International Society of
the Learning Sciences

What Does it Mean to be Literate in the Time of AI? Different Perspectives on Learning and Teaching AI Literacies in K-12 Education

Yasmin B. Kafai (co-chair), University of Pennsylvania, kafai@upenn.edu
Chris Proctor (co-chair), University at Buffalo, chrisp@buffalo.edu
Shuang Cai, New York University, sc8803@nyu.edu
Francisco Castro, New York University, francisco.castro@nyu.edu
Victoria Delaney, Stanford University, vldocherty@stanford.edu
Kayla DesPortes, New York University, kd90@nyu.edu
Chris Hoadley, University at Buffalo, isls2024@tophe.net
Victor R. Lee, Stanford University, vrlee@stanford.edu
Duri Long, Georgia Tech, duri@gatech.edu
Brian Magerko, Georgia Tech, magerko@gatech.edu
Jessica Roberts, Georgia Tech, jessica.roberts@cc.gatech.edu
R. Benjamin Shapiro, Apple & University of Washington, nerd@apple.com
Tiffany Tseng, Apple, tiffanytseng@apple.com
Vera Zhong, New York University, vera.zhong@nyu.edu
Carolyn Rosé (discussant), Carnegie Mellon University, cprose@cs.cmu.edu

Abstract: The pervasiveness of Artificial Intelligence/Machine Learning in the everyday lives of young people—impacting how they connect with friends, listen to music, play games, or attend school—coupled with the accessibility of applications powered by large language models and discussions about algorithmic justice has called for developing AI literacy in K-12 education. In this symposium, we offer different perspectives on what learning and teaching about AI could mean. Panelists will (1) address questions about how deeply do we want students to engage with AI, (2) examine in which ways critical agency can be developed, and (3) discuss implications for research and designs how teachers and learners can develop and integrate conceptual and critical understandings about Artificial Intelligence/Machine Learning that are increasingly important to participate in the world.

Overview

This symposium proposal addresses nationwide calls to support all learners in examining how artificial intelligence and machine learning (AI/ML) technologies work, how they may increase or undermine equity, and how they may broaden participation in K-12 STEM education (Department of Education, 2023; National Artificial Intelligence Research Resource Task Force, 2023; White House, 2023). Today's teachers and students need to develop an understanding of AI/ML but one of the key questions right now is what and how should students learn about AI/ML? Numerous proposals for AI literacy are currently under discussion, among them the five core ideas (Touretzky, Gardner-McCune, & Seahorn, 2022) or nine competencies (Long & Magerko, 2020). Some proposals see AI/ML as a new literacy to be taught across the curriculum, while others propose it as an expansion of current computing education efforts, which have primarily focused on procedural and object-oriented programming (Shapiro & Tissenbaum, 2020).

To situate discussions about AI/ML literacy, we draw on prior work on literacies as discussed in the learning sciences, with particular attention to how technology shapes cognition and communication. Building on work by diSessa (2001), Barton and Hamilton (1998), Gee (2004), Lee and Garcia (2014), and Jacob and Warschauer (2018), we define AI/ML literacies as a set of practices situated in a sociocultural context which utilize external computational media to support cognition and communication. We extend this definition to include critical perspectives which emphasize the ways reading and writing practices are located within broader power relations and how literacy functions as an instrument of power. AI/ML literacies would encompass phenomena at scales from the individual to the societal, as well as connections between these phenomena and the media which supports and shapes them.

In this symposium, we bring together different perspectives on what AI/ML computational literacies could mean. Panelists address AI literacy from a conceptual literacy perspective (HOADLEY), different contexts in which they are situated ranging from math classrooms (DELEANEY & LEE and ROBERTS, LONG & MAGERKO) as well as how they are situated in different learning activities (TSENG& SHAPIRO and DESPORTES, CASTRO, CAI & ZHONG). Panelists will (a) address questions about how deeply do we want students to engage with AI, (b) examine in which ways critical agency can be developed, and (c) discuss implications for research and designs how teachers and learners can develop and integrate conceptual and critical understandings about Artificial Intelligence/Machine Learning. The symposium is organized in four sections: (1) the chairs will introduce the topic; (2) each of the panelists will have 6-7 minutes to share their perspective on AI literacy, (3) followed by an invited discussion (GROVER), and (4) a Q&A with the audience and presenters.

Considering AI literacies syncretically

Christopher Hoadley

The problem of defining AI literacies for coming generations poses the question of what learners should know about AI, but this question is also embedded in why learners should know about AI and what they might be able to accomplish with that knowledge. Easy suggestions might be to become AI engineers in the future, or to apply general knowledge about applying AI, much like the definitions of "science literacy" that were debated in the late 20th century (Roberts & Bybee, 2014). Eventually advocates for scientific literacy have arrived on the concept that scientific identities and ways of knowing, including useful epistemological tools and practices, are at the core of a literacy for science. We anticipate that AI education may parallel science literacies in pointing towards AI literacy as new identities and ways of knowing including new technologically influenced epistemological tools and practices.

Current conceptions of AI literacy seem to be following a similar path, either preparing elite students to join in the specific techniques of professional AI creation or application such as machine learning techniques, or aiming towards an informed citizenry argument in which students may encounter little of the content of AI, but rather the social impacts or user-facing challenges of AI. These approaches do little to address some of the unique concerns AI raises in education as described in Hoadley and Uttamchandani (2021). Two such concerns are the unique ways in which AI and other technologies raise tensions around control in the educational environment, and ways in which learners are empowered or disempowered to participate in the creation and refinement of those technologies .

Our response to these challenges is to reexamine what conversations about AI learners may benefit from participating in, and what literacies would support those conversations. As Sylvia Scribner (1984) described when talking about literacy, it can be understood from the vantage of three metaphors: literacy as adaptation, literacy as power, and literacy as a "state of grace," or a way of ascribing literacy to people as a way to ascribe people as "endow[ed] with special virtues". AI literacies may be considered from each of these metaphors; adapting to AI, power with and through AI, and knowledge of AI as a way to distinguish oneself from others. When we consider the concepts from AI that may support transformation of learners, by allowing adaptation, power, and taking up an identity or epistemology associated with AI, the topic itself shifts. Although modern AI education tends to focus on particular computational techniques, the origins of AI instead explored more basic questions such as "What is intelligence?" "How can knowledge be represented externally, and how can such representations be manipulated, and to what ends?" (Lieto, 2021). In this panel, I argue that using Gutiérrez's notion of syncretic literacy (2014) challenges us to rethink what an AI literacy should be, and describe how we think new AI literacies in education should be new types of literacy that emerge from the tensions described above, including all of Scribner's metaphors.

Free-choice AI literacy

Jessica Roberts, Duri Long, Brian Magerko

AI programming has long been part of the curricula of university courses and is increasingly being adapted for K-12 educational efforts via integration with classrooms, summer programs, online learning, and development competitions (e.g. Judd, 2020; Touretzky et al., 2019). Yet, a significant gap remains in public education about AI, as these programs exclude the majority of the population who are not enrolled in CS programs or courses. As an increasing number of everyday technologies incorporate AI features, it follows that non-programmers must have a basic set of AI competencies (Long & Magerko, 2020) to engage with AI enabled devices safely and effectively.

Some research has investigated how adults develop “folk theories” as they interact with algorithms (Eslami et al., 2019) and how children and families engage with AI voice assistants (Porcheron et al., 2018). Our past work refined and tested as at-home AI literacy prototypes for families (Long, Teachey, & Magerko, 2022), demonstrating families were able to engage in learning talk (Roberts & Lyons, 2017) surrounding AI literacy activities. Yet, while these prototypes demonstrated success on a small scale, ultimately they face the same inclusion challenges as CS courses: families need to opt in to engage with them. Those who don’t view themselves as “belonging” in computer science are unlikely to commit time and resources to complete the activities.

Museums, on the other hand, have long served as learning environments where visitors can be exposed to a variety of topics and ideas with a lower barrier to entry. As free choice environments, museums provide introductions to topics to visitors who are able to walk away when the content is no longer engaging. However, though some museum exhibits have explored AI themes, we do not yet have theoretically grounded guidelines for designing exhibits aimed toward visitors who do not identify as belonging in CS.

This presentation will discuss our ongoing iterative design efforts toward creating a series of exhibits for a science museum that teach high-level AI concepts (e.g., supervised and unsupervised machine learning) drawing on embodied interaction and creative making as key design features. We describe formative feedback gathered during focus groups with middle schoolers toward understanding their interests, preconceptions, and misconceptions about AI to make culturally relevant designs (Belghith et al., 2024) and outline the tensions of balancing accuracy with simplicity to create experiences that will spark interest in AI for learners outside of computer science classrooms.

Learning from instructors’ embodied exploration of machine learning models

Kayla DesPortes, Francisco Castro, Shuang Cai, Vera Zhong

Whether we design for it or not, youth are already building their mental models of how AI/ML tools operate. Among others, youth are accessing models through various means and platforms—social media algorithms that guide their content consumption, AI voice assistants that they can ask questions to, or text-based conversational AI agents that they can use to guide exploration of concepts and ideas. Importantly, each of these types of interactions provides learners with a different interface and set of representational forms to reason around what the algorithm behind the system is and does. There is a growing question of what characteristics of these representational forms impact how youth are building their understandings of AI/ML systems, and how do we best optimize for various learning goals. Within interdisciplinary spaces like creative computing, various representational forms from each discipline merge together in ways that can support learning within and across the disciplines (Lehrer, 2022; Tytler et al., 2021). When we consider AI/ML, there are different disciplinary affordances for the type of data and interface that learners might engage in. In particular, dance provides a context that centralizes embodied, metaphorical representations that are key to how we explore, communicate, and understand our world (Lakoff & Johnson, 2008).

In this work, we designed and implemented five workshop sessions with six dance and computing instructors working with a creative computing software called danceON. danceON uses a computer vision model to provide users with body position data that they can use to code animations that are bound and responsive to their body’s location and movement. Within the workshops, participants individually and collaboratively explored the danceON environment and the machine learning model behind the system through dance, body movement, and coding. We recorded video and audio of the instructors learning about, creating with, and co-designing interdisciplinary computing activities centered around this system driven by a machine learning model. The recordings of the sessions were analyzed by four researchers, who coded the videos, attending to the ways instructors reasoned with their bodies and the computing systems.

We identified three themes. First, the participants used their bodies to explore the capabilities and limits of the ML model that was effectively black-boxed. The movement of their bodies in front of the camera provided a representational output they could use to reason around what the model could "see." The feedback between the body position key points and their movement let them think through how they could leverage that functionality for their own creative uses. Second, their bodies served as a tool for not only examining, but also communicating, asking questions, and demonstrating their knowledge to one another and the facilitator. Engagements with particular concepts were now present in the bodily states of the participants and instructors as they engaged in dialogue about the ML system. Last, the embodied nature changed how collaboration manifested around the ML system. Instructors were able to distribute tasks collaboratively through their bodies enabling one person to use their body positioning to debug their understanding of the system, while the other could iteratively update the code. By examining instructors' creative, embodied exploration and experimentation with machine learning models in a dance context, we are able to begin to understand how the various embodied representational affordances impact reasoning about a machine learning system and the collaborative practices that we could facilitate in a learning environment with youth.

Design opportunities and challenges when using t*he math of FaceID* as a context for high school statistics and AI literacy

Victoria Delaney, Victor R. Lee

Youth today encounter artificial intelligence (AI) in many commercial applications but operate largely with piecemeal understandings of how they work (Delaney, Sarin, & Lee, 2023). At the same time, it is unclear how much of the "black box" (that is, the inner workings of computational and mathematical algorithms by which AI-based tools operate) should be revealed by curriculum designers and teachers. Modern algorithms, particularly those that undergird most commercial AI applications, are notoriously complex. Many thoughtfully-designed AI literacy curricula succeed in their goals by refraining from guiding students through deep investigations of the mathematics of algorithms involved in AI technologies (e.g., MIT's DAILy curriculum). However, we argue that developing a preliminary understanding of the connection between mathematics and AI in students will enable them to become more critical consumers of AI technologies.

We present our own design case for how youth familiarity with commercial AI and required high school mathematical and statistical content could be brought together. Our case involves a five-lesson sequence titled *The Math of FaceID (TMoF),* intended for use in high school statistics classes*.* TMoF leads high school statistics students through exploratory, browser-based activities that investigate how a computer can make a binary classification decision (lock/unlock) given a photo of a face. It was co-designed between a veteran high school computer science and statistics teacher and the first author in an effort to combine intuitions about everyday AI technologies with required high school statistics learning standards (e.g., linear regression, representativeness, probability). Though the designers recognized a complete understanding of FaceID's algorithm would not be possible for several reasons, TMoF represents one approach for students to see how statistical ideas are relevant to AI.

In this presentation, we discuss the co-design of *TMoF*, trade-offs, successes, and challenges that emerged for three statistics teachers and their students as they jointly enacted TMoF. While students generally understood the presentation of statistical ideas within AI contexts, they struggled when their prior knowledge ran counter to new mathematical ideas, such as how a numerical output from a decision boundary could be used to answer a qualitative question ("is this a photo of me, or not?"). Similarly, when mean-squared error (MSE) was re-introduced to students in TMoF as a means of measuring the degree of similarity between two images, students struggled to use the MSE as a form of measurement, even though they were familiar with ideas of variability and error from statistics. In response, teachers spent more time in the lessons emphasizing mathematical and statistical ideas, but less on whole-group discussion about AI literacy ideas, such as connections between computational output and the ethics of FaceID.

Our major contention is that integrating AI curricula into classrooms in ways that make more deliberate contact with existing disciplines (Jiang et al., 2022) is feasible, but requires careful work. In particular, cautions must be taken by designers and teachers to balance mathematical procedures, technologies that connect mathematics to AI, and discussion that encourages collective sensemaking of novel ideas.

Collaborative modeling to engage in AI literacy

Tiffany Tseng, R. Benjamin Shapiro

Machine learning (ML) models are fundamentally shaped by data, and building inclusive ML systems requires significant considerations around how to design inclusive and representative datasets (Buolamwini & Gebru, 2018). Yet, few novice-oriented ML modeling tools are designed to foster hands-on learning of dataset design practices, including how to design for data diversity and inspect for data quality. Moreover, in computing, data practices are often devalued relative to algorithmic practices, despite the fact that even the best algorithms cannot fix data problems (Sambasivan et al., 2021).

In our work, we develop beginner-friendly tools for youth to work together to 1) curate their own datasets, 2) build ML models with these datasets, and 3) design custom applications that leverage these models to address personally relevant topics. Further, we believe this learning experience can be especially facilitated through a collaborative process in which diverse viewpoints for designing and testing models are represented.

We will share how these learning goals manifest in the design and use of Co-ML, an application where beginners can collaboratively build datasets and ML classifiers leveraging sensors on iPads. With Co-ML, beginners build image classifiers through a distributed experience where data is synchronized across multiple devices, enabling multiple users to iteratively refine ML datasets in discussion and coordination with their peers. We co-designed a 2-week-long AIML Summer Camp in collaboration with the non-profit Kode with Klossy, where approximately 50 young women and gender-expansive youth built custom ML-powered mobile applications. We discuss how, through a collaborative experience with Co-ML, students developed critical dataset design practices involving incorporating data diversity, evaluating model performance, and inspecting for data quality. We highlight how the combination of collaboration, model testing interfaces, and student-driven projects can empower learners to actively engage in exploring the role of data in ML systems.

References

Birhane, A. (2021). Algorithmic injustice: a relational ethics approach. Patterns, 2(2), 100205.

Barton, D., & Hamilton, M. (2012). *Local literacies: Reading and writing in one community*. Routledge.

Department of Education, 2023

Belghith, Y., Goloujeh, A., Magerko, B., Long, D., McKlin, T., and Roberts, J. (2024). Testing, Socializing, Exploring: Characterizing Middle Schoolers’ Approaches to and Conceptions of ChatGPT. In Proceedings CHI2024, Honolulu Hawaii, USA. ACM.

Buolamwini, J., & Gebru, T. (2018, January). Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Conference on fairness, accountability and transparency* (pp. 77-91). PMLR.

Delaney, V., Sarin, P., & Lee, V. R. (2023). Students’ Constructed Explanations for how Artificial Intelligence Generates Recommendations in YouTube. In *Proceedings of the 17th International Conference of the Learning Sciences - ICLS 2023*. Montreal, Canada: ISLS.

diSessa, A. A. (2001). *Changing minds: Computers, learning, and literacy*. MIT Press.

Eslami, M., Vaccaro, K., Lee, M. K., Elazari Bar On, A., Gilbert, E., & Karahalios, K. (2019, May). User attitudes towards algorithmic opacity and transparency in online reviewing platforms. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1-14).

Gee, James Paul. (2004). *Language learning and teacher education: A sociocultural approach* (M. R. Hawkins, Ed.). Multilingual Matters.

Gutierrez, K. (2014). Integrative research review: Syncretic approaches to literacy learning: Leveraging horizontal knowledge and expertise. In P. J. Dunston, L. B. Gambrell, K. Headley, S. K. Fullerton, & P. M. Stecker (Eds.), *63rd Literacy Research Association Yearbook* (pp. 48-60). Literacy Research Association.

Hoadley, C., & Uttamchandani, S. (2021). *Current and Future Issues in Learning, Technology, and Education Research.* Spencer Foundation. http://hdl.handle.net/2451/63364

Jacob, S. R., & Warschauer, M. (2018). Computational Thinking and Literacy. *Journal of Computer Science Integration*, *1*(1). https://doi.org/10.26716/jcsi.2018.01.1.1

Jiang, S., Lee, V. R., & Rosenberg, J. M. (2022). Data science education across the disciplines: Underexamined opportunities for K-12 innovation. *British Journal of Educational Technology, 53*(2), 1073-1079. doi:10.1111/bjet.13258

Judd S (2020). All Means All: Bringing Project-based, Approachable AI Curriculum to More High School Students through AI4ALL Open Learning. Proceedings of the 51st ACM Technical Symposium on Computer Science Education. :1409–1409.

Lakoff, G., & Johnson, M. (2008). *Metaphors we live by*. University of Chicago press.

Lee, C. H., & Garcia, A. D. (2014). “I Want Them to Feel the Fear…”: Critical Computational Literacy as the New Multimodal Composition. In R. E. Ferdig & K. E. Pytash (Eds.), *Exploring Multimodal Composition and Digital Writing* (pp. 364–378). Information Science Reference.

Lehrer, R. (2022). Promoting transdisciplinary epistemic dialogue. In *The Learning Sciences in Conversation* (pp. 27-38). Routledge.

Lieto, A. (2021). Cognitive science and artificial intelligence: death and rebirth of a collaboration. In *Cognitive design for artificial minds* (pp. 1-19). Routledge.

Long, D., & Magerko, B. (2020, April). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-16).

Long, D., Teachey, A., & Magerko, B. (2022, April). Family Learning Talk in AI Literacy Learning Activities. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (pp. 1-20).

National Artificial Intelligence Research Resource Task Force (2023). Strengthening and Democratizing the U.S. Artificial Intelligence Innovation Ecosystem: An Implementation Plan for a National Artificial Intelligence Research Resource.

Porcheron, M., Fischer, J. E., Reeves, S., & Sharples, S. (2018, April). Voice interfaces in everyday life. In proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1-12).

Roberts, D. A., & Bybee, R. W. (2014). Scientific Literacy, Science Literacy, and Science Education. In N. G. Lederman & S. K. Abell (Eds.), Handbook of Research on Science Education Volume II (pp. 545-558). Taylor and Francis. https://doi.org/10.4324/9780203097267

Roberts, J. & Lyons, L. (2017). The Value of Learning Talk: Applying a novel dialogue scoring method to inform interaction design in an open-ended, embodied museum exhibit. International Journal of Computer Supported Collaborative Learning. 12(4), 343-376. DOI 10.1007/s11412-017-9262-x

Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021, May). “Everyone wants to do the model work, not the data work”: Data Cascades in High-Stakes AI. In *proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1-15).

Scribner, S. (1984). Literacy in Three Metaphors. American Journal of Education, 93(1), 6-21. https://doi.org/10.1086/443783

Shapiro, R., & Tissenbaum, M. (2019). New Programming Paradigms. In S. Fincher & A. Robins (Eds.), *The Cambridge Handbook of Computing Education Research* (pp. 606-636). Cambridge: Cambridge University Press. doi:10.1017/9781108654555.021

Touretzky, D., & Gardner-McCune, C. (2022) Artificial Intelligence Thinking in K-12. In S. Kong, and H. Abelson, (Eds.), Computational Thinking Education in K-12: Artificial Intelligence Literacy and Physical Computing. MIT Press.

Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019, July). Envisioning AI for K-12: What should every child know about AI?. In Proceedings of the AAAI conference on artificial intelligence (Vol. 33, No. 01, pp. 9795-9799).

Tytler, R., Mulligan, J., Prain, V., White, P., Xu, L., Kirk, M., Nielsen, C., & Speldewinde, C. (2021). An interdisciplinary approach to primary school mathematics and science learning. *International Journal of Science Education*, *43*(12), 1926-1949.

U.S. Department of Education, Office of Educational Technology. (2023). *Artificial Intelligence and Future of Teaching and Learning: Insights and Recommendations*. Washington, DC.

White Houese (2023). Executive order. Washington, DC.

