar discipline, potentially magnifying inequities that already exist and/or foreclosing on opportunities for self-efficacy in one domain to bootstrap learning of another. Thus, because students arrive at integrated learning experiences at different points of expertise with respect to each of the domains, it seems critical to provide adequate support for students to elicit and leverage their current areas of expertise while simultaneously supporting them in developing facility with concepts and practices with which they may be less comfortable.

The practice-forward CT+S model leverages connections between CT learning and science and engineering practices (SEPs) emphasized in science standards [14, 15]. However, while CT is explicitly called out in national science standards, our conversations with teachers and district administrators across multiple projects suggest that CT does not yet consistently carry adequate face-validity for science teachers and districts to warrant extensive instructional time. This may be because few science teachers have had prior experience teaching CT, and the nascent state of broad integration of CT in science contexts offers slim guidance to science teachers to support deep pedagogical expertise for engagement with CT [43, 44]. Accordingly, our experiences developing CT+S instructional sequences echo growing recognition in the field that CT+S approaches are well-served when they integrate with SEPs long accepted as core epistemic practices in science (e.g., scientific modeling and data analysis) [12, 6, 16]. These core practices meet the needs of science classrooms to enable broad use, and importantly, bridge to and deepen familiar wells of expertise for science teachers. An important consideration for implementation, however, is that deep engagement with core science practices in conjunction with CT (e.g. working with big data, developing runnable scientific models with ground truthing) requires instructional time as well as educative supports for teachers. Instructional time may also need to be devoted to aspects of the practices themselves, for example deep attention to the nature and purpose of scientific models [45], or to reasoning about data [46]. Finally, even where CT is connected to more familiar disciplinary practices, practice-forward integration may still be met with skepticism if "content" is thin or if science concepts lie outside the standards.

The alternating CT+S model allows for depth of learning in both CT and S but lessens the demand for explicit synergy between the two content areas, thus affording a greater variety of options across their union. Still, there are tradeoffs: learning experiences in which disciplinary and CT learning are less tightly synthesized are less likely to disrupt subject area silos of expertise among students or to facilitate transdisciplinary learning that supports engagement with the "grand challenges" in contemporary computational science [47]. An additional challenge for implementation of the alternating integration model is the instructional time required to support students in drawing productive connections between CT and science learning. Touching back on the example of students coding the simulated pollination movements of bees discussed in section IIB, students may build disciplinary understanding of ecosystem interdependence in lessons focused on science concepts, yet only attend to superficial aspects of these concepts (e.g. the distance moved by the bee, or the position of differently colored flowers) when engaged in CT learning. Because engagement in each domain is temporally and/or conceptually distinct, care must be taken in the design of alternating CT+S curricula to promote synthesis and sensemaking at the intersection of domains so that students perceive science and CT learning as integrated—in service of one another, as opposed to disparate activities connected through mere temporal adjacency.

C. *Conclusion*

The typology of CT+S models is intended to serve as a tool to advance continued research, design, and implementation of integrated (CT+S) curricula that center equity for all students. As a research object, the typology provides a way to map the terrain of CT+S efforts, a starting place for the field to investigate and refine the boundaries of different integrated (CT+X) models, and further illuminate their affordances and limitations for inclusive and equitable learning. The typology offers evaluators a way to clarify a project's theory of action and expected outcomes, and provides curriculum developers with a starting place to consider alignment between learning goals and instructional design. For practitioners, including classroom teachers and district curriculum leads, the typology offers a framework to interrogate commercial offerings and align local initiatives with desired outcomes.

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