High School Youth PEER AUDITING of Machine Learning Applications to Promote Computational Literacies

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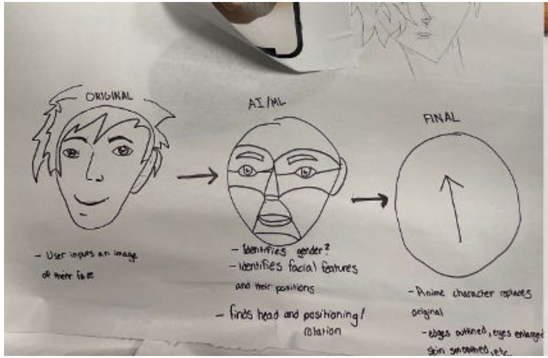
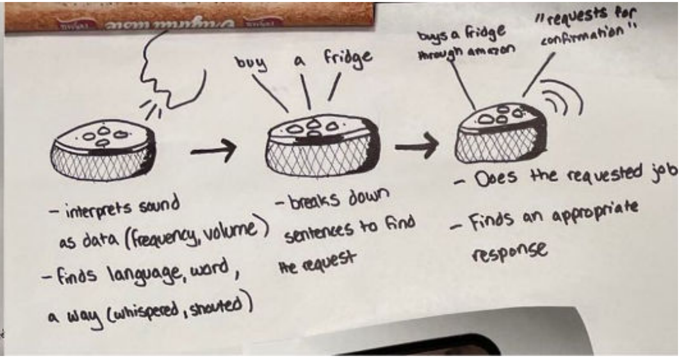
Youth interact with AI/ML applications everyday

- Through their daily interactions they develop some understandings about how that ML applications learn from data and how applications recognize patterns
- Their everyday ideas have implications for the design of tools and activities to introduce youths to ML





Morales-Navarro, L., & Kafai, Y. B. (2024). Investigating Youths' Everyday Understanding of Machine Learning Applications: a Knowledge-in-Pieces Perspective. Proceedings of the 18th International Conference of the Learning Sciences - ICLS 2024. Buffalo, NY: International Society of the Learning Sciences.

SEE ALSO:
Coenraad, M. (2022).
Salac, J., Oleson, A., Armstrong, L., Le Meur, A., & Ko, A. J. (2023, August).
Solyst, J., Xie, S., Yang, E., Stewart, A. E., Eslami, M., Hammer, J., & Ogan, A. (2023a).
Solyst, J., Yang, E., Xie, S., Ogan, A., Hammer, J., & Eslami, M. (2023b

AI/ML

📉 Focus on **DATA** rather than sequences of steps

📦 **OPACITY** of how models work

🧪 Empirical and inductive **NATURE** of development

Challenge

"The challenge facing many young people today is that they generally speaking have **a limited understanding of technology and computing**, not only in terms of its construction but how it affects their lives. Hence young people have very limited capacity to **pose demands for technology**, **make informed choices about technology** in their lives, and **take part in the development of technology** and the cultures that surround it."

Dindler, Iverson Caspersen & Smith, 2022, p. 120

OVERVIEW

AI Literacies

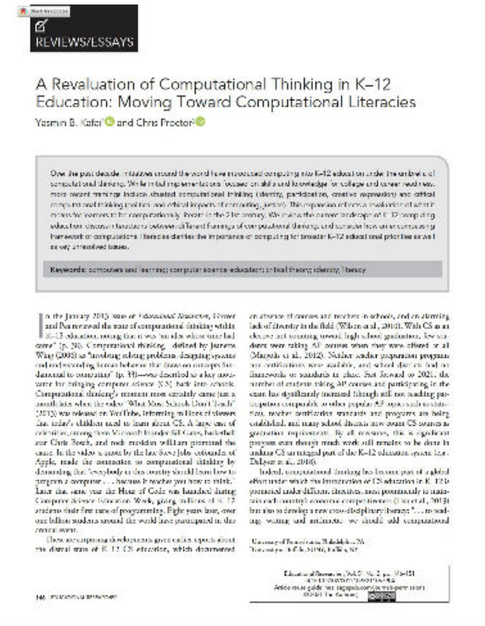
Algorithm Auditing

PEER AUDITING WORKSHOP & FINDINGS

Discussion

Next Steps

Computational Literacies



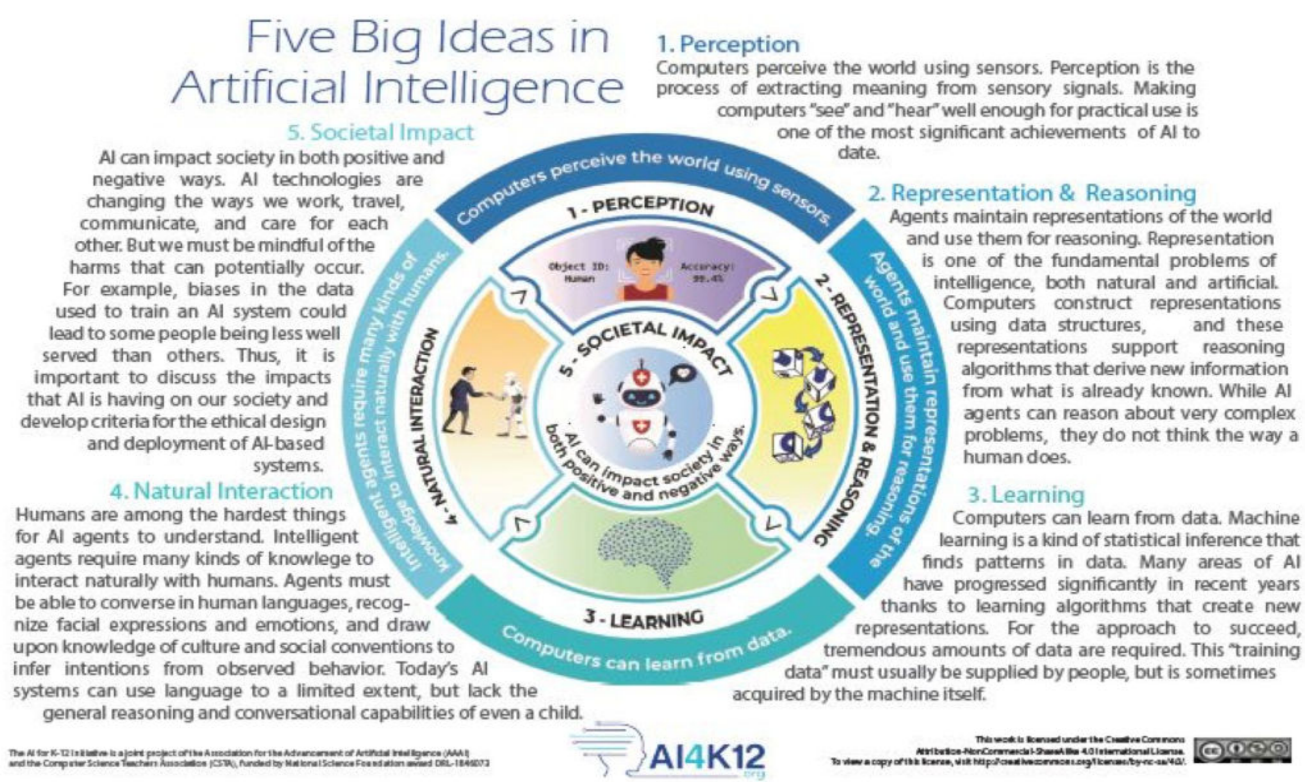
We define *computational literacies* as a set of practices situated in a sociocultural context which utilize external computational media to support cognition and communication. Computational literacies encompass phenomena at scales from the individual to the societal, as well as connections between these phenomena and the media which supports and shapes them. …

In our view, the question of what to teach in K-12 CS **need not have a single answer**, but could instead have many answers **grounded in the computational literacy practices of diverse communities and cultures**.

Kafai & Proctor, 2022, p.148

Kafai, Y. B., & Proctor, C. (2022). A revaluation of computational thinking in K–12 education: Moving toward computational literacies. *Educational Researcher*, *51*(2), 146-151.

Five Big Ideas



Touretzky et al., , 2019

Computational Thinking 2.0


CT 2.0

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Figure 1: Children creating a gesture recognition model on an image recognition system. (GDPR compliant photo.)

ABSTRACT

CCS CONCEPTS

KEYWORDS

1 INTRODUCTION

Table 1: Comparison of educational concerns in traditional programming education vs. education for creating ML and other data-driven models.

	CT1.0	CT 2.0
Problem solving: Stage 1	Formalize the problem	Collect data from the intended context
Problem solving: Stage 2	Design a solution	Filter and clean data. Label data.
Problem solving: Stage 3	Implement the solution in a stepwise program	Train a model from the available data
Problem solving: Stage 4	Compile and execute the program	Evaluate and use the model
Universality of solution	Weakly context-dependent	Strongly context-dependent
Goodness of solution	In some cases clearly works or doesn't. Can be formally proven to be either correct or incorrect (at advanced levels). Effectiveness can be proven.	Models may display higher or lower confidence. Efficiency can be established through testing. Statistically better or worse (at advanced levels).
Testing	Black-boxed or glass-boxed cross checking of the outputs and the program code	Evaluate the model against predictions, completely black boxed
Debugging	Tracking and tracing program states and code for error.	Experimenting with data, parameters, and hyperparameters, based on trial and error
Philosophy of problem solving	Deductive	Inductive
Structure	Transparent. Visualization tools available.	Black boxed
Notional machines	Stepwise, deterministic, discrete flow of program through states (as contents of memory locations).	Parallel, possibly nondeterministic, passing data through a network
Complexity concerns	Prepare for worst case, optimize for average case	No time / space variance between passing data through a network
Portability	Tedious to make portable to different platforms.	Straightforwardly portable
Trial and error	Discouraged	Necessary
Software life cycle	Traditional, well established life cycle. Clear versioning.	More data create new "versions". Documenting is based on empiricism and reporting of training data.
Syntax and semantics	Syntactically strict, highly structured	Data can be unstructured, loose semantics

16 Competencies

What is AI Literacy? Competencies and Design Considerations

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ABSTRACT

Artificial intelligence (AI) is becoming increasingly integrated in user-facing technology, but public understanding of these technologies is often limited. There is a need for additional HCI research investigating a) what competencies users need in order to effectively interact with and critically evaluate AI and b) how to design learner-centered AI technologies that foster increased user understanding of AI. This paper takes a step towards realizing both of these goals by providing a concrete definition of *AI literacy* based on existing research. We synthesize a variety of interdisciplinary literature into a set of core competencies of AI literacy and suggest several design considerations to support AI developers and educators in creating learner-centered AI. These competencies and design considerations are organized in a conceptual framework thematically derived from the literature. This paper's contributions can be used to start a conversation about and guide future research on AI literacy within the HCI community.

Author Keywords

AI literacy; AI education; AI for K-12; artificial intelligence; machine learning; computing education

CSS CONCEPTS

- **General and reference→Surveys and overviews**
- **Social and professional topics→Computing literacy**
- **Computing methodologies→Artificial intelligence**

INTRODUCTION

Artificial intelligence is becoming increasingly integrated in user-facing technologies. However, algorithms on common platforms can be opaque to users, who often do not recognize they are interacting with AI [10,54,55]. These misconceptions can limit people's ability to effectively use, collaborate with, and act as critical consumers of AI [57]. Widely held misconceptions about AI can also lead to misdirected regulatory action [124] and public letdown if expectations for development are not met [57].

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Design and education both play a role in contributing to public misunderstandings about AI. Black-box algorithms (i.e. algorithms with obscured inner-workings) can cause misunderstandings about AI [55]. On the other hand—even with more transparent technologies—a lack of technical knowledge on the part of the user can lead to misconceptions [25]. There is a clear need for a better understanding of this space from the perspectives of both learners and designers.

Researchers in the HCI community have begun to address public misconceptions of AI by investigating how people make sense of AI (e.g. [46]) and exploring how to design more understandable technology (e.g. [67]). However, there is a need for additional research investigating what new competencies will be necessary in a future in which AI transforms the way that we communicate, work, and live with each other and with machines. We refer to this set of competencies as *AI literacy*.

Emerging research is exploring how to foster AI literacy in audiences without technical backgrounds. Within the past year, companies have pursued initiatives to broaden AI education to underrepresented audiences in an effort to increase workforce diversity [5,148], educators have published guides on how to incorporate AI into K-12 curricula [145], and researchers are exploring how to engage young learners in creative programming activities involving AI [45,79,132,146,149]. The "AI for K12" working group is currently developing a set of standards for K-12 classrooms to determine what each grade band should know about AI [130]. The group has also identified five "big ideas" of AI to guide the standards development: 1) "Computers perceive the world using sensors"; 2) "Agents maintain models/representations of the world and use them for reasoning"; 3) "Computers can learn from data"; 4) "Making agents interact with humans is a substantial challenge for AI developers"; and 5) "AI applications can impact society in both positive and negative ways" [130].

The five "big ideas" of AI provide a strong foundation for future research on fostering AI literacy. However, most of the research on AI education for non-technical learners has just been published within the last year. In contrast, AI as a field has been active since the 1950s, and there is a variety of existing research (scattered across disciplines and venues) that could contribute to understanding what competencies should be included in a definition of AI literacy and how to better design educational experiences that foster AI literacy.

Competency 1 (Recognizing AI) Distinguish between technological artifacts that use and do not use AI.

Competency 2 (Understanding Intelligence) Critically analyze and discuss features that make an entity "intelligent", including discussing differences between human, animal, and machine intelligence.

Competency 3 (Interdisciplinarity) Recognize that there are many ways to think about and develop "intelligent" machines. Identify a variety of technologies that use AI, including technology spanning cognitive systems, robotics, and ML.

Competency 4 (General vs. Narrow) Distinguish between general and narrow AI.

Competency 5 (AI's Strengths & Weaknesses) Identify problem types that AI excels at and problems that are more challenging for AI. Use this information to determine when it is appropriate to use AI and when to leverage human skills.

Competency 6 (Imagine Future AI) Imagine possible future applications of AI and consider the effects of such applications on the world.

Competency 7 (Representations) Understand what a knowledge representation is and describe some examples of knowledge representations.

Competency 8 (Decision-Making) Recognize and describe examples of how computers reason and make decisions.

Competency 9 (ML Steps) Understand the steps involved in machine learning and the practices and challenges that each step entails.

Competency 10 (Human Role in AI) Recognize that humans play an important role in programming, choosing models, and fine-tuning AI systems.

Competency 11 (Data Literacy) Understand basic data literacy concepts such as those outlined in [107].

Competency 12 (Learning from Data) Recognize that computers often learn from data (including one's own data).

Competency 13 (Critically Interpreting Data) Understand that data cannot be taken at face-value and requires interpretation. Describe how the training examples provided in an initial dataset can affect the results of an algorithm.

Competency 14 (Action & Reaction)
Understand that some AI systems have the ability to physically act on the world. This action can be directed by higher-level reasoning (e.g. walking along a planned path) or it can be reactive (e.g. jumping backwards to avoid a sensed obstacle).

Competency 15 (Sensors)
Understand what sensors are, recognize that computers perceive the world using sensors, and identify sensors on a variety of devices. Recognize that different sensors support different types of representation and reasoning about the world.

Competency 16 (Ethics)
Identify and describe different perspectives on the key ethical issues surrounding AI (i.e. privacy, employment, misinformation, the singularity, ethical decision making, diversity, bias, transparency, accountability).

Computational Literacies

Scribner (1984) which outlines three core dimensions of literacy: **FUNCTIONAL, CRITICAL AND PERSONAL.**

Literacies of any kind always address a ***functional*** dimension of “the level of proficiency necessary for effective performance in a range of settings" (p. 9).

The ***critical*** dimension of literacy equips individuals with critical consciousness to examine conditions in their community and lead effective action for a just society.

The ***personal*** dimension frames becoming literate as a form of self-enhancement to better communicate, interact with others, and build relationships.

ALGORITHM AUDITING

“Repeatedly querying an algorithm and observing its output in order to draw conclusions about the algorithm’s opaque inner workings and possible external impact.”

Metaxa et al., 2021, p. 10

ALGORITHM AUDITING as DECODING

Deconstruction involves describing, evaluating and reflecting on the values and intentions embedded in sociotechnical systems and considering their possible implications (Dindler et al., 2020; Schaper et al., 2022). This involves

(1) Assessing the properties of a system in terms of its inputs, outputs and materials,

(2) Inquiring on the intended use and actual use of a system,

(3) Foregrounding the values, worldviews, and assumptions embedded in the system, and

(4) Impacting individuals, communities and the environment.

We argue that algorithm auditing is a method that can support learners in deconstructing AI/ML applications.

Examples Of Algorithm Auditing

housing | employment | product pricing | health | search

Algorithm Auditing in Five Steps

1. Generating a hypothesis
2. Generating systematic, thorough, and thoughtful inputs to test the hypothesis
3. Running the test and keeping track of the inputs and output pairs
4. Analyzing the data
5. Reporting findings

Everyday audits

Toward User-Driven Algorithm Auditing: Investigating users' strategies for uncovering harmful algorithmic behavior

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ABSTRACT

Recent work in HCI suggests that users can be powerful in surfacing harmful algorithmic behaviors that formal auditing approaches fail to detect. However, it is not well understood how users are often able to be so effective, nor how we might support more effective user-driven auditing. To investigate, we conducted a series of think-aloud interviews, diary studies, and workshops, exploring how users find and make sense of harmful behaviors in algorithmic systems, both individually and collectively. Based on our findings, we present a process model capturing the dynamics of and influences on users' search and sensemaking behaviors. We find that 1) users' search strategies and interpretations are heavily guided by their personal experiences with and exposures to societal bias; and 2) collective sensemaking amongst multiple users is invaluable in user-driven algorithm audits. We offer directions for the design of future methods and tools that can better support user-driven auditing.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in collaborative and social computing**; **Computer supported cooperative work**; **Empirical studies in HCI**; • **Information systems** → *Web searching and information discovery*.

on Human Factors in Computing Systems (CHI '22), April 29-May 5, 2022, New Orleans, LA, USA. ACM, New York, NY, USA, 19 pages. https://doi.org/10.1145/3491102.3517441

1 INTRODUCTION

The presence of biases and inequities in algorithmic systems has led researchers to develop new approaches for algorithm auditing to detect biased, discriminatory, or otherwise harmful behaviors[1] (e.g., [17, 22, 31, 46, 53, 59, 62, 66, 74, 82]). Typically these auditing techniques are led by experts such as researchers, activists, industry practitioners, and government agencies [20]. For example, in "scraping audit" techniques, experts query an algorithmic system and investigate and compare the outputs [66]. As another example, in a "sock puppet audit", experts use computer programs to impersonate different types of users, inject fake data into the system, and evaluate the results [66]. Although expert-led auditing approaches have been greatly impactful, the absence of the actual context of use and everyday users in the auditing process can still result in major blindspots in practice. As well as experts' cultural blindspots, social dynamics, changing norms, and new circumstances can hinder experts' detection of many types of algorithmic biases and harms [22, 35, 45, 69, 71, 81]. In contrast, recent years have seen many cases in which *users* uncover and raise awareness about harmful algorithmic behaviors that they encounter while interacting with

Everyday Algorithm Auditing: Understanding the Power of Everyday Users in Surfacing Harmful Algorithmic Behaviors

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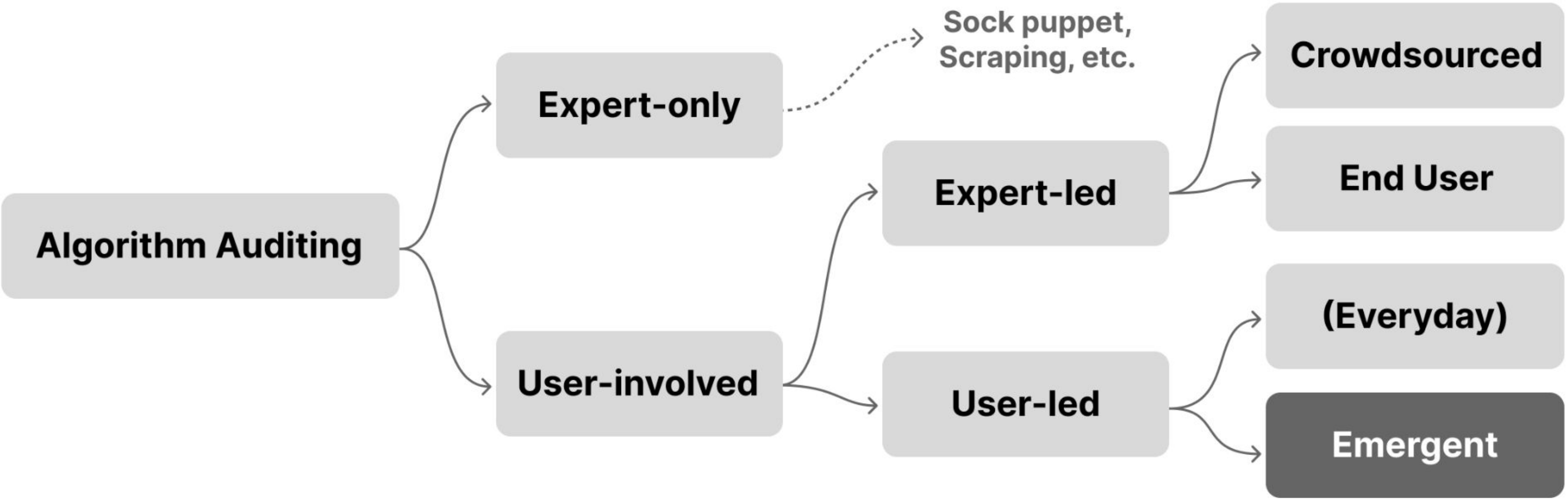
A growing body of literature has proposed formal approaches to audit algorithmic systems for biased and harmful behaviors. While formal auditing approaches have been greatly impactful, they often suffer major blindspots, with critical issues surfacing only in the context of everyday use once systems are deployed. Recent years have seen many cases in which *everyday users* of algorithmic systems detect and raise awareness about harmful behaviors that they encounter in the course of their everyday interactions with these systems. However, to date little academic attention has been granted to these bottom-up, user-driven auditing processes. In this paper, we propose and explore the concept of *everyday algorithm auditing*, a process in which users detect, understand, and interrogate problematic machine behaviors via their day-to-day interactions with algorithmic systems. We argue that everyday users are powerful in surfacing problematic machine behaviors that may elude detection via more centrally-organized forms of auditing, regardless of users' knowledge about the underlying algorithms. We analyze several real-world cases of everyday algorithm auditing, drawing lessons from these cases for the design of future platforms and tools that facilitate such auditing behaviors. Finally, we discuss work that lies ahead, toward bridging the gaps between formal auditing approaches and the organic auditing behaviors that emerge in everyday use of algorithmic systems.

CCS Concepts: • **Human-centered computing** → **Human computer interaction (HCI)**; *Empirical studies in HCI*.

Additional Key Words and Phrases: Everyday Algorithm Auditing; Auditing Algorithms; Algorithmic Bias; Everyday Users; Fair Machine Learning

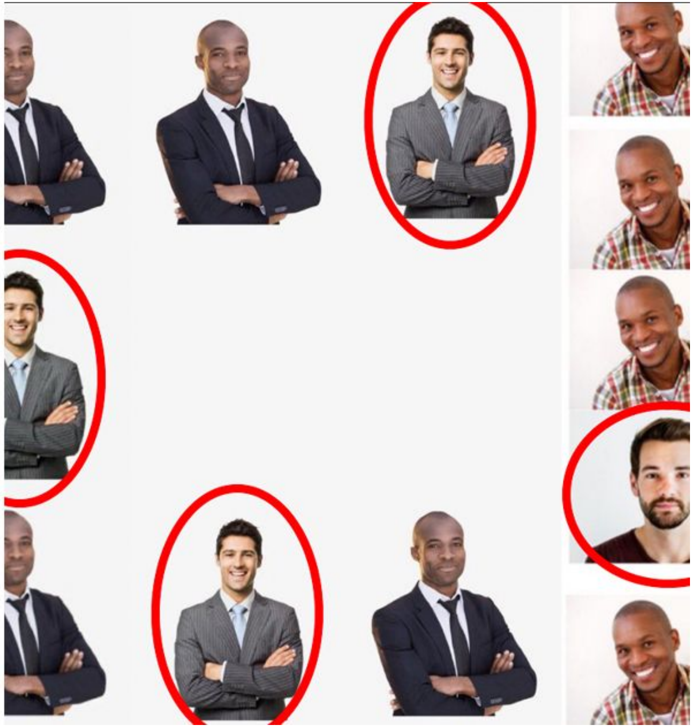
ACM Reference Format:
Hong Shen, Alicia DeVos, Motahhare Eslami, and Kenneth Holstein. 2021. Everyday Algorithm Auditing: Understanding the Power of Everyday Users in Surfacing Harmful Algorithmic Behaviors. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 433 (October 2021), 29 pages. https://doi.org/10.1145/3479577

Expert and user-involved audits



Encarnación et al., under review

Everyday emergent audits



Youth’s perspectives towards algorithmic justice

- Research on learning and algorithmic justice has focused on rights and protections (Ito et al., 2023) and high-stake issues such as police surveillance (Vakil & McKinney de Royston, 2022)
- Youth’s ideas about algorithmic justice are **grounded in their lived experiences** with technologies (Coenraad, 2022; Salac et al., 2023; Solyst et al., 2023)

Testing in AI/ML Education

- Some studies mention testing but provide little to no details about how students test models and what they learn from testing activities.
- The studies that address testing show interesting findings: testing helps learners build hypotheses about model performance

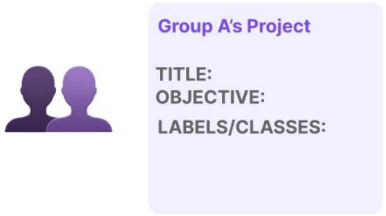
Morales-Navarro, L., Shah, M., & Kafai, Y. B. (2024, March). Not Just Training, Also Testing: High School Youths' Perspective-Taking through Peer Testing Machine Learning-Powered Applications. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1* (pp. 881-887).

Auditing ≠ Testing

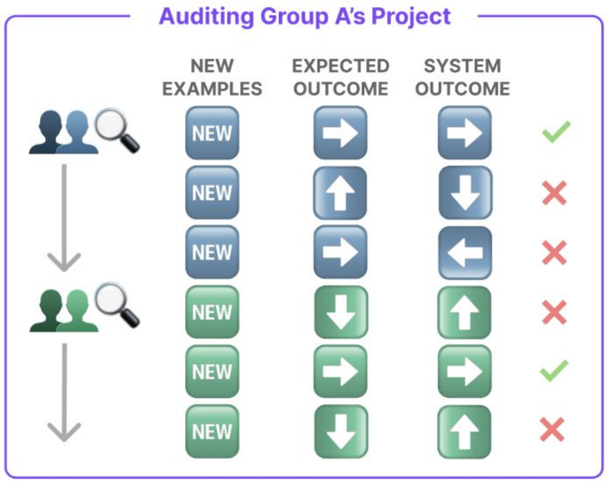
- Auditing **emphasizes the system** rather than user interaction/reaction
- Auditing is **systematic and iterative** process with the goal of drawing conclusions at the level of the system rather than about individual test cases
- Audits are generally **external evaluations** done by independent third parties from the outside-in

Metaxa et al., 2021

Peer Auditing



1. A group builds a project and creates project factsheet



2. Peer auditors receive project with factsheet and audit it. Every five minutes a new group of auditors evaluate the system by comparing expected outcomes to system outcomes.

3. Peer auditors read through all evaluation instances and write an auditing report.

PEER AUDITING WORKSHOP

Youth as Peer Auditors: Engaging Teenagers with Algorithm Auditing of Machine Learning Applications

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As artificial intelligence/machine learning (AI/ML) applications become more pervasive in youth lives, supporting them to interact, design, and evaluate applications is crucial. This paper positions youth as auditors of their peers' ML-powered applications to better understand algorithmic systems' opaque inner workings and external impacts. In a two-week workshop, 13 youth (ages 14-15) designed and audited ML-powered applications. We analyzed pre/post clinical interviews in which youth were presented with auditing tasks. The analyses show that after the workshop all youth identified algorithmic biases and inferred dataset and model design issues. Youth also discussed algorithmic justice issues and ML model improvements. Furthermore, youth reflected that auditing provided them new perspectives on model functionality and ideas to improve their own models. This work contributes (1) a conceptualization of algorithm auditing for youth; and (2) empirical evidence of the potential benefits of auditing. We discuss potential uses of algorithm auditing in learning and child-computer interaction research.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; • **Social and professional topics → K-12 education**; *Computing literacy*.

Additional Key Words and Phrases: youth, algorithm auditing, algorithmic justice, machine learning, child-computer interaction, artificial intelligence

ACM Reference Format:
Luis Morales-Navarro, Yasmin B. Kafai, Vedya Konda, and Danaë Metaxa. 2024. Youth as Peer Auditors: Engaging Teenagers with Algorithm Auditing of Machine Learning Applications. In *Interaction Design and Children (IDC '24), June 17–20, 2024, Delft, Netherlands.* ACM, New York, NY, USA, 22 pages. https://doi.org/10.1145/3628516.3655752

Luis Morales-Navarro, Yasmin B. Kafai, Vedya Konda, and Danaë Metaxa. 2024. Youth as Peer Auditors: Engaging Teenagers with Algorithm Auditing of Machine Learning Applications. In Interaction Design and Children (IDC '24), June 17–20, 2024, Delft, Netherlands. ACM, New York, NY, USA, 22 pages

Context of the study

W1: ML classifiers, physical computing, ML pipeline, Auditing session.

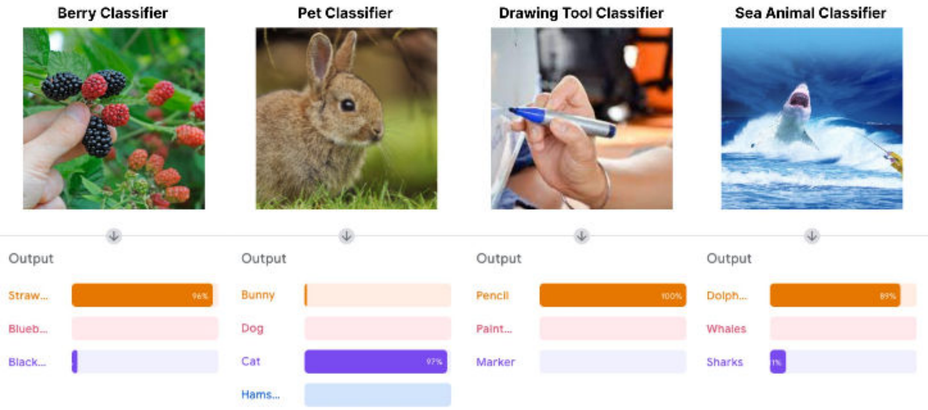
W2: Working on ML-powered electronic textile (e-textile) physical computing projects. Auditing session.

Pseudonym	Age	Gender	Race & Ethnicity	Previous CS experience
Kayla	14	Female	Black	Yes
Lou	15	Female	Black	No
Jerome	15	Male	Native American & Black	Yes
Bryan	15	Male	Asian & White	Yes
Jackie Star	15	Female	White	Yes
Fatimah	14	Female	Black	Yes
Andrés	14	Male	Latinx	Yes
Richard	14	Male	White	Yes
Iván	14	Male	Latinx & White	No
Emily	14	Female	Black	Yes
Luke	15	Male	Black & Latinx	Yes
Stephanie	15	Female	Black & White	Yes
Walter	15	Male	Asian	Yes

Youth projects

Interview protocol

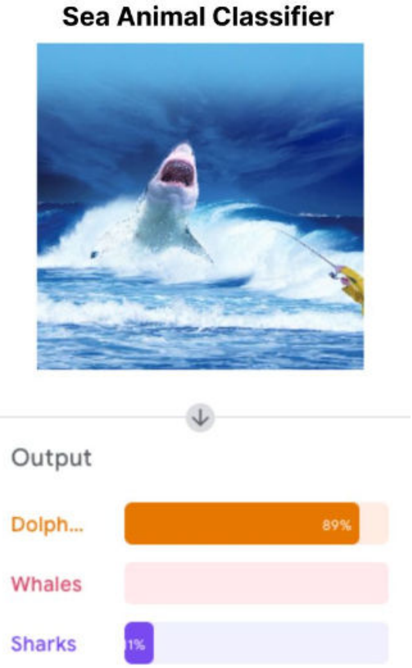
Classifier tasks



Text-to-image tasks

How did youth's identification of potential algorithmic biases and harm change?

All participants identified potential algorithmic biases in post (compared to 9 in pre). Biases related to body shapes, breed (in the case of animals), color, size, shape, and context/location, race, and relevancy.



How did youth's identification of potential algorithmic biases and harm change?

In post they reflected on personal and societal biases.

"from **my personal experience**, teaching as a very female-dominated profession." Iván

"A lot of YouTube channels it has... I feel like it's mainly run by White guy gamers." Iván

How did youth's identification of potential algorithmic biases and harm change?

Considering harm and justice (7 in pre to 12 in post).

Diverse ideas about harm and justice.

"For the scientists, like kids saying they want to be scientists, **if nobody that looks like me is a scientist, then should I really become one?**" Luke

"Lizzo, everyone calls her beautiful but none of the generated pictures looked like her. **If you look like her it can make you feel bad**" Andrés

"Yeah, **it just excludes**. Like in this **context**, with just generating pictures. I don't know if it's really impactful, it could in other contexts." Jackie Star

"**I don't think it can be harmful**. I do think it's discriminatory. You're not gonna, like, get offended by the AI." Richard

How did youth's inferences about data and model design change?

Youth made more inferences to data and model design issues in post from 6.9 to 12.8 average inferences per participant.

Increased in post:

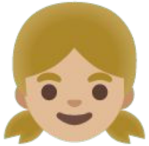
- Model features
- Data composition
- Data diversity
- Data context
- Data sources
- Class balance

Decreased in post:

- Data quantity

How did youth’s inferences about data and model design change?

“provide more features to the model so that it would know what to look for” Fatimah



“yeah, definitely a bias towards sharks if it was close up to a face, because that’s probably all that it really is like taught on” Jackie Star

What benefits did youth find in auditing applications and having their applications audited?

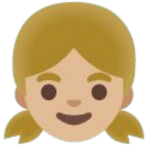
Auditing provided with new perspectives about model functionality and performance.

“not just getting more diverse user input, but feedback from people that don’t think like you.” Iván

“you also get different standpoints because people think in so many different ways that, like, you wouldn’t have thought of something and now you can incorporate that.” Lou

What benefits did youth find in auditing applications and having their applications audited?

Auditors provided helpful feedback



“people were like, well, you could have added more variety to this class” Jackie Star

“helped me humble myself, helped me realize, okay, there are changes I can make, or actually my project is doing much better than I thought it would” Fatimah

What benefits did youth find in auditing applications and having their applications audited?

Looking at projects from new perspectives

“you can turn around and improve that yourself” Iván

“I use the logic that I use in their project of challenging it to see what would break it on our project.” Jerome

DISCUSSION

ALGORITHM AUDITING

- AS A *SOCIO-TECHNICAL PROCESS*
- FOR *ALGORITHMIC JUSTICE*
- AND *COMPUTATIONAL EMPOWERMENT*

AUDITING AS SOCIO-TECHNICAL PROCESS

- Youth benefited from cognitive distance and being able to **“take perspective”** of their own applications and those of their peers. This enabled them to provide recommendations for their peers and to apply what they saw as auditors to their own projects.

- Youth took a **more adversarial approach,** describing how, for some of them, the goal was to try to “break” the applications or find “all the problems”. This approach differs from the stance of expert auditors

AUDITING FOR ALGORITHMIC JUSTICE

PRE

SOME youth were able to identify potential biases.

Previous research shows that both adults and teenagers participating in cooperative inquiry sessions and think-aloud interviews can engage with these topics by building on their rich experiences as users of AI/ML-powered applications [13, 49, 56].

POST

ALL youth identified potential biases.

AUDITING AS COMPUTATIONAL EMPOWERMENT

“We define computational empowerment as a concern for the method used by students, as individuals and groups, to develop the capacity to understand digital technology and its effect on their lives and society at large and their ability to engage critically and curiously with the **construction** and **deconstruction** of technology.”
Dindler, Iverson Caspersen & Smith, 2022, p. 121

AUDITING FOCUSES ON **DECONSTRUCTION** OF TECHNOLOGY:

Supporting youth in analyzing applications designed by other people to **interrogate the values encoded in them and their impact on society** (Schaper et al., 2022).

ALGORITHM AUDITING as DECODING

Deconstruction involves describing, evaluating and reflecting on the values and intentions embedded in sociotechnical systems and considering their possible implications (Dindler et al., 2020; Schaper et al., 2022). This involves

(1) Assessing the properties of a system in terms of its inputs, outputs and materials,

(2) Inquiring on the intended use and actual use of a system,

(3) Foregrounding the values, worldviews, and assumptions embedded in the system, and

(4) Impacting individuals, communities and the environment.

Algorithm auditing is a method that can support learners in deconstructing AI/ML applications.

NEXT STEPS

- **DESIGNING AND AUDITING** ML APPLICATIONS
- **INTRODUCING TEACHERS** TO AUDITING ML APPLICATIONS
- **INTEGRATING** AUDITING ACTIVITIES IN CS **CLASSROOMS**

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Thank you!