Machine learning for middle-schoolers: Children as designers of machine-learning apps

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***Abstract*— This Research to Innovative Practice Full Paper presents a multidisciplinary, design-based research study that aims to develop and study pedagogical models and tools for integrating machine-learning (ML) topics into education. Although children grow up with ML systems, few theoretical or empirical studies have focused on investigating ML and data-driven design in K–12 education to date. This paper presents the theoretical grounds for a design-oriented pedagogy and the results from exploring and implementing those theoretical ideas in practice through a case study conducted in Finland. We describe the overall process in which middle-schoolers (*N* = 34) co-designed and made ML applications for solving meaningful, everyday problems. The qualitative content analysis of the pre- and post-tests, student interviews, and the students' own ML design ideas indicated that co-designing real-life applications lowered the barriers for participating in some of the core practices of computer science. It also supported children in exploring abstract ML concepts and workflows in a highly personalized and embodied way. The article concludes with a discussion on pedagogical insights for supporting middle-schoolers in becoming innovators and software designers in the age of ML.**

Keywords— Machine learning, K–12, computational thinking, design-oriented pedagogy, data-driven design, design-based research

I. Introduction

Developments in machine learning (ML) have had a massive impact on today's society, work life, and on people's everyday lives. Yet, ML and its societal effects have been given only minor attention in K-12 computing education, which mainly focuses on rule-based programming. However, ever-younger children are active users of ML-based technologies [1] and there is an evident need to prepare young people for the emerging work life that is currently being greatly disrupted by ML and the automation of knowledge work [2]. Furthermore, understanding the power and limitations of ML has been acknowledged as crucial for active citizenship as well as for the prosperity of democratic societies [3].

While much has been written about the impact of new, data-driven ML on the labor market, education, professions, societies, and on people's social lives, to date, few theoretical or empirical studies have focused on investigating ML in K–12 education. Research initiatives that involve ML technologies have been rare due not only to the relatively recent rise of ML as a practicable technique in computing, but also to the inherent difficulties in bringing such multifaceted and highly abstract phenomena into children's creative grasp. Meanwhile, an entire generation of children is growing up with ML systems and, thus, there is an urgent need for education that prepares students for the data-driven world in which they live [4][5].

This study is part of a multidisciplinary, design-based research (DBR) project that aims to develop and study pedagogical models and tools for integrating ML topics into education. The long-term aim is to support students in developing their data agency and skills to become contributing members in a data-driven society. The present article describes a pedagogical framework for middle-schoolers to become co-designers and makers of their own ML applications. Moreover, it presents an empirical case study conducted in a 6th-grade classroom of a Finnish school and reports on an exploration of what kinds of activities and applications were pursued during the ML co-design process. The paper addresses the following specific research questions:

RQ 1. What kinds of activities and applications were pursued during the ML co-design process?

RQ 2. How do middle-schoolers perceive the ML co-design process?

II. Pedagogical Framework

This study's pedagogical approach is based on a design-oriented pedagogy rooted in the pioneering ideas of Seymour Papert and his followers. Papert argued that when children design, build, and program artifacts, they can learn important skills in computational thinking, making, and action in the world [6][7][8]. In contrast to long-standing educational practices that favor learning how to use applications, Papert's [9] constructionism represented a profound pedagogical change toward design-oriented learning that regards children as innovators, designers, and as builders of knowledge [10].

While many current models of instruction consist of relatively simple, build-a-thing tasks, or step-by-step coding exercises, a design-oriented pedagogy emphasizes open-ended, real-life learning tasks [11]. Such tasks have no single solution or "right" answer; instead, they provide students with opportunities to generate different kinds of solutions to problems that the students themselves consider to be meaningful [12]. This resonates with the idea of tackling those problems so that there will be a perceived need for both a theoretical and conceptual understanding underlying those problems as well as their solutions [13].

Moreover, with a design-oriented pedagogy, students share the task of inventing and creating real artifacts that play a fundamental role in mediating the processes of learning and collaboration [14]. This pedagogy emphasizes a creative process in which students need to use tools, technologies, and external representations to communicate with each other [15], including various kinds of conceptual artifacts (e.g. questions, spoken or written ideas) and material/digital artifacts (e.g. graphs, drawings, prototypes, programs) [14]. Such an iterative process of creating external representations, followed by collaborative advancement and the refinement of externalized ideas, can lead to increasingly sophisticated understandings of the content domain being represented [16].

What is more, one of the central underlying principles of a design-oriented pedagogy is that students are engaged in problem-solving activities that are similar to the activities of expert communities [12][17][18][15]. When solving problems and co-designing shareable artifacts, students are expected to actively communicate, share their expertise and previous knowledge, make joint decisions, as well as negotiate roles and responsibilities for the advancement of ideas and collaborative work [19][17]. It is also worth noting that these key elements of collaborative design are nowadays often referred to as twenty-first-century skills such as the ability to communicate and collaborate to solve complex problems, the ability to adapt and innovate in response to new demands and changing circumstances, and the ability to use technology to create new knowledge [20].

Seitamaa-Hakkarainen et al. [17] added that, in order to truly appropriate expert-like practices, students also need to have reciprocal relations with domain experts and work together with them. A key aspect of such collaboration is "guided participation" or "cognitive apprenticeships," in which the expert provides encouragement, the means, and metacognitive support for the novice to solve problems or complete tasks that he or she does not yet have the skills to do independently [21][22]. Through participation in expert practices, the students may also begin to acquire the norms, values, and skills that shape the core identity of the community [23]. This includes the tacit dimension of knowing and making underlying the professional practices of experts; that is, the deeply ingrained expertise and strategies that the experts themselves have internalized and automatized and no longer have conscious access to [24][25]. In other words, when students collaborate with domain experts, they may also participate in *computational practices* and see how science and engineering can be applied to solve important problems in the world. This may also influence young people's beliefs about what it means to be a computer scientist or computational designer and it may lower the barriers of entry into the core practices of computing.

A. From rule-based to data-driven design

While there is a vast amount of research available on learning by designing and how it can be applied in many different educational contexts, researchers are only just beginning to direct their attention to the ways in which children can become designers and makers of ML applications. The few examples available illustrate ML workshops and projects where children imagine the smart devices and toys of the future [4], build models of their own physical activity [26], and explore how object recognition works through their own drawings [27]. In all, these initiatives have highlighted the importance of engaging learners in exploring the basics of ML through a process that positions children as active subjects and teachers of ML systems, and not as objects of teaching, which is typical of more traditional instructional models.

The democratization of artificial intelligence (AI) technologies has opened up the possibilities for children to communicate with machines, not only via rule-based programming, but also via natural language and other ML-enabling technologies and interfaces [4][28][29]. For example, Google's Teachable Machine, the tool used for the present case study, is very easy to use, even for very young children, as no writing or programming experience is required. Google's Teachable Machine (GTM) is a web-based system that connects state-of-the-art classification algorithms with an intuitive and easy-to-learn graphical user interface. GTM supports children in exploring the principles and basic workflows of ML applications and it does not require any programming skills. The tool is completely web-based and allows for the trained model to be exported, which can be embedded in a custom web or mobile application. The exported models are Tensorflow.js models and they can be used in any system that runs JavaScript.

Currently, GTM offers three alternatives to train predictive models. The aim of the *Images* tool is to teach an ML model to classify images, where the training data are either uploaded to the GTM environment from the user's computer or captured from the user's web camera. The *Poses* tool can be used in a similar fashion to detect different bodily movements (the system uses PoseNet for real-time human-pose estimations). The features that are important for poses are, for instance, the angle of a certain body part and the orientation of a limb, whereas the features that are important for image classification are objects in the images and their distinctive features. With the *Sounds* tool, users can train a model to distinguish different sounds or audio such as different people speaking or different sounds in the world.

The latest developments in these technologies enable children to interact with the computer through their own voice, facial expressions, gestures, and bodily movements. Rather than deductive reasoning and rule-based programming that drove earlier programming language experiments in education, by using well-designed ML-based tools, children can also engage in the process of data-driven design and programming by providing the machine with a training dataset and then using the trained model to control the machine. These new computational paradigms and ML tools can expand the design possibilities for students while also offering them new ways to explore and make sense of the world they live in. However, learning by data-driven design is essentially unstudied in the field of education and, thus, there is an urgent need to investigate pedagogies and the educational technology for supporting students to become innovators and software designers in the age of ML.

III. Methodology

This multidisciplinary project employed a DBR methodology—an approach that has been widely promoted in the learning sciences for the development of new learning environments and models through parallel processes of design, evaluation, and theory-building [30]. Moreover, our approach followed the current trends of including children as contributing members and meaning-makers in the cutting-edge practices of research and development work [31][32]. This was promoted through the idea of meta-design that aims to provide the kinds of learning tasks, technologies, and pedagogical processes that position children as designers and creators in the evolving process of collaborative learning (cf. [33]). A unique strength of participatory methods, combined with a design-oriented pedagogy, is that they also enable children's voices, views, ideas, and experiences to be heard when introducing AI and ML into K–12 education.

A. Research participants and context

The intervention was designed by a multidisciplinary team of researchers from the fields of computer science and education. Moreover, the design and implementation processes were co-configured with participating schools to serve their curriculum needs. The participants were two classes of 6th-graders (34 pupils aged 12 to 13 years) and their two teachers from an elementary school in Eastern Finland.

The Finnish National Core Curriculum [34] guides the nation's education system. The national curriculum for basic education (grades 1 to 9) defines the main objectives for different subjects as well as seven transversal competence areas that need to be developed in all schools in Finland. Moreover, the curriculum also encourages practicing and enhancing these transversal competences through collaborative phenomenon- and project-based studies to extend the boundaries of individual school subjects. While the national curriculum for basic education defines the shared values and objectives for all Finnish schools, considerable freedom still exists, as the Finnish education system is built on a culture of co-operation and trust, as well as competent and highly educated, committed, and autonomous teachers [35].

As the Finnish National Core Curriculum [34] emphasizes the development of transversal competences and project-based studies, these ML projects were implemented as part of the regular curricular activity. The guardians of all the participating students gave their informed consent to conduct the research and consent was also sought from teachers and school administrators. The ML project included three workshops (each lasting about 2–3 hours, depending on the class schedule) over a period of two weeks.

B. *Data collection*

The data consisted of a pre- and post-test, children's group discussions, children's design ideas and co-designed applications, and structured group interviews organized at the end of the project. Structured interview guidelines were drawn up, including general and follow-up questions based on three themes: 1) the children's background and general interest in technology; 2) the co-design process (origin of their app ideas, reflection on the process of design and learning, organization of team work, possible problems in how the app works, new ideas); and 3) data agency (ML-based automation in children's everyday lives). The length of the group interviews varied from 14:59 minutes to 47:11 minutes (average 21:02 minutes). What is more, the researchers made observations and took many photos to record the emerging activities throughout the intervention. In line with the design-oriented approach, data collection was integrated as part of curriculum activities, as elaborated in the findings section.

C. *Data analysis*

The audio data from the collaborative discussions and interviews were transcribed for analysis. The data were analyzed using qualitative content analysis [36]. To identify the kinds of activities and applications pursued in the emergent process of co-design (RQ 1), we first analyzed the students' ML design ideas and their development. More specifically, we analyzed the students' descriptions of 1) their design problem(s); 2) the use or function of the applications they proposed; and 3) the type of model the idea required (image, sound, poses). Secondly, we explored how these ideas were elaborated as explicated datasets and interface designs, and how the tools and technologies were used as mediational means. Then, we proceeded to explore the improvement needs that the students identified when testing their own applications. Finally, we analyzed how middle-schoolers described their experiences in relation to these main phases of co-design and the outcomes of it (RQ 2). Accordingly, we aimed to de- and reconstruct the emerging process by focusing on what kinds of ML ideas, activities, and experiences were connected in the three main phases of co-design. We triangulated the data by combining and examining consistency from multiple data sources in the analysis [37].

IV. RESULTS

A. *Contextualizing and exploring ML*

The ML project began with an orienting assignment—the "pre-test"—, in which students were given a white paper and an individual task to draw and/or write down what they knew or thought they knew about ML [38]. More specifically, the students were asked to externalize their thoughts about how one could teach a computer. In this activating stage, it was emphasized that there were no "right" or "wrong" answers, but that all thoughts and ideas were welcome. The analysis of the pre-assignment indicated that most participants felt they did not have any experience of "teaching" the computer. Typically, the students' descriptions and illustrations included computers, humans, and Internet symbols, while there were only a few indicators of ML-type concepts or procedures. The interviews confirmed this interpretation, as most students said that they did not have any experience of ML-based educational technology. While this "white-paper" test has roots in expert–novice studies, in this kind of pedagogical setting, it served both the research and learning activities with the aim of supporting students to externalize their prior knowledge and experiences though writing or artwork (Figure 1).

Fig. 1. Examples from the children's artwork for the pre-test.

The first workshop began with a short introduction to ML and how it is present in our everyday life. The students were also told that in this ML project, they were to work in teams and to co-design a novel ML-based solution for some everyday problem. The co-design task, co-configured between the teachers and researchers, was open-ended by nature and deliberately challenged students to generate ideas and solutions to real-life problems that they had identified.

The first workshop emphasized the ideation process, and it had a special focus on collaborative discussions that aimed at contextualizing ML in the students' everyday lives. The students worked in small groups of four to five and they were asked to discuss different situations where they thought that machines could learn (e.g., programs, apps, games, places). In addition, the students were asked to write down their answers and elaborate on their encounters with ML (e.g., what kind of information is collected, how is that information collected and used, and what is it used for?). These group discussions were recorded for research purposes, and the students were asked to ponder similar questions in the group interviews after the project. These joint discussions and interviews revealed that most of these 12–13-year-old students were very active users of many ML-powered applications such as Instagram, WhatsApp, Snapchat, Tiktok, Facebook, YouTube, Steam, Netflix, and Spotify. However, there were no signs of these apps in the pre-test phase.

In the first workshop, the students also familiarized themselves with the possibilities of GTM 2 and with our in-house-developed educational ML application [27]. With the support of a computer scientist, the students explored how image classification works by training their own ML system. In line with previous co-DBR, these activities emphasized playful exploration, where the children used their own voices, bodies, and drawings to teach the ML systems things that they considered to be meaningful. For example, some of the girls taught the PoseNet to recognize their own cheerleading moves, while others explored ML through their own drawings of different animals (Figure 2). The photo in Fig. 2 from the exploration of the *Poses* tool also shows how the whole body is used to interact with the computer; those physical, bodily forms of interaction also contributed to the socially shared meaning making.

Fig. 2. Exploring the possibilities of machine learning.

B. *Idea generation and development*

The idea of contextualizing ML in children's everyday life experience was also embedded in the individual homework that students were given at the end of the first workshop. At this point, the students were tasked with searching for and identifying everyday problems that could be solved by using ML-powered technologies. The task was aimed at brainstorming design ideas and supporting children to bridge their formal and informal learning experiences [18]. These design ideas of the students included, for example, home automation applications (e.g. a gesture-based door-opener, recycling robot), applications for school work and homework automation (e.g. a writing inspector, pupils' attendance detector), ideas for service automation (e.g. an automated shopping list, fake product detector), as well as ideas for improving security and privacy (e.g. an application that hides other applications, criminal detector for the police), and well-being (e.g. health detector, ambulance caller, mood improver).

In the final interviews, some students mentioned that they considered the invention of ML ideas to be difficult, as depicted by Reetta: "*Well, in my opinion, the most difficult part was the homework ... it was so difficult to invent them.*" However, the analysis showed that the ML ideas were connected to different kinds of everyday problems and they were also often based on image recognition or the recognition of sounds or poses—the technologies that students had been exploring in the first workshop. For example, one boy described a cat food dispenser: "*The Teachable Machine recognizes the cat's face and when the cat meows, the robot gives the cat kibble.*" As most of these students did not have any experience in ML-powered educational technologies, nor were there hardly any signs of the recognition of ML in everyday life in the pre-test, the prevalence of applicable ML insights in students' ideas indicates the important role of playful, hands-on exploration with the tool that provided different modes of interaction with a machine: images, sounds, and gestures. Of particular importance here is the way in which the multimodal interaction with the computer contributed to these design ideas, and apparently how it also supported students in pondering everyday life situations and artifacts from a new perspective.

C. *From ideas to explicated datasets and interface designs (second workshop)*

Before the second workshop, the computer scientist selected nine students' ideas to be further developed into web-based ML applications. The selection was mostly based on the feasibility of the idea in terms of the design constraints; namely, the particular ML technologies that were used by the students within the limited timeframe of the project. The data collection and training of the model were done over the second workshop. While every idea could not be further elaborated, it was suspected that the expansion of action possibilities with respect to the students' own and co-authored ideas would also influence their perceived ownership of the learning.

At the beginning of the second workshop, the students were divided into co-design teams based on their interests, with some support from teachers. Nine design teams were formed and the first task for the students was to further articulate and develop the selected ML application idea. For that, the teams were given an ML design template that asked students to negotiate what the app should do, what kinds of data should be collected, and from where (image, sound, position), how many different categories the model should recognize, and under what kinds of conditions the teaching data would be fed into GTM. Here, the idea was to progressively refine the selected ideas by adapting basic ML concepts to the particular problems that students were trying to solve. These ideas were further defined in collaborative discussions with computer scientists who also gave on-demand support when the students were training data sets for their own ML applications.

Six of the selected ideas were based on GTM's image classification. These included an application that was aimed at identifying colors for color-blind individuals, a berry and mushroom detector, as well as an app that detected users' moods. Moreover, three groups focused on the automation of schoolwork by designing apps that aimed to recognize numbers or letters and correct errors. The data for these apps were pictures from the Internet or the data consisted of students' hand-written letters or numbers.

Two of the selected ideas were based on GTM's sound-recognition tool. These included a silence detector for teachers that recognized which students were talking, especially in situations when the teachers had to leave the classroom. The data for the application were collected by recording the students' own speech. The second sound app aimed to recognize music on different instruments, and for that, the group of students recorded the sounds of different instruments. Moreover, one of the selected ideas was based on the *Poses* tool with the aim of building a door-opener that recognized the feelings of people from their faces and from their different bodily movements. The data for that tool consisted of the students' own poses.

The second workshop emphasized active making, as some of the groups were training a machine to recognize their poses, others were searching for or making images, and one group was recording their own instruments being played in the music class. In this way, some of the key concepts of ML were explored in a very practical and contextualized fashion. The following quotes from Heikki and Hanna illustrate a meaningful moment in making and testing their own application:

> Interviewer: *Yeah, well, when you worked together on that and you did that, so what was the most enjoyable phase or thing when working? Heikki could start.*
>
> Heikki: *Mm ... playing.*
>
> Interviewer: *Yeah. Hanna?*
>
> Hanna: *Mm, I think afterwards it was nice to try out how it worked when playing, like, a guitar, and it would recognize it. So, the testing.*

Training their own ML models for applications also included an important feedback loop, as the students could receive immediate feedback on the implementation of their own design idea; that is, they could test the quality of their own data. GTM did not always work as students expected; hence, the students also had to reason about the relationship between their own input and the output provided by GTM.

What is more, at the end of the workshop, the students were also asked to externalize their evolving ideas and draw interface designs for their own applications. At this point, ML concepts such as class, training, and confidence were also beginning to emerge as part of the students' design functionalities, as illustrated in Figure 3. These interface designs provided one indicator of the growing conceptual understanding of the students.

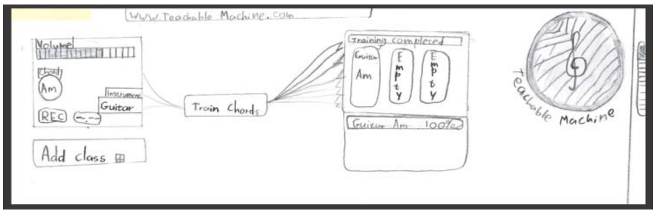

Fig. 3. Interface design of an application to recognize different instruments and chords.

Based on the students' specifications and on the neural network-based models they had taught, we then built nine simple web applications.

D. *Testing ML applications and reflecting on the process of learning and design*

The third and final workshop started with researchers explaining the application development process and giving feedback to the students on their designs and plans. After that, the students were given URLs to the sites with their applications, and they tested and then presented their applications to their peers and group teachers (Figure 4).

Fig. 4. Testing the co-designed ML applications.

At the end of the project, each student team was interviewed. The student teams were asked to reflect on the design process and to give feedback about the applications. Typically, the feedback focused on the prediction accuracy as well as on the functionality of the application. Moreover, the students were also asked to give explanations if their app was not functioning as expected. An example of the students' own data-driven reasoning is provided by Teemu, Hanna, and Timo:

Teemu: *Then it doesn't work.*

Hanna: *Mm.*

Interviewer: *Okay. Well.*

Timo: *It took those particular chords that we taught it.*

Hanna: *So, it should have been taught more.*

Timo: *Mm.*

Interviewer: *Mm. Okay. So, it probably doesn't work in every situation?*

Hanna: *No.*

Timo: *No.*

Interviewer: *Yeah. And what do you think is the reason for that or for why it does not work?*

Timo: *Mm.*

Hanna: *It doesn't have enough data, for example, about the piano or the guitar, or it has too much information about one and a little less about the others.*

The emergence of data-driven reasoning and design was confirmed by our analysis of the post-tests, which showed that the students were increasingly using some of the basic ML concepts when illustrating and explaining how machines could learn. While "white-paper" tests captured the changes in student thinking [38], the analysis also revealed how these evolving explanations were often connected to the particular ML applications that were co-designed by the learners. This is illustrated in Figure 5, which presents examples from the pre- and post-tests for one boy, Saku, who co-designed an application that recognizes the students' own handwriting and letters. Of particular importance here is that the original idea for the application was not invented by Saku, but in the post-test, his evolving conceptual knowledge is contextualized and represented through the particular applications he helped to co-design.

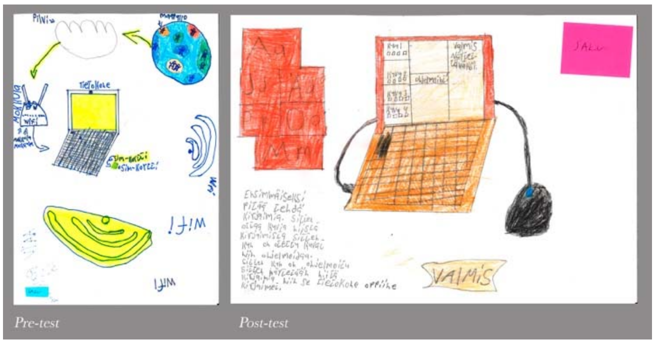

Fig. 5. Examples from the pre- and post-test data from the study.

In the final interview, the student groups were also asked to reflect on their own learning. In the following, the group that co-designed the mushroom and berry detector collaboratively reflects on their meaningful moments and learned skills:

Juhani: *You get to be in a group with your friends and then you get to do a bit of it yourself too.*

Interviewer: *Yeah. What do you think?*

Janne: *You can test different stuff.*

Interviewer: *Yeah.*

Iiro: *And learn at the same time.*

Interviewer: *Yeah.*

Janne: *Yeah.*

Interviewer: *What do you learn from it?*

Iiro: *Well, that you can make such an application on your own.*

Janne: *Use a computer.*

Iiro: *Yes. Teach a computer yourself like that.*

Interestingly, what these students say they learned captures something that is often considered as essential for 21-century skills (cf. [20]). It is further evident from these students' reflections that they described themselves as "teachers and makers of applications" in a future tense. Moreover, the ownership of the designed artifacts was often part of these reflections, as illustrated by the four girls who, at the end of the final interview, insisted that their application should be published in an app store:

> Katja: *So, can you still change that* [co-designed] *application?*
>
> Reetta: *Yeah.*
>
> Interviewer: *Well, maybe you and he* [computer scientist] *can think about it.*
>
> Jonna: *And then it could be downloaded on that Google Play.*

V. DISCUSSION

While ML is becoming a commonplace feature of people's everyday lives, to date, there is still a very limited body of theoretical or empirical studies focused on investigating how to support students to become innovators and software designers in the age of ML. This understanding is, however, vital if we wish to enhance children's active participation in our data-driven society and support them to gradually develop computational fluency and data-driven thinking to help them to understand the world they live in [2] [4] [5] [11]. This exploratory case study was aimed at addressing this gap by studying the process of middle-schoolers' ML co-design projects and the students' own experiences of them.

The process description presented in this paper, including the theoretical framework and general description of its implementation, addresses our first research question by illustrating how one can make arrangements that involve collaborative learning and design activities with expert communities. Apprenticeships of that type revealed that conceptual knowledge was contextualized, encouraging both a deeper understanding of the meaning of the concepts themselves as well as creating a rich web of memorable associations between them and the real-life problem-solving contexts [22]. The results further illustrated how bodily modes of interaction with computers not only lowered the barriers for participating in some of the core practices of computer science, but also supported children in exploring some of the abstract ML concepts concretely and in a highly embodied way.

The results of the study highlight the affordances of the social and technological environment that supported an interest-driven exploration of ML. Although the outcomes of this very short intervention were limited by the fact that the students did not implement these apps themselves, the results of the study revealed that basic ML concepts and the procedures of ML design are not out of reach for middle-schoolers. The results of the study further indicated that when co-designing and making ML applications, the students were not limited to culturally dominant stereotypes about the types of people who can do computer science (cf. [39]). Instead, the results of the study suggest that co-designing personalized artifacts was also connected to the perceived ownership of learning and may support students when developing their identities as computational designers.

In terms of our second research question concerning the students' experiences, the results of the study indicate that the children appreciated the opportunity to become designers and makers of their own applications. Although today's children are active users of different ML-powered services and applications, they seem to play rather passive roles, and are not familiar with how the mechanisms of these services work or how ML can be used for different purposes [1] [5]. This paper provides an example of how to provide students with the possibility of working with ML in an active role: designing new artifacts and taking advantage of ML where necessary. We see this experiment as a step toward providing students with an understanding of the invisible world powering their everyday technologies. Because ML plays an ever-increasing role in governance, business, and citizenship [3], innovation projects like this are needed in order to help children build their data agency and desire to become responsible designers and makers in the age of ML.

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