Machine Learning Introduces New Perspectives to Data Agency in K–12 Computing Education

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***Abstract*—This innovative practice full paper is grounded in the societal developments of computing in the 2000s, which have brought the concept of information literacy and its many variants into limelight. Widespread tracking, profiling, and behavior engineering have set the alarms off, and there are increasing calls for education that can prepare citizens to cope with the latest technological changes. We describe an active concept, data agency, that refers to people's volition and capacity for informed actions that make a difference in their digital world. Data agency extends the concept of data literacy by emphasizing people's ability to not only understand data, but also to actively control and manipulate information flows and to use them wisely and ethically.**

This article describes the theoretical underpinnings of the data agency concept. It discusses the epistemological and methodological changes driven by data-intensive analysis and machine learning. Epistemologically the many new modalities of automation are non-reductionist, non-deterministic, and statistical; the models they rely on are soft and brittle. This article also presents results from a pilot study on how to teach central machine learning concepts and workflows in K–12 through co-creation of machine learning-based solutions.

***Index Terms*—K–12, Machine Learning, Computing Education, Data Agency, Data Literacy, Artificial Intelligence, Neural Networks**

I. Introduction

The directions that computing and information technology took in the 2000s have brought the concept of data literacy and its many variants into limelight. Pervasive computing, data-intensive analysis, cloud computing, social media, and the Internet of things have enabled tracking and profiling of people at massive scale both in the physical and virtual realms [1]. The new technologies enable ubiquitous and unobtrusive tracking of users' behavior, and collection of vast amounts of traces people leave while using apps, gadgets, and online services: location data, pictures, tweets, sensor data, "likes," information about their moods, the music they are listening, movies they are watching, goods they are shopping, and so forth. But data on its own does not do anything: the "smartness" of smart devices and services arises from the ability to profile and statistically infer single users' preferences and future intentions from massive amounts of population-level data available to the smart services. Users of apps, gadgets, and web services leave traces that either directly reveal, or can be used to infer, the users' media preferences, moods, political affiliations, and many of their secrets [1], [2].

Variations of the concept of data literacy have emerged in a number of fields [2], [3]. Data literacy involves, for instance, understanding what data one creates, what happens to them, and with what consequences. A more active concept, data agency, refers to people's volition, skills, attitudes, and capacity for informed actions that make a difference in their digital world. Data agency extends the concept of data literacy by emphasizing people's ability to not only understand data, but also to actively control and manipulate information flows and to use them wisely and ethically. What citizenship in the 2000s requires is not just passive knowledge of information flows that surround people and influence their behavior, but active ability to take control of those flows and harness them for use. The datafied world requires also understanding of the many facets of automation, including data-driven machine learning and rule-based programming.

This article describes the theoretical underpinnings of the "data agency" concept. It discusses the epistemological and methodological changes driven by data-intensive analysis and machine learning. Epistemologically the many new modalities of automation non-reductionist, non-deterministic, and statistical; the models they rely on are soft and brittle. This article also presents results and new perspectives from a pilot study on how to teach central machine learning concepts and workflows

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in the primary school. The article presents lessons from participatory making and learning machine learning concepts through co-creation of tensor flow-driven solutions.

II. The Data-Driven Turn of Technology

Many key insights behind computerization, datafication, and automation of society's functions are very old. Nation-scale automatic data processing projects were done in the late 1800s [4], and early visions of information society span to the first half of the 1900s [5], [6]. The modern computer architecture and its key design insights were born in the mid-1940s [7]. Key principles and technological innovations of the Internet are more than fifty years old [8]. Computing has been a part of science for centuries [9], with different kinds of computing devices appearing and disappearing [10], and as soon as the modern computer was born, the new computing technology started its march into the academia [11] and into businesses [12].

Computerization of society has been driven by a number of parallel technological trends, such as miniaturization, embedding, connectivity, sensorization, mobility, usability, ubiquity, location-awareness, and cloud computing. They have fueled exponentially growing data transfer speeds, data storage density, number of connected users, and number of transistors on microchips [13]. Those technological trajectories enabled in the 2000s collection and analysis of rich, unstructured, multi-format data at an unprecedented scale in society [14], which in turn made possible services and apps of value and worth for individuals, companies, and societies: Take, for example, the platform economy, immediate access to all the world's information, new means of expression, and personally tailored information flows. At the same time, they enabled surveillance society, massive-scale tracking of people [1], swaying of people's moods [15], deepfakes [16], spread of mis- and disinformation, and unprecedented breaches of privacy [2].

Rising abstraction levels have driven a democratization of computing from the hands of a few into the hands of many. Decade by decade programmers have been liberated from tedious lower-level tasks (electronics, machine code, and assembly language, for example), allowing better productivity, efficiency, and easier entry to programming. For instance, in the past decade, there has been less and less need for learning pointer arithmetic and implementation of data structures and algorithms, and the effort that was spent on learning those can be spent on higher-level concerns. Apps development packages, cloud-based automation systems, and development environments have made ICT innovation and implementation accessible to ever larger numbers of programmers.

In the 2000s data-intensive analysis, machine learning (ML), and new tools for gathering and working with data provided new means of data-driven analysis, prediction, intervention, and automation [17], [18]. The most hyped forms of ML are based on the technological developments described above, on new insights on how to fit functions to data, on improved ability to represent real-world phenomena by function approximation, and on new measures of success [19]. Classifiers based on artificial neural networks offer new ways of working with data, beyond old statistics [18]. Most importantly, once machine learning matured it became clear that for many classes of real-world problems, collecting data for training ML systems turned out to be much easier than writing rule-based programs that exhibit the desired behaviors [20]. When ML-based systems started to be successfully used for automating a rapidly increasing number of human jobs that previously were thought to require human type cognition, insight, or intuition, a number of economists went as fas as to declare that a new industrial revolution is at hand [21].

Recent educational initiatives in computing recognized the conceptual shifts that accompany the shift from rule-driven traditional programming to data-driven machine learning algorithms [22]. Many machine learning algorithms employ a non-reductionist, non-deterministic, and statistical epistemology, and their models are soft and brittle, which lends them great flexibility but also limits their utility [17], [23]. The basic principles of how ML algorithms drive today's popular apps and services are not very difficult to learn, and there is a wealth of initiatives and easy introductions to machine learning, optimization, dynamic content generation, filtering, tracking, and behavior engineering. They do, however, require new perspectives into computing, information flows, the data life span, and ethics of computing.

At the moment machine learning has changed how people consume media, conduct business, do their shopping, and even choose their loved ones [24]. People's material worlds and virtual worlds have become deeply intertwined through sensors, actuators, and servos—as well as ubiquitous tracking on numerous channels. The challenges of these changes to educational systems have been recognized [2], [3], [22], [25], but there is little research on what to teach about machine learning and how to do it at different levels of education. One of the major differences compared to previous technology education and computing education is that ML involves a number of epistemological differences compared to earlier technology.

III. Challenges to Computing Education

From the 1950s onward, the dominant paradigm of computing was thoroughly deterministic. In that paradigm, computer programs are sets of transition rules between states, where each program step is unambiguously determined by the rules and states of the system. All computer systems, no matter how complex, are ultimately reducible to lower and lower levels of abstraction, with logic gates at the bottom. These twin pillars of computing, determinism and reductionism, were the cornerstones of the "good old-fashioned rule-driven programming," which mixed analytical/inductive verification of correctness of computer programs with empirical/deductive testing of those programs [26].

Machine learning changes much of the above. Firstly, machine learning models are opaque: The problem of explainability is that once taught, it is nigh impossible to know why the model behaved as it did [23], [27]. Although a human

operator can look into the massive, gigabyte size matrices of weights, understanding how the weights cause the behavior is completely opaque to a human observer [23], [28]. The first challenge for computing education comes from that opaqueness: We currently have neither the tools for explainable AI nor the pedagogy for teaching how to debug machine learning systems.

Secondly, ML models are brittle: A well trained machine learning system can excel in what it does as long as a certain (large) number of assumptions are met and certain environmental variables remain constant. The problem with fragility is that ML systems can be completely derailed by even the smallest changes in their input data, which humans might not even notice, such as change of a few pixels [23], [29]. The brittleness problem requires the users of ML systems to settle with the understanding that there is no guarantee that their system will not catastrophically fail in some new situation. The trust in systems need to be based on statistics of how well has it worked previously.

Thirdly, users of ML need to accept that in many cases ML-based systems work extremely well because they have collected massive amounts of data from users: Many enough people need to give up some of their privacy for the systems to work. Where to draw that line is difficult, and has frequently led to public debate about surveillance society [30]–[32]. The more data systems require about their users, the better informed the users need to be about the power of ML systems for revealing almost all their secrets, and the higher their context-awareness and data literacy need to be.

Fourthly, ML systems are always biased. Notorious examples of bias in ML systems include a parole system categorizing black prisoners incorrectly as probable reoffenders far more often than white prisoners [33], an Internet-crawling language semantics analyzer becoming prejudiced in human-like ways [34], and a crime prediction system focusing law enforcement efforts to areas with high proportion of racial minorities no matter what the real crime rate there was [35]. Algorithmic bias creeps in at all levels: For example, the inscription error is the tendency to impose a set of assumptions on the task domain, on the ML system, and on the relation between the two, and then reading those assumptions back from the results of the system as if they were independent empirical discoveries [36, p.50]. Biases enter the system through framing the problem, defining what data to collect, the actual data collection, data cleaning and curation, and interpreting the results—and they are often so deeply rooted in the domain that even when identified, they may turn out to be very hard to weed out [36]–[39].

Those changes, and the dilemmas that data-driven machine learning systems introduce (such as the problems with explainability, fragility, bias, fakes, cost, military uses, employment, surveillance, and control [23]), require re-thinking computing education [22], media education [40], and technology education at all ages. Insofar as technology education needs to prepare learners to shape and change technology-pervaded world for the benefit of themselves and others, understanding ML principles plays an increasingly important role. For example, the principles of data-driven algorithms behind social media technology, such as filtering, tracking, dynamic content creation, and optimization, are not very difficult to learn, but they necessitate epistemic shifts in computing education. Correctness and optimal solutions have given way to consistently achieving very good results with very high probability but with no guarantee of how good the results are [19], [41]. Principles of ML are important for understanding the new powers that the data-driven, info-computational revolution has given to governmental and non-governmental stakeholders [42]. They are important for becoming an active participant in one's world, capable of shaping social realities [2], [43], [44]. For a shorthand for that capacity, we use the term *data agency*: people's volition, skills, attitudes, and capacity for informed actions that make a difference in their digital world.

IV. Data Agency

The increasing datafication of society has prompted calls for new kinds of data literacies to increase one's awareness of institutionalized data collection, surveillance society, and uses of personal data [1], [25], [43]. A large number of data literacy, digital literacy, proceduracy, and other kinds of new literacy models have been identified in the past decade [25], [45]. They typically involve skills for understanding and using data, identifying the uses of one's personal data, understanding sources of data, and controlling personal data practices [25], [46]. The different definitions of data literacy emphasize a range of skills and competences important for civic society, but research shows a widespread lack of understanding of what data one generates. as well as how, why, and by whom are those data collected and analyzed [43].

The *data agency* concept complements the different conceptions of data literacy. It differs from them by focusing on the active parts of one's capacity—not just knowledge and competence important for digital consumers, but the necessary attitudes and skills for actively becoming makers and producers in the digital world. Agency has been a debated concept in fields ranging from philosophy to computing [30], [47], [48], and as those debates are out of scope of this paper, the paper adopts a simple, sociotechnically oriented position that views agency as a horizon of capacities for active participation in the digital realm. Table I presents examples of skills and attitudes related to data agency.

Developing one's data agency is important for not only just understanding the new roles of information flows. It fosters active participation in a world of information flows, reflexive and critical attitude towards digital being, ownership and control of one's own data, informed ethical and moral decision-making, as well as creating and shaping digital worlds.

There is an existing body of research on how the new modes of computing have affected different segments of society. Children who grow up in an unprecedentedly cyberphysical world, have been studied especially well [3], [43], [49]. Children are exposed to massive data collection efforts, enabled by data they produce themselves while using popular apps

TABLE I
EXAMPLE SKILLS AND ATTITUDES RELATED TO DATA AGENCY

	Skills and attitudes related to data agency
Info-computational epistemology	Interpreting the world as a complex of ever-changing and interdependent information flows.
	Identifying the information flows hidden and visible to oneself, and recognizing the potential of combining and pooling those flows.
	Recognizing computational and algorithmic analysis, simulation, automation, and manipulation of information flows.
Virtual metacognition	Understanding one's digital selves as extensions of, but also distinct from, one's physical self, personas, or identities.
	Critically evaluating, improving, and re-constructing one's own digital self and the digital world around it.
	Differentiating and situating one's digital self (including mental states) amidst those of others.
Computability and complexity	Delineating between what can and what cannot be efficiently automated and knowing the limits of data-driven automation.
	Compensating the weaknesses of machines and humans with the strengths of the other.
Cyberethics	Perceiving the moral and ethical responsibilities as well as autonomy of oneself and others in a data-driven environment.
	Acknowledging the algorithmic bias and biases in data.
	Demarcating what should be automated from what should not.
Digital and data-driven design	Actively creating and shaping one's data environment, controlling and automating information flows.
	Exploring human communities and their needs, combining technical deftness with socio-emotional skills, creating new value and worth, ideas, questions, innovations through data-driven design.
	Combining data-driven and virtual elements with physical elements into cyber-physical systems.

and services, but also by data their family members, friends, schools, hobbies, and parents produce about them [49], [50]. Despite legal restrictions on advertisement to children, they are targets of relentless, cross-border marketing efforts. Unbridled data collection activities on minors expose their whole lives to data-intensive analytics that enable unparalleled insights to those children's whole life histories, minds, and bodies [2]: Among the current generation of minors, those most active in the virtual realms will have few secrets when they are adults.

Recently research efforts have turned into the datafied child [49], with many results portraying youth as "digital natives" confident with their skills as safe users of new technology [51]. The "digital natives" myth has, however, been dispelled: There are great gaps in children's and youth's understanding of how "safe" they are online, of privacy of their data, of visibility of the content they create, and of uses of data they create [3], [51]. As massive data collection has been normalized in many societies, informed consent and user agreements have become just a one-click hurdle to access services and to use apps, legislation and regulation are dragging behind, and parents often have little idea of the risks and compromises related to use of services and apps [2], [51].

V. EXPLORATION ON ADVANCING DATA AGENCY

A. Methodology

We explored ways of advancing children's data agency in a series of educational interventions in K–12. We adopted a design-based research (DBR) methodology in which children were involved as contributing members and meaning-makers, and as designers and creators in the learning process [52], [53]. The participants of the study were 34 sixth-grade pupils aged 12 to 13 years. Informed consent for participation was acquired from the children, their guardians, teachers, and the school administration. The ML intervention consisted of three workshops, three hours each, over a period of two weeks. The intervention was conducted as a part of regular school curriculum, and as such, it required no ethical permission from the Ethical Council.

Data for analysis consisted of pre-and post-tests, transcripts of children's group discussions, written and drawn design ideas, co-designed applications, and structured group interviews. As this study focuses on children's data agency, in particular children's own descriptions of their own data practices, the main data reported in this paper are the children's group discussions and structured group interviews that covered three themes: 1) children's background and interest in technology, 2) co-design process (ideating apps, reflecting on the design and learning process, organization of team work, tackling problems with the app, and future development ideas) and 3) data agency (machine learning in children's everyday lives). The length of the group interviews varied from 14:59 minutes to 47:11 minutes (mean length 21:02 minutes). Interviews were transcribed in full for analysis purposes and analysed by two of the authors using the Atlas.ti software. Of the three research themes above, this paper focused on the third one; data agency (machine learning in children's everyday lives). The first phase of the analysis was conducted using content based analysis aiming at bringing out students' different interpretations and experiences in their own words. The responses were typically short, a few words or a sentence.

B. Workshops

Before the co-design project started, pupils were given a "white-paper test" task to tell, by drawing or writing, what they knew about artificial intelligence before, and how they thought one could teach a computer. White-paper tests of this kind originated in expert-novice studies [54], but in this research context it served research and learning purposes. In the first workshop, students familiarized themselves with two machine learning tools: our own in-house developed ML education application, and a closed beta version of Google's Teachable Machine 2 (TM2). Our own ML education application is an image recognition tool that classifies images by just two features for clarity. Google's TM2 runs state-of-the-art classification algorithms on top of child-friendly graphical user interface for training three different kinds of models: image classifier, body pose recognition, and sound recognition. The body pose recognition uses TensorFlow-based PoseNet

for recognizing human body poses in real-time. After learning how TM2 works, children were given homework to think about situations in their lives where machine learning could be helpful.

Children's ideas for ML-based apps were innovative and they were of many kinds. One group proposed an app that recognizes one's mood, and if that mood is bored or sad, help with recreational or comforting ideas. Another group, whose hobby was cheerleading, proposed an app that recognizes cheerleader poses. One group suggested an app for the teacher that would be taught the voices of all students in the class, and keep track of who are disrupting studies the most. One group suggested an app that is taught mushrooms and berries and that can identify poisonous ones.

Between the first and second workshops, a computer science researcher screened the students' ML ideas and selected nine that could be simple and straightforward to train and implement as a mobile app. In the second workshop, students were divided to nine teams that were tasked to define the functional requirements and draft user interfaces of their ML apps. They were taught how seemingly inessential changes in input data (such as web camera background and noise) affect the confidence of the trained ML models. The workshop emphasized active co-design and active making. Students trained the models and tested how well those models did what they were supposed to do. Fig. 1 shows students training machine learning models: Sound recognition, PoseNet, and image recognition, respectively.

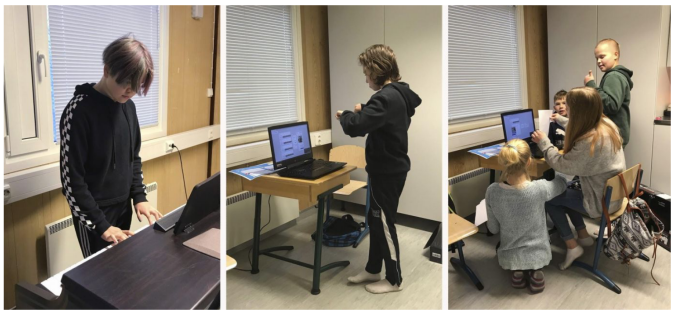

Fig. 1. Students creating training data sets for classifiers (sound recognition, pose recognition, image recognition).

After the second workshop, the computer science researchers built rough-and-ready prototypes of mobile apps using the machine learning classifiers trained by the children. In the third workshop, students tested their apps, and demonstrated their apps to other groups.

C. Results on children's data practices

In the interviews, most children said that they did not have any experience of ML-based educational technology. However, the final interviews as well as the post test showed increased familiarity with the machine learning workflow and basic ML concepts, such as training data, model, classification, confidence, and model softness (Fig. 2). The interview data also indicated that the children had not themselves recognised ML as part of their everyday life nor consciously reflected their own data practices or strategies before the intervention. However, most of them were very active users of social media services such as WhatsApp, Snapchat, Instagram, TikTok and YouTube (also Tinder was once mentioned in the children's group discussions in which the adults were not present). While children were very like-minded when naming the ML-based services they used, similar to the findings of [51], a typical norm across the groups was also a rejection of Facebook. One group explained the escape from Facebook by invasion of parents in the same service:

> *Bernard*: Facebook.
> *William*: Bernard is like sixty years old. [laughter]
> *Interviewer*: Is Facebook for sixty year olds?
> *William*: Yes.
> *Dolores*: Yes, it is.
> *William*: It was ruined for us.
> *Dolores*: Who needs it anymore…?
> *William*: Our parents.

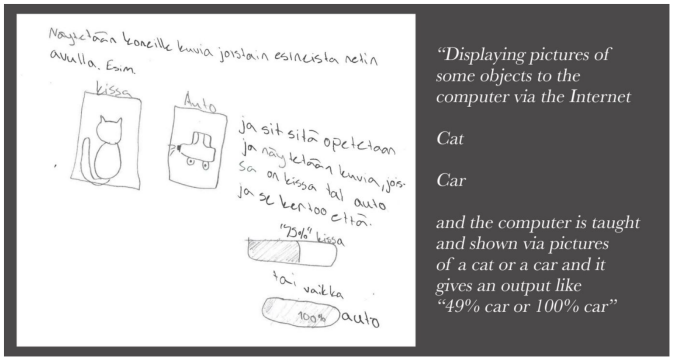

Fig. 2. Student's example of machine learning concepts (training a model, confidence, softness) from the post-test.

The analysis of data further indicated that there was not much awareness over the creation and use of personal data. For example, when asked to elaborate who produces data about children, the answers included such as "*We ourselves*" (Clementine), "*Sometimes your friends, on permission*" (Elsie), "*Artificial intelligence*" (Teddy), ''*Like the phone or smart device*" (Ashley). Children typically reasoned that data collected about them included the likes of their name and age, and some of the children also had their own strategies and practices for providing information: "*you can lie all your birth dates*." Moreover, in the final interviews, the children were also able to provide responses that reflected their ability to recognize some of the mechanisms of ML, such as recommendation systems, within the applications and services they use:

> *Elsie*: Yeah and it also has it so that if you, in like IG, like some kinds of pictures, it shows you a cer…like same style or something, and in Youtube also, it shows you your kind of stuff.
> *Interviewer*: So how does it learn ... the app?
> *Elsie*: With your likes.
> *Interviewer*: Yeah.

Charlotte: And what you're watching.

The interviews showed few signs of awareness of any specific third parties and why they collect people's personal data. When asked, the children named applications or guessed some stakeholders, but typically without elaboration of how or where personal data was used: "*Nah, maybe some dictators* [collect and use data]" (Hector), "*Well maybe the app itself that has collected the*m [uses the data]" (Teddy), "*I guess the companies and their ... their ... workers*" (Lee), "*That machine ... or I don't know*" (Angela). Yet, in the children's group discussions, one girl explained how she had recognized her being an object to targeted advertisement: "*But I mean the phone is listening to you all the time, so if you talk to it, or I check out some Marimekko's like purse, so after that I got only Marimekko purse ads ... and once I checked Adidas flip flops and went to buy them, and after that I got those ads all the time*". The analysis also revealed that the most immediate concerns of children were related to the misuse of their data for purposes such as "*Well, someone may pose as you*" (Hector), "*You can use them to make threats*" (Dolores), and "*Bullying*" (Charlotte). One boy extended his pondering of the problems related to hacking systems beyond his immediate environment: "*It's in principle for those servers where we have all that data, so you have a little backdoor lets someone in, so it's thus that in principle all data of all people in the world who have visited, like, Google, and they have it alone*" (William).

One notable difference between children was found in their own data "protection" strategies related to reading the Terms of Service. Many children said that they did read the Terms of Service, and the children had specifically paid attention to the access of their personal galleries, messages, and location data: "*For example if you have, you must give that app permission to do something with my phone like look at my gallery, messages, or like so. Camera... Location and so*" (Robert). One girl was also aware of potential risks of combining of personal data: "*Um it may know where you move if you gi... like give location and um may like know how you look like, know age, name, so in principle it knows everything*" (Emily).

However, there were few indicators of "fully" reading the Terms of Service. Such contracts can appear to children as very uninteresting and difficult to understand [51]. One girl also referred to time limits imposed by the adults: "*I'd otherwise read it but they have like a million pages so the time I have for downloading the app and playing with it would go to me reading small print about it*" (Dorothy). Some children also described that parents also read the Terms of Service when the children downloaded a new application. The strong influence of peers was also evident in the context of personal data practices: "*and if you've got app from your friend, so you've like seen your friend play and then asked your friend about those information, so I can't be bothered to read the terms of service when I have some new app that I think that okay I'll just test it but I read it if it's a bit like this can do some harm, in that case I read it and then think if I accept of not*" (Maeve). There again, some children considered the use of personal data as an acceptable trade-off and were even happy to simply dismiss how personal data was used: "*I don't care, they can take my human rights away, I just want to be in Youtube*" (William).

Based on the interviews, developing data agency will be a challenge, but we were able to pinpoint preliminary signs related to nascent data agency. The results indicated that ML and datafication of society are an important part of Finnish children's lives. Respondents mentioned several applications and services, such as YouTube, Snapchat, TikTok, Netflix, and Spotify, which they used on a daily basis. Their knowledge was lowest with questions about how apps and services collect data about them and use that data. Children's responses to the questions about who collects data about them and who should be able to decide over the use of that data, were more or less guesses. Typically students said that their parents should be the ones deciding on the use of the data.

Furthermore, respondents showed some ability to identify ML mechanisms in the applications and services they used. They indicated that applications learn about you when you provide them information about you, in concrete ways, such as when you tell your name or age. In addition, the responses indicated some understanding that machines learn based on their own activities: Students noticed that their apps learn when they listen to music, watch videos, or do something online: "*Well, like YouTube, if I watch a movie then it recommends me another similar movie*." These examples reflect students' ability to notice and name elements of ML as part of their everyday activities. That ability is an important step toward data agency, toward agentic processes giving shape and direction to future possibilities within data society [48].

VI. Conclusions

While critics have begun to draw attention to the ways in which continuous personal data generation is influencing people's lives, researchers are only just beginning to direct their attention to children's perspectives and agency in the age of machine learning [49]. This paper contributes to this gap by providing a rationale and theoretical perspectives for data agency, as well as by exploring children's descriptions of their own data practices. While this study was limited by its sample, it offers new insights into the nature of children's data practices, and it raises several important questions concerning children's data agency.

The results showed that co-designing ML was able to promote transparency of technology and understanding of how it works: In just three short workshops students learned a good number of basic ML concepts and were able to train models that worked relatively well. The post-tests showed clear advancement in students' knowledge of ML workflows, limitations, and possible uses.

The results of the study revealed that the majority of children were very active users of ML-driven services, but they generate personal data with little understanding of where, how, or why the data are being collected and processed [43]. While this short intervention successfully engaged children in co-designing their own ML applications, which also supported

their understanding of the basic concepts and mechanism of ML [55], it was less successful in raising children's critical stance towards ML-driven services and data-driven practices of their everyday life. The children were able to reflect on their personal data flows in the final interviews, and they showed ability to identify some ML techniques in the applications and services they use.

While many of the data agency-related skills and attitudes introduced in Table I did not appear in children's own descriptions, the results did show children's deliberate efforts to control their personal data flows in their own sociocultural practices. These strategies included, for example, the protection of youth culture from parents, relying on peers when accepting the terms of use, and denying an application access to some information that the children themselves considered to be private, such as photo galleries or private messages. However, if third party use of personal data, targeted advertisement, behavior engineering, or attention harvesting are not recognized or considered to be a problem, there are few opportunities for informed actions that make a difference in one's digital world [51]. Thus, these results suggest that children should not be left alone with identifying how and where personal data are generated and processed. Nor can they be expected to figure out how to control personal data traces or to create impactful data strategies on their own. Accordingly, there is an evident need for progressive ML education that responds to the real needs and practices of the children in the data-driven world that they already live in.

The co-design pedagogy engaged students in creating design ideas applicable to their everyday lives. With the help of beginner-friendly learning environments, students, who had little to no experience on ML before, were able to train models that recognized expressions, poses, sounds, and images. The children's ideas originated from playful exploration with easy-to-use tools that did not require traditional programming concepts or syntax. Accessible educational technology lowered the cognitive overhead to ML development tools and enabled children to do requirements definitions, model training, and testing the model in practice, with real data and real situations. What the children learned is not directly relevant to most groups of data agency in Table I, but they did learn elements of the fifth group, digital and data-driven design; especially skills related to actively creating one's data and automation environment, to exploring people's needs, and to creating new value and worth.

There is little doubt that machine learning will play a major part in computer and information systems of the future. At the moment there is very little research on machine learning-related pedagogy and educational technology in K–12, but based on our results, ML-based systems are in many ways more accessible to young learners than traditional rule-based programming environments are. Their bodily nature, real-world application areas, and immediate access to a wealth of readily useful data make them especially appealing to school environments. Machine learning really shines with media-related application areas—video, pictures, and sound—and they allow one to work with those without syntax or semantics by shifting the focus from rules to data. There is, however, much work ahead in developing working pedagogical practices, view of notional machines, motivating problem spaces, and good learning environments for teaching ML.

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