2023 Annual Conference & Exposition
Baltimore Convention Center, MD | June 25 - 28, 2023
The Harbor of Engineering Education for 130 Years
Paper ID #37062

Board 313: Implementing Computational Thinking Strategies across the Middle/High Science Curriculum

Dr. Thomas Tretter, University of Louisville

Thomas Tretter is professor of science education, Director of the Center for Research in Mathematics and Science Teacher Development, and Director of the Gheens Science Hall & Rauch Planetarium at the University of Louisville. His scholarship includes collaborative efforts with science and engineering faculty targeting retention of engineering students and K-12 teacher connections with engineering.

Dr. Olfa Nasraoui, University of Louisville

Olfa Nasraoui is Professor of Computer Engineering and Computer Science, Endowed Chair of e-commerce, and the founding director of the Knowledge Discovery and Web Mining Lab at the University of Louisville. She received her Ph.D. in Computer Engineering a

Kyle Dylan Spurlock
Breanna Graven, University of Louisville

PhD candidate in curriculum and instruction with a focus on informal science education. Current graduate research assistant for the First-Year Engineering department studying ways to improve student retention and persistence to graduation.

Implementing Computational Thinking Strategies across the Middle/High Science Curriculum

Abstract

This NSF Research Experience for Teachers (RET) "*Research Experience for Teachers in Big Data and Data Science*" (award number: 1801513) engaged four middle/high school science teachers in summer 2022 with research related to big data and data science, with follow-up school year implementation of related curricula. These teachers developed curricula related to their summer research experience in big data and data science that spanned a range of student ages and topics: middle school science, 9th grade biology, 9th grade health, and 11th grade chemistry. Despite the wide range of student ages, curricular content, and instructional goals, all teachers found rich and varied curriculum applications related to data science and AI that fit within their existing curriculum constraints. In particular, teachers found that the Next Generation Science Standards [1] practice of "*computational thinking*" was the best lens for developing their aligned big data instruction. After exploring a taxonomy of computational thinking in mathematics and science [2], the teachers collectively eventually settled on a core set of four computational thinking skills [3] most likely to be productive for their teaching focus; algorithmic thinking, decomposition, abstraction, and pattern recognition. This paper reports on the variety of connections teachers developed with the practice of computational thinking, from data clustering as an active practice for simulating early generation of the periodic table in a chemistry class, to sampling/resampling populations in outdoor aquatic environments, to programming in middle school science, to adapting explainable AI for analyzing student-generated data in a health education class. Teacher reports of their own learning about research in data science, and how they were able to adapt that learning for the benefit of their middle/high school students, will capture the flexibility and value that this experience provided.

This work was supported by National Science Foundation grant NSF CNS-1801513.

Literature Review

Growing Societal Importance of Big Data

The fast pace of low-cost technological innovation and data-centered operations and management have led to an explosion of data, along with related applications, services, and human-machine interaction. This abundance of data has given rise to a thriving ecosystem of "big data" algorithms and applications that can discover patterns and relations between different phenomena to make predictions and forecast the future. The combination and analysis of large amounts of data from diverse sources promises new insights into relationships and interactions between humans, the environment, and the myriad of physical entities or Internet Of Things [4]. Thanks to big data algorithms, large amounts of data can reveal new knowledge for decision making in healthcare, education, scientific discovery, finance, policy, journalism, and environmental science, etc. [5]. Furthermore, as more humans become direct consumers of – and are affected by – big data algorithms, considerations related to fairness, transparency and adaptability [6] come into the fore of big data research.

Moreover as big data permeates through all the sectors of society, big data problems often arise in diverse disciplines, not just the computing field. In particular, the data-enabled approach is revolutionizing the way that scientists and engineers in many fields practice, understand, and make discoveries in diverse disciplines. This means that big data can have a significant impact on all STEM subjects. Therefore, big data, with its myriad socially relevant applications and interdisciplinary reach, is a good way to interest students and teachers in computer science as a discipline and as a powerful problem solving approach in a wide range of disciplines.

Computational Thinking and K-12 STEM Education

In the education research literature, computational thinking has been described as "the core of all modern Science, Technology, Engineering and Mathematics (STEM) disciplines and is intrinsic to all other disciplines from A to Z." [7]. It is a way of viewing everyday phenomena and solving problems by using concepts that are fundamental to computer science, such as finding patterns in data, breaking a problem down into smaller parts, simulating systems and using technology to automate the problem-solving process.

Computational thinking is a core skill at the heart of applications of big data solutions – scientists and engineers need to develop the computational processes for analyzing and synthesizing large data sets into meaningful interpretations guided by human purposes. Across all scientific and engineering disciplines, computational thinking is a core practice essential for understanding and explaining scientific concepts and designing solutions to engineering problems, and is a key component of both K-12 mathematics standards [8] and Next Generation Science Standards (NGSS) [1]. Computational thinking practices envisioned by the NGSS include strategies for organizing and searching data, creating algorithms, and using and developing new simulations of natural and designed systems to make predictions, solve problems, test solutions, support claims, or craft scientific explanations. Unfortunately, the development of computational thinking in K-12 students is not well understood and is infrequently assessed [9], [10]. Supporting high school teachers and their students to engage in this new way of thinking is a critical role of science and engineering education.

Current research on computational thinking in grades K-12 includes studies on ideal computational thinking learning environments. For example, Repenning and colleagues [11] found that effective computational thinking environments and tools for school children should be easy enough to start using right away, yet powerful enough to satisfy the needs of more advanced learners. The tools should scaffold to build skills and knowledge, support equitable use, enable transfer of skills, and be sustainable. Sengupta and colleagues [12] developed a theoretical framework for integrating computational thinking and programming into K-12 science curricula. This framework lays the groundwork for the development of a long-term curricular progression in which students can engage in learning science using computational modeling and thinking over a span of multiple years. Grover and Pea [13] have summarized recent research into computational thinking with school-aged children and have identified several gaps in the field. They recommend bringing the cognitive science of how people learn into discussion, as well as the idea of computing as a teaching medium for other subjects. Moreover, there are many questions about the dispositions for, attitudes toward, and stereotypes concerning computational thinking and how they connect to stronger learner identity. Very little research has been published on how teachers learn to incorporate computational thinking into their content.

Research Question

Given the centrality and growing importance of computational thinking as a vital skill for making sense of patterns in an increasingly data-rich world, and the paucity of evidence for how to best support K-12 STEM teachers to integrate computational thinking instruction into their ongoing instruction, this study will explore:

In what ways do a spectrum of middle and high school STEM teachers effectively incorporate computational thinking instruction into their instruction?

Methods

Research Design

Given the relatively wide spectrum of ages of students (6th grade – 11th grade) and of disciplines taught (mathematics, health, biology, chemistry), each teacher's integration of computational thinking into their instruction will be treated as a separate case. This case study approach permits uncovering both similarities and differences in how one might effectively integrate a common skill set across a spectrum of contexts.

Participants

In summer, a group of four middle/high school teachers (see Table 1) participated in a 6-week Research Experience for Teachers (RET) at University of Louisville. During those six weeks, they engaged in conducting big data research (in pairs) with engineering faculty and engineering doctoral students (see Table 1), and also had structured support for considering possible curriculum and instructional integration for their own students in the coming school year.

Table 1: Participating Teachers and their Summer Research Projects

Teacher [a]	Grade level/ Subject	Big Data Research Project
Heather	6th grade math & science	Explainable Machine Learning
Darius	9th grade health	Explainable Machine Learning
Jennifer	9th grade biology	Wearable Device Data Visualization
Sam	11th grade chemistry	Wearable Device Data Visualization

[a] All teacher names are pseudonyms

Brief Big Data Research Project Descriptions

The explainable machine learning project focused attention on the need for users to be able to understand the reasons for machine learning algorithms to produce a certain output given specific input. Often, these algorithms are black box processes – the software processing millions of data points and arriving at best guesses for the next input based on learning from those millions of prior decisions, but given the complexity of processing across millions of data points, it is often impossible to know why or how a certain output is predicted. Because there can often be bias inadvertently built into these systems, and because human decision-making is best served when reasons for considering options are transparent, this project supported teachers in understanding and designing relatively simple explainable machine learning algorithms.

The wearable device data simulation project centered on seeking actionable information from a suite of physiological data collected by patients with a wearable device. In this project, teachers investigated a novel visual analysis tool to aid the exploration of multimodal data streams at scale, as well as the detection and representation of collective anomalies across modalities. The automated interpretive interface, being sought, should allow one to query, explore, and aggregate large volumes of multi-dimensional time series in near real time. Querying and visualizing large volumes of time series data often faces issues such as a long time in information retrieval, but this could be ameliorated by leveraging a big data search and analytics engine to store, search, and analyze big volumes of data in near real time.

Curriculum Implementation Support

In addition to conducting big data research, teachers also had some structured support for considering how they might wish to implement related instruction in their classes the following school year. They read select papers on approaches for operationalizing computational thinking skills into four core concepts [3] and another into nine core concepts [14]. They also had access to a variety of computational thinking lesson plan ideas for consideration [15], [16], [17], [18], [19]. Ultimately, through discussion and interaction with each other as well as the professor of science education supporting the curriculum work, the teachers selected the 4-part skill frame proposed by Sheldon [3]: algorithmic thinking, decomposition, abstraction, pattern recognition. They then used that framing of computational thinking to explore how best to integrate into their various classes.

Results

Prior Experiences and Goals for Themselves Pre-Project

Prior to beginning their RET-big data experience, the teachers reported some prior experiences with having their students use mathematical or computational thinking – including analyzing data – as occurring at least weekly for most (3 of the 4) of the teachers. Their students had less frequent experiences with carrying out open-ended investigations (half of them indicated only doing so approximately monthly). By comparison, all 4 teachers indicated that they had their students frequently – at least weekly – collaborating with peers as part of their instructional strategies. When asked at the beginning of the summer program for the areas they would be most interested in improving or making changes, the most common improvement areas were: improving student learning, improving curriculum, improving their own teaching techniques. These 3 focus areas for improvement are internally self-consistent – by improving one of them (e.g. curriculum or teaching) it is likely to have a positive effect on the others, including improved student learning.

Some common challenges teachers indicated at the start of the program was that they realized that they lack specific knowledge about big data and data science, and that they would be learning new ideas and information. While learning new skills and ideas was a unanimous reason they indicated they chose to participate in this summer research project, most (3 of 4) also recognized that this feeling of not knowing something can lead to some insecurity or anxiety. In addition to expressing a desire to learn about big data and data science concepts that would be new to them, the teachers equally expressed that they hoped they would gain valuable insight and ideas to be able to explain or teach related concepts to their future K-12 students.

Teacher Judgements of Program Impacts Post Summer

Teachers largely (3 of 4) agreed or strongly agreed that the summer program met their expectations for the project, with all 4 indicating they were satisfied or very satisfied with their summer experience overall. Likewise, all teachers (4 of 4) indicated that they would recommend this RET experience to their colleagues. In terms of perceived relevance to their professional interests and with acquiring ideas they wished to incorporate into their classroom teachers, the teacher unanimously "strongly agreed" that both of these professional and teaching goals were met by the summer RET project.

When asked to predict what aspects of the summer RET experience they expect to incorporate into their middle/high school classroom practices, teachers unanimously indicated that the engineering practices related to big data and computational thinking was high on their list. They unanimously indicated an intent to integrate these engineering practices into their upcoming teaching in the school year.

Instructional Integration in Subsequent School Year

During the subsequent school year, teachers invited project leadership to visit and observe their teaching of their middle/high school students on days when they would be intentionally implementing instruction informed by their summer RET experiences. Having visited and observed – and conversed – with each of the teachers at various times during the subsequent school year, every teacher actively and systematically incorporated some aspect of the RET summer learning into their classes. In particular, each of the four teachers identified and implemented computational thinking skill development into their respective courses in different ways. Table 2 summarizes the approaches each took.

Table 2. Integrating computational thinking across a spectrum

Teacher	Computational Thinking Skill Focus	Student Learning Outcomes Targeted
Heather	Algorithmic thinking, Decomposition	Code a small robot to conduct preplanned motions and modify code as goals change
Darius	Pattern recognition, Algorithmic thinking	Apply explainable machine learning to selves via health data collection and analysis with a machine learning algorithm
Jennifer	Decomposition, Abstraction	Conduct systematic sampling of target vegetation outdoors, create a dichotomous key
Sam	Pattern recognition, Algorithmic thinking	Replicate development of periodic table by investigating properties of elements and seeking pattern for how they might be organized

Each of the four teachers were observed teaching their lesson(s) as summarized in Table 2. Table 3 summarizes the nature and intent of their instructional approaches for incorporating computational thinking skills into their curriculum.

Table 3. Instructional Approaches for Incorporating Computational Thinking

Teacher	Instructional Summary
Heather	During an enrichment period, students were taught the basics of programming in order to program a small hand-sized robot to move as designated by students. Students worked in small groups to develop the code, implement the code, troubleshoot, and modify the code. They also incorporated coding and robotic movements into a science unit on motion.
Darius	Throughout a unit on personal health and wellness, students daily collected data about themselves in terms of markers for health, including: amount slept (enough, too little, very little); food (3 healthy meals, 2 healthy meals, 1 healthy meal, 0); amount of moderate exercise (>30 min, 15-30 min, <15 min); and their self-rating of how well (energetic, awake, ready-to-go) they felt on a 4-point scale as the outcome variable. After all 25 students entered these multiple data points for a month, this became the machine learning data set from which the algorithm would predict future states of being. In particular, when processing these data, the teacher emphasized the explainability since these were all topics addressed in health class, and then the output of the machine learning algorithm was used to predict how individuals felt that day. Connections to social media data, suggestions for purchasing, etc. were made.
Jennifer	Using grids to systematically sample select vegetation (dandelions) in the school courtyard, students collected data, generated visible characteristics of dandelions/not dandelions, and ultimately generated a dichotomous key as a tool for population sampling. As part of the experience the students engaged in decomposing the features of dandelion leaves compared to others, and then abstracted these characteristics to reliably account for natural variations.
Sam	Before exploring the structure and patterns in the periodic table of elements, students began by grouping a random assortment of Lego bricks into piles with shared characteristics, deciding within their small group which features to use and how. After sharing with the rest of the class, the students discussed the most and least useful techniques for establishing a rule (algorithm) for sorting and grouping. Then cards, describing sets of characteristics of select elements, were distributed, and in small groups while debating with each other, students determined patterns and features that would be helpful in rules. After discussion of their thinking, a periodic table was reviewed to highlight how their pattern seeking and algorithmic approach to making decisions reflected how the original periodic table was constructed based on observable properties of elements.

Across all cases, teachers reported that students found the instruction engaging. Teachers reported that they found that applying a lens of computational thinking – especially as operationalized by the four computational thinking skills they had identified that summer, was fruitful for considering how to frame the instruction for their class.

Discussion

The summer experience for teachers was not only fruitful for the teachers to expand their knowledge horizons to better understand concepts of big data and data science, but they also discovered that applying a computational thinking lens to their instruction was fruitful for the students they teach. They were able to realize their twin personal goals of learning something new for themselves, and learning about additional ideas and strategies for strengthening their classroom instruction for their students. The teachers reflected on how at first the field of big data and related programming seemed a bit intimidating because it was new, but that the scaffolded approach by the project leaders enabled all to find comfortable starting points and grow their own knowledge at their own pace. They reflected how they seek to replicate similar approaches for their own students who likewise represent a similar array of variation.

Teachers were especially satisfied with their ability to build connections and examples for their students that introduced some of the core thinking skills needed to engage in productive computational thinking, and were able to advance the science, math, or health learning targets of their course by doing so. In spite of the widely varying instructional topics and learning goals, some combination of the small set of computational thinking skills was found to be useful for helping students scaffold their thinking. The combination of directly engaging with new concepts and ideas for themselves, coupled with curriculum development support and follow-up in the subsequent school year, has enriched both them personally as well as instructional experiences for their students.

References

[1] National Research Council, *A framework for K-12 science education: Practices, crosscutting concepts, and core ideas*. Committee on a Conceptual Framework for New K-12 Science Education Standards. Board on Science Education, 2012.

[2] D. Weintrop, E. Beheshti, M. Horn, K. Orton, K. Jona, L. Trouille, and U. Wilensky, "Defining computational thinking for mathematics and science classrooms," *Journal of Science Education and Technology*, vol. 25, pp. 127-147, 2016.

[3] E. Sheldon, "Computational thinking across the curriculum: Four of the skills used to solve computer science problems can be applied in other classes as well," *Edutopia*, March 30, 2017.

[4] C. P. Chen, and C. Y. Zhang, "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data," *Information Sciences*, vol. 275, pp. 314-347, 2014.

[5] D. E. O'Leary, "Big data: The internet of things and the internet of signs," *Intelligent Systems in Accounting, Finance and Management*, vol. 20 no.1, pp. 53-65, 2013.

[6] B. Abdollahi and O. Nasraoui. "Transparency in fair machine learning: the case of explainable recommender systems." in *Human and machine learning: visible, explainable, trustworthy and transparent, 1st ed.* Springer, 2018, pp. 21-35.

[7] P. B. Henderson, T. J. Cortina, and J. M. Wing, "Computational thinking," In *ACM SIGCSE Bulletin*, vol. 39, no. 1, pp. 195-196, March 2007.

[8] National Council of Teachers of Mathematics (Ed.), *Principles and standards for school mathematics*, vol. 1, 2000.

[9] S. Basu, G. Biswas, P. Sengupta, A. Dickes, J. S. Kinnebrew, and D. Clark, "Identifying middle school students' challenges in computational thinking-based science learning," *Research and Practice in Technology Enhanced Learning*, vol. 11 no.1, p. 13, 2016.

[10] K. Brennan, and M. Resnick, "Using artifact-based interviews to study the development of computational thinking in interactive media design," Paper presented at annual *American Educational Research Association meeting*, Vancouver, BC, Canada. 2012.

[11] A. Repenning, D. Webb, and A. Ioannidou, "Scalable game design and the development of a checklist for getting computational thinking into public schools," In *Proceedings of the 41st ACM technical symposium on Computer science education*, pp. 265-269, March 2010.

[12] P. Sengupta, J. Kinnebrew, S. Basu, G. Biswas, and D. B. Clark, "Integrating computational thinking with K-12 science education using agent-based computation: A theoretical

framework," *Education and Information Technologies*, vol. 18, pp. 351-380, doi: 10.1007/s10639-012-9240, 2013.

[13] S. Grover, and R. Pea, "Computational thinking in K–12: A review of the state of the field," *Educational Researcher*, vol. 42 no. 1, pp. 38-43, 2013.

[14] V. Barr, and C. Stephenson, "Bringing computational thinking to K-12: What is involved and what is the role of the computer science education community?" *ACM Inroads*, vol. 2 no. 1, pp. 48-54. doi: 10.1145/1929887.1929905, 2011.

[15] W. Fastiggi, "Teaching computational thinking without using a computer." https://technologyforlearners.com

[16] V. Kite, and S. Park, "Boom bust build: Teaching computational thinking and content through urban redevelopment," *The Science Teacher*, pp. 22-28, March 2018.

[17] C. Sneider, C. Stephenson, B. Schafer, and L. Flick, "Exploring the science framework and NGSS: Computational thinking in the science classroom," *Science Scope*, pp. 10-15, November 2014.

[18] C. Sneider, C. Stephenson, B. Schafer, and L. Flick, "Computational thinking in high school science classrooms," *The Science Teacher*, pp. 53-59, Summer 2014.

[19] Unplugged computational thinking, http://code.org