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Machine learning for middle schoolers: Learning through data-driven design

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ABSTRACT

An entire generation of children is growing up with machine learning (ML) systems that are greatly disrupting job markets as well as changing people's everyday lives. Yet, that development and its societal effects have been given minor attention in computing education in schools, which mainly focuses on rule-based programming. This article presents a pedagogical framework for supporting middle schoolers to become co-designers and makers of their own machine learning applications. It presents a case study conducted in the 6th grade of a Finnish elementary school and analyzes students' (N=34) evolving ML ideas and explanations. Data consists of a children's artwork, students' design ideas and co-designed applications, and structured group interviews organized at the end of the ML project. The qualitative content analysis revealed how hands-on exploration with ML-based technologies supported students in developing various kinds of design ideas that harnessed face recognition, gestures, or voice recognition for solving real-life problems. The results of the study further indicated that co-designing ML applications provided a promising entry point for students to develop their conceptual understanding of ML principles, its workflows, and its role in their everyday practices. The article concludes with a discussion on how to support students to become innovators and software designers in the age of machine learning.

1. Introduction

During recent years, a major technological shift has triggered discussions about the need to amend computing education at all education levels (Shapiro, Fiebrink, & Norvig, 2018). Traditional, rule-based automation has been joined by machine learning (ML), which, when provided with enough computing power and data, has enabled new classes of jobs to be automated, and thus expedited automation in society, the workplace, and in people's everyday lives. ML also poses several challenges for education. On the one hand, there is an evident need to prepare young people for emerging work life that is currently being greatly disrupted by ML and automation of knowledge work (Denning & Tedre, 2019). On the other hand, today's children and youth are growing up in a new media ecology where ubiquitous data collection is part of their everyday life (Lupton & Williamson, 2017; Pangrazio & Selwyn, 2019; Vartiainen & Tedre & Kahila & Valtonen, 2020). Understanding the power and limitations of ML is also important for active citizenship as well as for the prosperity of democratic societies (Hintz, Dencik, & Wahl-Jorgensen, 2019).

However, ML has gained very little attention in K-12 computing education and pedagogy of programming, which mainly focuses on rule-based programming (Druga, 2018; Shapiro et al., 2018). As machine learning is becoming part of everyday interactions as well as the core computing knowledge, there is an evident need for empirical research for building a more robust understanding of what existing preconceptions non-programmers have about AI and what are the best practices are for teaching AI to a non-technical audience (Long & Magerko, 2020; Shapiro et al., 2018). Yet, exploration of machine learning applications in education has been challenging due to inherent difficulties in bringing such abstract and highly complex phenomena into children's creative grasp (Vartiainen & Tedre & Valtonen, 2020). Meanwhile, an entire generation of children are growing up with machine learning systems and thus, there is an urgent need for education that prepares students for the data-driven society in which they live (Druga, 2018; Druga, Vu, Likhith, & Qiu, 2019; Shapiro et al., 2018; Vartiainen & Tedre & Valtonen, 2020).

This study is a part of a multidisciplinary, design-based research project that aims to develop and study pedagogical models and tools for integrating ML topics into education. The long-term

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aim is to support students to develop their data agency and skills to become contributing members in a data-driven society (Tedre, Vartiainen, Kahila, Toivonen, Jormanainen, & Valtonen, 2020; Valtonen, Tedre, Mäkitalo, & Vartiainen, 2019). This article presents a proof of concept of the pedagogical framework for supporting middle schoolers to become co-designers and makers of their own machine learning applications. It presents an exploratory case study conducted in a 6th grade classroom of a Finnish elementary school and devotes special attention to the ML ideas and ML applications that students (aged 12 to 13 years) co-designed for solving meaningful problems encountered in their everyday life. To analyze students' design ideas and ML explanations the paper focused on the following research questions:

RQ 1. What kinds of design ideas do the students propose for ML?

RQ 2. How does co-designing ML promote transparency of technology and a better understanding of how it works?

This article starts by introducing the theoretical and pedagogical framework for learning by collaborative design. Then, it presents the research methodology, research setting, and the empirical work and analysis that illustrate children's evolving ML ideas and explanations. The article concludes with a discussion on how to support children to become innovators and software designers in the age of machine learning.

2. Pedagogical framework

This study's pedagogical approach for learning machine learning is rooted in the pioneering ideas of Seymour Papert and his followers. Papert envisioned a world in which children design, create, and program artifacts, and by doing so learn important skills of computational thinking, making, and action in the world (Guzdial, 2015; Resnick, 2017). In contrast to longstanding educational practices that favor learning how to use applications, Papert's (1980) constructionism entails that students are positioned as innovators and software designers rather than just consumers of off-the-shelf products (Resnick, 2017). As such, Papert's visions represented a profound pedagogical change from dissemination and acquisition of information toward design-oriented learning that regards students as builders of knowledge (Papert & Harel, 1991).

In short, the design-oriented pedagogy appears to emphasize three main features that differ from more traditional models of instruction. The first feature to note is the nature of learning tasks that organizes the process of design and learning. While many current models of instruction consist of scripted build-a-thing tasks or step-by-step coding exercises, the design-oriented pedagogy is based on open-ended, real-life problems (Vartiainen & Tedre & Salonen & Valtonen, 2020). Such tasks have no single solution or "right" answers; instead, they provide students with opportunities to generate different kinds of solutions to the problems that the students themselves consider to be meaningful (Krajcik & Blumenfeld, 2006; Seitamaa-Hakkarainen, Viilo, & Hakkarainen, 2010). According to Roth and Lee (2006), the expansion of action possibilities with respect to meaningful problems is also closely connected to students' interests and perceived ownership of learning.

A second and equally important feature in design-oriented pedagogy is the relation between conceptual and tangible aspects of learning (Vartiainen & Tedre & Salonen et al., 2020). While engaged in the design process, the students need to create various kinds of conceptual (e.g. questions, spoken or written ideas) and material/digital artifacts (e.g. graphs, drawing, prototypes, programs) (Hennessy & Murphy, 1999; Seitamaa-Hakkarainen et al., 2010). Such multimodal interaction supports new forms of dialog that make students' ideas and reasoning processes more explicit as well as visible for others (Hennessy & Murphy, 1999; Seitamaa-Hakkarainen et al., 2010). Moreover, an iterative process of creating external representations, followed by collaborative advancement and the refinement of ideas, can lead to increasingly sophisticated understandings of the content domain being represented (Enyedy, 2005). The growing body of research has also revealed how making and constructing technology can be a powerful and generative fairway for exploring key concepts in computer science in a highly meaningful, engaging, and contextualized fashion (e.g. Krajcik & Blumenfeld, 2006; Seitamaa-Hakkarainen et al., 2010; Vartiainen & Tedre & Valtonen, 2020).

Thirdly, the design-oriented pedagogy moves from individual exercises to collaborative learning that appears to mirror the process of expert problem solving (Kangas, Seitamaa-Hakkarainen, & Hakkarainen, 2013; Krajcik & Blumenfeld, 2006; Seitamaa-Hakkarainen et al., 2010). By working together in small groups, students are expected to actively communicate, share their expertise and previous knowledge, make joint decisions as well as to negotiate roles and responsibilities for the joint work (Hennessy & Murphy, 1999). Seitamaa-Hakkarainen et al. (2010) argue that in order to truly appropriate expert-like practices, students also need to have strong, reciprocal relations with domain experts and work together with them. Through participation in the expert practices, the students may, at least initially, begin to acquire the norms, values, and skills that shape the core identity of the community (Brown, Collins, & Duguid, 1989; Kangas et al., 2013), including the tacit dimension of knowing (Polanyi, 1966). In other words, when students are working with domain experts, they may also participate in the *computational practices* and see how science and engineering can be applied to solve important problems of the world. This may also influence young people's beliefs about what it means to be a computer scientist or computational designer, and lower the barriers to entry in the core practices of computing.

2.1. From rule-based to data-driven design

Nowadays, there is a vast amount of research available on learning by designing and how it can be applied in many different educational contexts from science learning (e.g. Kolodner et al., 2003), material making (e.g. Resnick, 2017; Roth & Lee, 2006), digital fabrication (e.g. Kafai, Fields, & Searle, 2014) to programming digital and material artifacts, robotics and games (e.g. Seitamaa-Hakkarainen et al., 2010; Vartiainen & Tedre & Valtonen, 2020). However, researchers are only just beginning to direct their attention to the ways children can become designers and makers of ML applications. The few examples available describe ML projects and workshops where children imagine smart devices and toys of the future (Druga et al., 2019), build models of their own physical activity (Zimmermann-Niefield, Turner, Murphy, Kane, & Shapiro, 2019) and explore how object recognition works through their own drawings (Mariescu-Istodor & Jormanainen, 2019) or through their own facial expression and bodily gestures (Vartiainen & Tedre & Valtonen, 2020). Moreover, there are increasing numbers of games and applications to teach AI and ML concepts to young children (Giannakos, Voulgari, Papavlasopoulou, Papamitsiou, & Yannakakis, 2020). In all, the democratization of AI technologies has opened the possibilities for children to communicate with machines, not only via code but also via natural language and pattern recognition technologies (Druga et al., 2019; Zimmermann-Niefield et al., 2019).

When tinkering with ML, a child does not necessarily need to learn program syntax or write down explicit rules. Rather than deductive reasoning and rule-based programming that drove earlier programming language experiments in education, by using well-designed machine learning-based tools, a child can engage in the process of data-driven programming: providing the machine with a training dataset and then using the trained model to control the machine (Vartiainen & Tedre & Valtonen, 2020). 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. GTM combines state-of-the-art classification algorithms with an intuitive and easy-to-learn graphical user interface. Children can, for example, examine representations created by intelligent agents by having a computer learn to recognize their voice, facial expression, or bodily gestures (Touretzky, Gardner-McCune, Martin, & Seehorn, 2019).

Currently, GTM offers three alternatives to train predictive models. The aim of the *Images* tool is to teach a machine learning 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 second tool, *Poses*, can be used to detect different bodily poses in a similar fashion (the system uses the TensorFlow-based PoseNet for real-time human pose estimation). The key difference between the poses and image classification is that the features important for poses are, for instance, the angle of a certain body part and the orientation of a limb, whereas the features important for image classification are objects in the images and their distinctive features. The *Sounds* tool is built for sound recognition. With the tool, users can train a model to distinguish different noises or audio, such as different people speaking or different sounds in the world. The tool also allows exporting the trained model, which can be embedded in a custom web or mobile application.

In summary, these new computational paradigms can expand the design possibilities for students while also offering them new ways to make sense of the world they live in. Understanding how machine learning models the world also represents one form of data agency (Tedre et al., 2020), which can empower children to understand and question ML systems and data-driven practices that they encounter in their everyday lives, such as those used in face recognition, voice recognition, and other kinds of pattern recognition (Zimmermann-Niefield et al., 2019). However, learning by data-driven design is essentially unstudied in education and thus, there is a clear need to investigate different approaches on how to support children to become innovators and software designers in the age of machine learning.

3. Methodology

This multidisciplinary project employed a design-based research (DBR) methodology—an approach that has been widely promoted in the learning sciences for the development of novel learning environments and models through parallel processes of design, evaluation, and theory-building (e.g. Design-Based Research Collective, 2003; Edelson, 2002). Earlier publication has introduced our first design experiment with very young children exploring GTM in nonschool settings (Vartiainen & Tedre & Valtonen, 2020). The new, unanswered questions that emerged from this earlier study relate to the ways to facilitate children and school students to design and make their own machine learning applications and in a manner that enable children's voices, views, ideas, and experiences to be heard when introducing AI and machine learning to school education.

The present 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. In all, our approach also followed the current trends of including children as contributing members and meaning-makers in the cutting-edge practices of research and development work (Druin, 2002; Fails, Guha, & Druin, 2012). This was promoted by providing the kinds of learning tasks, technologies, and pedagogical processes that position children as designers and creators in the evolving process of collaborative learning and design with expert communities.

3.1. Research participants and context

The participants of the study were two classes of 6th graders (34 pupils aged 12 to 13 years) from a Finnish elementary school. The guardians of all the participating children gave informed consent to conduct the research and consent was also asked from teachers and school administrators. The ML project included 3 workshops (each about 2–3 h, depending on the class schedule) during a period of two weeks. As the Finnish National Core Curriculum [FiNCC, 2016] emphasizes the development of transversal (generic) competences and project-based studies, these ML-projects were implemented as a part of regular curricular activity. As the study was part of the school's normal activities, no additional ethical review was needed from the Ethical Council.

3.2. Data collection and analysis

In this project, the data collection was embedded in learning tasks with the aim of supporting students to externalize their prior knowledge and evolving ideas. Accordingly, the data consisted of a (1) individual introductory task (given at the beginning of the project), (2) children's group discussions (first workshop), (3) brainstormed design ideas (at the end of the first workshop), (4) interface designs (the second workshop), (5) co-designed applications (third workshop), and (6) individual post-task (given at the end of the whole project). Moreover, (7), structured group interviews were organized at the end of the project, including general and follow-up questions based on three themes: (1) children's background and general interest in technology, (2) 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 min to 47:11 min (average 21:02 min). Moreover, the researchers made observations and took many photos to record the emerging activities throughout the intervention.

3.3. Implementation of the project

Before the co-design project, the students were given an introductory task to draw and/or write what they knew or thought they knew about artificial intelligence (Liljeström, Enkenberg, & Pöllänen, 2013). More particularly, the students were asked to externalize their thoughts and ideas 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. 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 (Liljeström et al., 2013). At the end of the project, the students were given the same task to capture the changes in student thinking (post-task).

The first workshop began with a short introduction of the fundamental ideas and use cases of ML and how it is present in people's everyday life. The students were also told that in this ML project, the students were to work in teams and to co-design

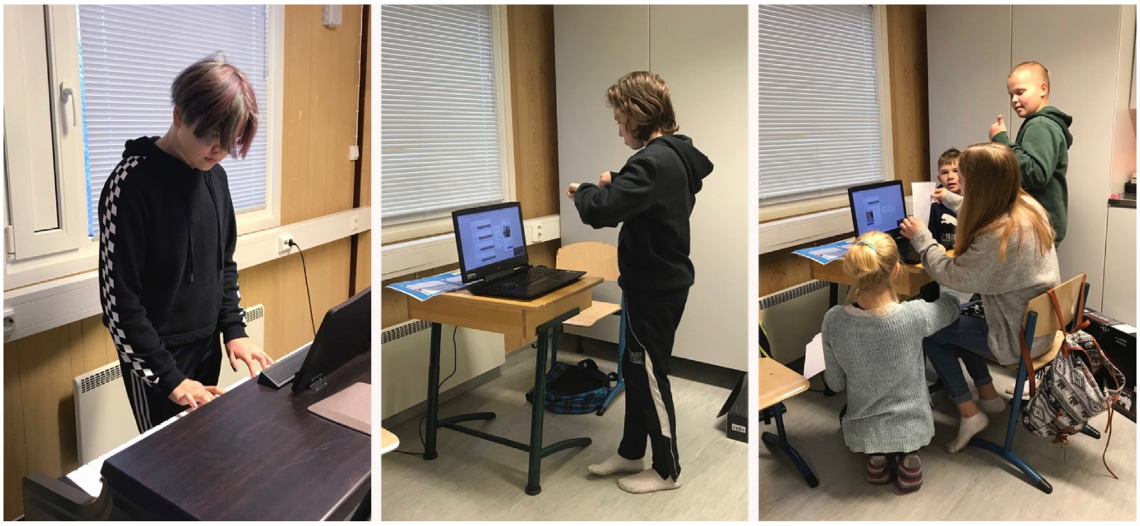

Fig. 1. Creating training datasets for ML applications (sound, pose, image).

a new 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 ML-based solutions to real-life problems that they had identified.

In all, the first workshop emphasized the ideation process, and it had a special focus on contextualizing ML in 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.

Moreover, the students were also familiarizing themselves with the possibilities of Google's Teachable Machine 2 (GTM2), and our own in-house developed educational application for ML (Mariescu-Istodor & Jormanainen, 2019) though playful exploration. GTM2 was used as the main tool for co-designing and creating ML-applications, and our own educational app was presented in the first workshop as a tool for exploring how object recognition works. The application recognizes objects based on just two features both of which the children can easily understand—aspect ratio and fullness. It visualizes to learners how it classifies each picture, and lets children experiment with some of the parameters (Mariescu-Istodor & Jormanainen, 2019). At the end of the first workshop, the students were assigned an individual homework task that asked them to search and identify everyday problems that could be solved by using ML-based technologies. The task was aimed at brainstorming contextualized design ideas for students' own ML applications and it also provided research data on how students' ideas about ML develop.

Before the second workshop, the computer science researchers selected nine student ideas that were to be further developed as web-based ML applications. The selection was based on the feasibility of the idea in terms of the design constraints; namely the particular ML technologies that were used by the students in the limited timeframe of the project. 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 and ML design.

At the beginning of the second workshop, the students were divided into co-design teams based on their interests with selected ideas, with some support from teachers. Nine design teams were formed and the first task for the teams was to further articulate and develop the selected ML application idea. For that, the teams were given a ML design template that asked students to negotiate what the app does, what kind of data are collected and from where (image, sound, poses), how many different categories should the model recognize and under what conditions the teaching data will be given (such as background noise or background setting). 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 though their designs.

These ideas were further defined in collaborative discussions between children and computer science researchers who also gave on-demand support as the children were training datasets for their own ML applications by using GTM2. The second workshop emphasized active making; some of the groups were training a machine to recognize their poses, others were searching or making images while one group was recording instruments in the music class (Fig. 1). What is more, at the end of the workshop the teams of students were also asked to draw interface designs for their own applications. These visual interface designs provided research data on the evolution of children's ML design ideas and explanations. Moreover, based on the students' designs, we then developed a mobile-friendly web application for each group.

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 (Fig. 2). At the end of the final workshop, each student team was interviewed and asked to reflect on the process of collaborative design and learning as well as to give feedback about the applications. Few days after the whole project, the students were given the individual post-task to draw and/or write down, again, what they now knew or thought they knew about artificial intelligence.

Fig. 3 summarizes the applied instructional model and related dimensions of the learning environment.

3.4. Data analysis

The data were analyzed through qualitative content analysis (Chi, 1997). To identify students' ideas and their advancement

Fig. 2. Testing co-designed ML applications.

Fig. 3. The instructional model for a design-oriented pedagogy and related dimensions of the learning environment.

during the process of co-design and learning (RQ 1), we constructed a theory-driven coding template to explore the primary elements of mediated action (see Vygotsky, 1978). We began by exploring the students' design ideas in the individual brainstorming task assigned to them after the first workshop. First, we analyzed students' descriptions of the object of activity; the problem to be solved and its justification. Secondly, we mapped with each activity the type of ML model used in each idea (image, sound, poses). Thirdly, we identified for whom the design solution was meant (subjects).

After analyzing students' initial design ideas, we then proceeded to analyze how students elaborated their application ideas in their dataset and interface designs, and how they used the tools and technologies as mediational means for collaboratively creating training datasets for ML applications (second workshop). We proceeded to analyze the improvement needs that the students identified when testing their own applications (third workshop). To track down how students elaborated their ML ideas over the main phases of co-design (Fig. 3), we triangulated (Quinn Patton, 1999) the data by combining and examining consistency from multiple data sources: from the interface design, interviews, and co-designed applications.

In order to explore how co-designing ML promotes transparency of technology and a better understanding of how it works (RQ2), we searched for children's descriptions of ML concepts and data-driven processes particularly from the children's artwork (introductory task, post-task, interface designs), and from the final interviews (in which the children were asked to elaborate on the functionalities of their designs and explain in their own words when, how, and why their app was not functioning as expected). Combining multiple data sources allowed us to better understand children's emerging data-driven reasoning and how their evolving conceptual knowledge was contextualized through the co-design process and children's own app designs.

To increase the reliability of the data analysis, the results of the analysis were negotiated between the researchers. Furthermore, four authors observed every workshop to support in-depth analysis of the data. With respect to the limitations of this qualitative study, the empirical research was situated in complex, real-life settings, where numerous interrelated contextual factors, variables, and processes were present (Squire & Barab, 2004). To address these concerns, a deliberate effort was made to provide a rich description of the guiding goals and theory, the design features and implementation of the intervention, and the impact that these features seemed to have on the process of learning and co-design (Squire & Barab, 2004). As an exploratory case study, this study did not aim at generalizability, however, detailed descriptions of the research context, data, and methods support the transferability of the findings (Shenton, 2004).

4. Findings

This section provides more specific descriptions of the emergent process of co-design and learning, together with illustrative quotations. First, we present students' ML ideas. Second, we present student explanations of ML, elaborated with their recognition of ML-based automation in their everyday lives.

4.1. Students' ML design ideas

After the first workshop, the students brainstormed various kinds of design ideas or problems that could be solved by using ML. These ideas included, for example, home automation applications that used face recognition for access control, gestures for opening doors, automated alarm systems, as well as sound and image recognition for feeding cats. Moreover, students' ideas also focused on automation of homework, such as applications that show mistakes or correct answers when taking a picture of homework.

Some of the students ideated improvements of their personal privacy, such as replacement of Snapchat and Instagram passwords through face or voice recognition. One girl also ideated an application that hides other applications: "*The name of the application would be "monster". It would "eat" or inside of it, one could transfer other apps on the touch screen or on the computer to keep them secret. When the program was downloaded, you had to input your photo and voice. Whenever you open an application, you have to show your face and say something with the same voice. But if you have the flu, and your voice is different, then you can enter a password that can be changed, but with the same face and voice.*"

What is more, some of the ideas expressed design empathy in relation to understanding other people's needs. This became evident as the students ideated applications that help other people in their work or everyday life. These included things such as face or voice recognition applications that help teachers monitor student attendance or silence, a health detector that reduces visits to the doctor as well as a face recognition system that helps police officers to detect criminals. Moreover, students' ideas included a color detector for color-blind people as well as an application that helps children and adults to identify edible berries and mushrooms. Some of the students also generated ideas for service automation, such as an automated shopping list, fake product detectors, as well as stores that identify customers and automatically detect when a person buys something. Perhaps the most comprehensive description of a design idea came from a girl who was also pondering the consequences of her idea related to service automation:

"a shop could recognize who goes there and a person could be identified from their face, for example, or there could be some code that would then be given to the one who goes inside the shop. The store could also recognize when a person buys something so it would have a sensor where it would take the payment and identify who took an item. There would be a small camera on the store shelf that would recognize who was buying the product and take payment out of their bank account. But of course, if that were the case, there would be no cashiers and those cashiers would lose their jobs".

The analysis showed that while the ideas were connected to different kinds of everyday problems, they typically were based on image recognition or recognition of sounds or poses: the technologies that students had been presented. As most of these students did not have any experience in ML-based educational technologies, the analysis of students' ideas indicates the important role of playful, hands-on exploration with the tool that provided different modes of interaction with a machine: image, sound, and gestures.

4.2. From ideas to explicated datasets and interface designs

In the second workshop, the student teams were guided to develop the selected ideas and to produce training data sets for their own applications. Table 1 presents the co-designed applications together with students' own descriptions of their specific purpose.

The analysis of co-designed applications revealed that the students did not refine their original ideas, but were more focused on pondering how to implement these ideas in practice. This involved the guiding and coaching activities of the computer scientist who familiarized the students with planning regulations as well as requirements and conditions of building a good dataset. When the process progressed to the phase of creating data sets for ML applications, children's embodied contributions turned the design ideas into a digital form. The student teams were working with data in terms of their own ideas and thus, some of the groups were, for example, recording their own emotional expressions or gestures while other students played famous songs by Metallica. Training ML models for their own applications also included an important feedback loop on the implementation of their design ideas, as the students could receive immediate feedback and test and improve the quality of their own data. GTM2 did not always work as students expected: For instance, voice recognition had trouble with background noise, and image recognition was affected by webcam background. Hence, the students had to reason about the relationship between their own training data, test data, and the ML model output.

What is more, these ideas were further externalized through interface designs in which students gave visual and processual descriptions of their applications. The analysis of interface designs revealed that ML concepts such as class, training, and confidence were emerging as a part of the described functionalities of the design (Fig. 4). These drawings not only externalized evolving design ideas but also provided one indicator of children's growing conceptual understanding.

Interestingly, one group of four girls was very keen on contextualizing their design idea in terms of ML-based apps found on their own smartphones (Fig. 5). The interviews confirmed that most of these 12-13-year-old students were very active users of many ML-based applications such as Instagram, WhatsApp, Snapchat, Tiktok, Facebook, YouTube, Steam, Netflix, and Spotify.

4.3. Improvement ideas

The final meeting (workshop Day 3) was held two weeks after the model training. For this meeting, we built nine simple web applications based on the students' specifications and on the neural network based models they had taught. After the students

Table 1
Presents the co-designed applications.

Design team	GTM's model type and data	Description of design problem/idea
Group 1 (3 girls and 1 boy)	Image recognition: different color pictures derived from the Internet and color paper	*"Identification of colors for color-blinds"*
Group 2 (3 girls)	Image recognition: Students' own facial expressions and poses	*"An app that detects your mood. If you are bored the app will tell you something to do and if you are feeling sad, the app will comfort you."*
Group 3 (5 boys)	Image recognition: pictures from the internet and text books	*"When children or adults collect mushrooms and berries, they may not be sure the mushroom or berry is toxic. So it would be good for them to have something that helps them to check it. That's why I thought it would be good to have an application that could check this."*
Group 4 (3 boys)	Image recognition: students' hand-written letters	*"An application that allows you to take a picture of an essay and it recognize the letters and correct errors automatically."*
Group 5 (4 girls)	Image recognition: students' hand-written numbers	*"It can check math calculations but also handwriting. So you show the calculations to the camera and if it doesn't understand the handwriting then you need to improve it. Then, when the handwriting is good, it shows whether the calculation is right or wrong."*
Group 6 (2 girls and 2 boys)	Image recognition: students' hand-written numbers	*"calculator, if you can't count something on your head then you can use it."*
Group 7 (4 girls)	Sound recognition: students' own speech	"Vahturi" ("watchman")—*When the teacher leaves the classroom, she/he leaves the app to record the speech of the students. The app recognizes who talks and counts how much each student talked."*
Group 8 (3 boys and 1 girl)	Sound recognition: students playing their own instruments	*"Teachable Machine could be taught to recognize music on different instruments .. and different chords of guitar and other instruments"*
Group 9 (3 boys)	Posenet: Students' own poses	*"Door opening it with Teachable Machine that recognizes the feelings of people's from their faces, for example, if you are angry, that program also recognizes different positions"*

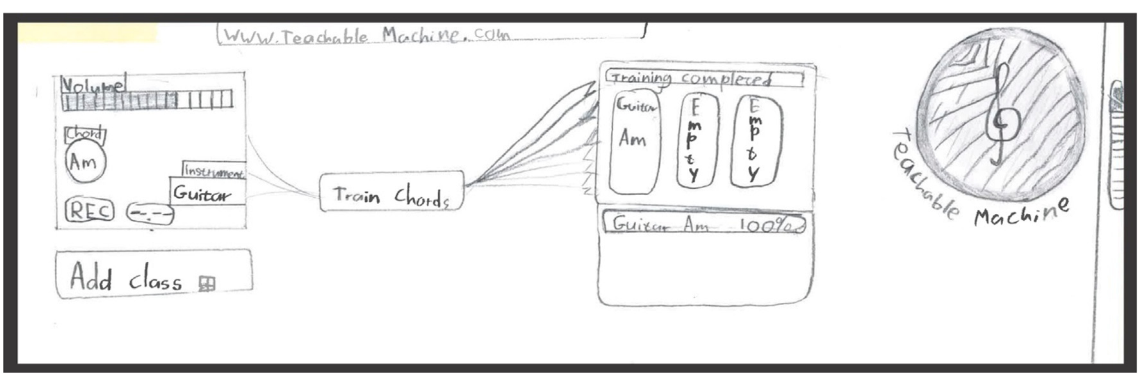

Fig. 4. Interface design of an application to recognize different instruments and chords.

had tested all the applications, they were asked to give feedback about the applications as well as to ponder improvement ideas. Typically, these improvement needs focused on the prediction accuracy as well as functionality of the application, as illustrated in the following example from group 5—which also shows limitations in students' understanding of what exactly does pattern recognition do:

Interviewer: *Well, what are the things that you are satisfied* [with your own application]?

Marjaana: *That it*

Outi: *That it can identify numbers. Somehow.*

Marjaana: *Somehow.*

Interviewer: *Yes*

Outi: *It is supposed to be a calculator so it counts additions and these are...*

Marjaana: *Yes*

Outi: *…but in only recognizes numbers and does not do anything else.*

Moreover, the students were also keen on ideating more image classes for recognizing new objects and some of the groups even wished their applications would be published in app stores. In the interviews, many of the students also mentioned that the invention and design experience was challenging, but at the same time, the most fun during the ML project. Some of the students also reflected on the process of design in terms of the change in

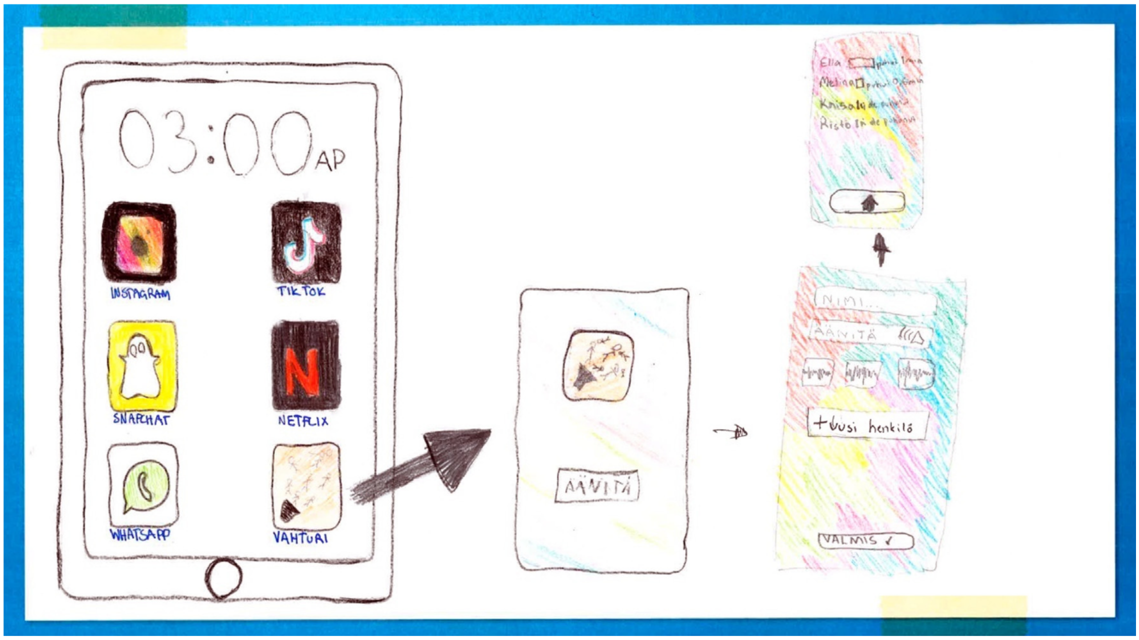

Fig. 5. Interface design of the "Vahturi" ("watchman").

their experienced agency, as depicted in the following example from a group of four girls

Jonna: *But, I guess, it was also nice to plan and...*
Katja: *Yes. And talk.*
Jonna:*... and implement and...*
Pirita: *Yes and we could make ourselves...*
Jonna: *...invent our own ideas and finally influence ourselves...*
Katja: *The most annoying thing was to write these.*
Jonna: *...because usually it is what the teachers says.*

4.4. Evolving ML explanations

In the interviews, most of the children said that they did not have any experience of ML-based educational technology. The analysis of the introductory task, organized before the intervention, showed drawings that typically included computers, humans, and Internet symbols or provided short written explanations, such as "*I think that a computer learns from humans or from a cloud*". The analysis of data also indicated that the children had not themselves recognized ML as part of their everyday life nor consciously reflected their own data practices before the intervention. While some of the students returned the paper nearly empty with one question mark, a few of the students produced rather informative descriptions of object recognition as illustrated in Fig. 6.

The analysis also revealed that after the project, ML concepts, such as training set, prediction accuracy, and class label were emerging in the students' illustrations (post-task). Many of the students also recognized that the training data can be in diverse formats, including text, picture, voice, or a pose (the GTM standard types). For example, one girl who returned the introductory task with only one question mark, described the process of teaching a machine in the post-task in the following way: "The machine can be taught in many ways, for example, with the thing that we made. That machine learning program. The machine learns when it is shown, for example, a picture of a number or some other artifact, picture or a person". After the project some students created more detailed process descriptions, as depicted in Fig. 7:

In the post-task, some of the students were even considering the relationship between data and confidence in the process of data-driven design, as evidenced in the written process description of one boy: *"Make an idea → implement it → everything is not working → more examples → some things are working → more data → everything is working → voluntary more data"*. In a similar vein, the students engaged in data-driven reasoning in the interviews when asked to elaborate on the accuracy of their own application, as illustrated in the discussion of group 6:

Interviewer: *Development. So what was difficult?*
Erno: *Well, to teach those numbers to it, because it did not learn everything.*
Kaisa: *At the beginning it did not recognize anything, maybe three numbers...*
Interviewer: *Yes...*
Kaisa: *Then we tried to give more pictures to it and then it began to recognize.*

Below is another example of students' explanations of how the training data affects the results, provided in the interview by a team that co-designed an application to recognize different instruments and chords (see also Fig. 4).

Teemu: *Then it does not 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 does not 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 does not 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*

In the post-task, however, there were no connections between the ML design process and ML-based technologies that these

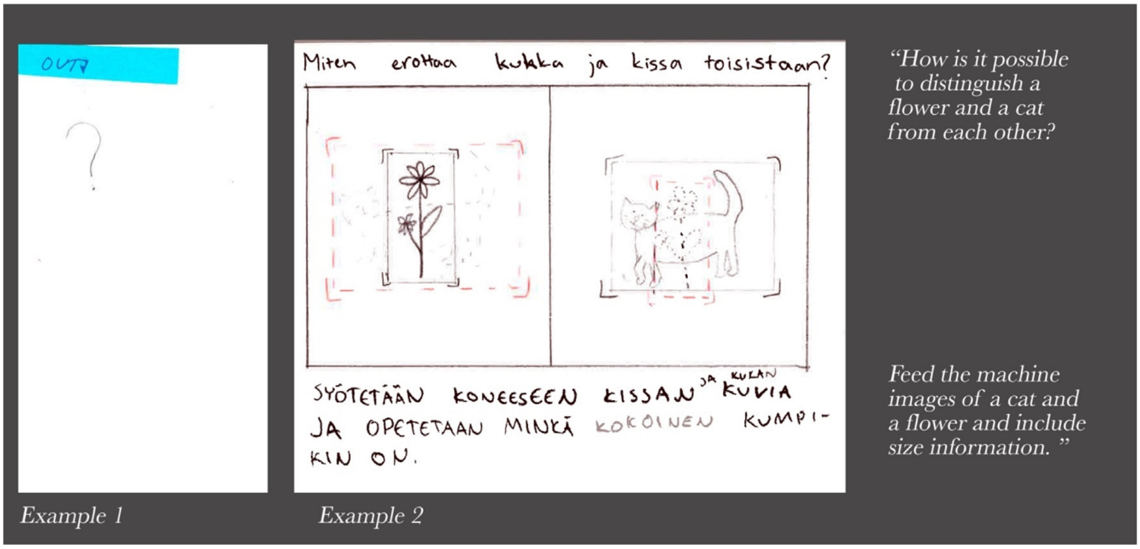

Fig. 6. Two examples from the pre-test.

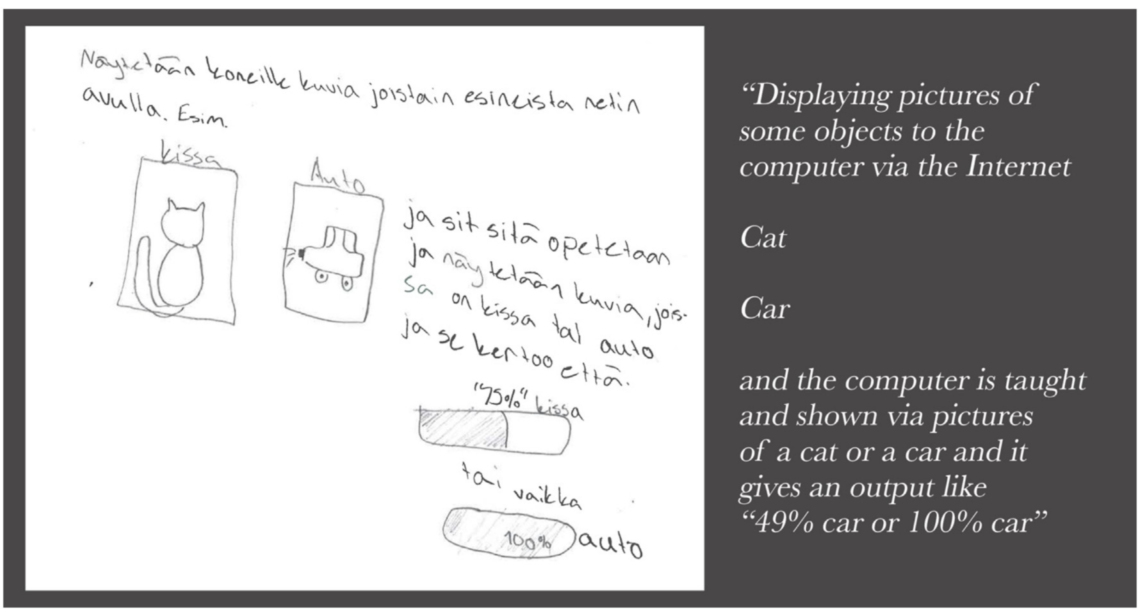

Fig. 7. Example from post-task.

students use in their everyday lives. There again, 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 actively use:

Interviewer: *Do you use any of those apps that your peers mentioned, such as What'sApp, Instagram, Snapchat*
Elmeri: *I use them.*
Nuutti: *Yes.*
Saku: *Yes.*
Interviewer: *You all use them?*
Nuutti: *Yes.*
Interviewer: *So what do they learn from you?*
Nuutti: *This and that* [laugh]...
Interviewer: *Any ideas? How does this kind of app learn? You said some ideas earlier.*
Elmeri: *Well, YouTube, for example, from those videos that you watch, so it watches what kind they are...and then similar kinds and who they are from, and it recommends similar videos.*
Saku: *Mm.*
Interviewer: *Yes.*
Saku: *And then WhatsApp—if you use emojis in WhatsApp, so those you have used the most often are listed first.*

5. Conclusions and discussion

An entire generation of children is growing up with machine learning (ML) systems that are greatly disrupting job markets as well as changing people's everyday lives. Yet, that development and its societal effects have been given minor attention in computing education in schools. While there is a solid body of research on technology education and design-oriented pedagogy to draw from (e.g. Resnick, 2017; Seitamaa-Hakkarainen et al., 2010; Vartiainen & Tedre & Valtonen, 2020), there is also a clear need to investigate how to support students to become innovators, designers, and informed citizens in the age of machine learning. This exploratory case study was aimed at addressing this need by studying students' ML ideas and applications that they co-designed for solving meaningful problems of their everyday life.

Regarding the first research question, "*What kinds of design ideas do the students propose for ML?*", the analysis of ML design ideas revealed that students, who with few exceptions had no experience of ML, could produce various kinds of design ideas that harnessed face recognition, gestures, or sound recognition for helping people in their everyday life and work. Evidently, these ideas were mediated by and derived from the playful exploration with ML in the first workshop where children could communicate with a machine via voice and pattern recognition technologies and PoseNet. Accordingly, such bodily modes of interaction not only lowered the barrier of entry to using ML and experimenting with the possibilities of ML, but also supported children to imagine solutions to problems beyond their immediate experience. It is also worth noting how children's ML ideas exhibited empathy in relation to understanding other people's needs, and that is an essential part of design-thinking.

In the second workshop, these ideas were further developed by explicating and defining requirements. The analysis of interview data as well as children's interface designs revealed how advancement of design ideas challenged children to engage in inductive reasoning, as they needed to produce the relevant datasets for their own applications as well as to evaluate the accuracy of the model. The collaborative creation of training data also relied on bodily modes of interaction with computers that supported children to explore some abstract ML concepts in a tangible and highly personalized way (Vartiainen & Tedre & Valtonen, 2020). Furthermore, the interactive ML tool provided an immediate feedback loop and opportunity for students to reflect on how the computational agent might represent the world and perceive the information it receives (Druga et al., 2019). Accordingly, the ways in which children's design ideas evolved were not determined merely by the object of action or students' own contributions, but were also mediated by the ML tool that afforded co-design activities.

Moreover, children were also externalizing their evolving ideas through their own interface designs that illustrated the visual and functional properties of their applications. That process made visible the students' evolving ideas, enabling their collaborative advancement (Hennessy & Murphy, 1999; Seitamaa-Hakkarainen et al., 2010), in shared activities with domain experts. While the children did not code these apps themselves, at the same time they participated in and practiced many core practices of design and computing with expert communities. This study supported these reciprocal relations with domain experts (Seitamaa-Hakkarainen et al., 2010) by harnessing students' own ideas and interests for collaborative activities with more mature members of the community. The freedom to design meaningful applications also gave room for development of students' agency and ownership of learning and design.

In the testing phase, the students were challenged to evaluate their designs and functionalities of their applications. At this point, some students were still dissatisfied with the efficiency of their trained ML models and were able to give informed explanations of why their app did not function as expected. While students often have difficulty identifying the limits of ML (Long & Magerko, 2020), the results of this study suggest that having learners create personally relevant training data sets as well as test their own applications may support students to recognize ML's strengths and weaknesses.

Regarding the second research question, "*How does co-designing ML promote transparency of technology and a better understanding of how it works?*", the results suggested that apprenticeship of that type provides a promising entry point for students to develop their conceptual understanding of ML by creating a rich web of memorable associations between concepts themselves and the real-life problem-solving contexts at hand (Enyedy, 2005). In the post-task, some basic ML concepts appeared in the artwork and in the final interviews, and children were also able to give informative explanations of the problem spaces in which their own app worked. This illustrates how the new conceptual knowledge was applied in design practice as well as for improvement of ideas. The results confirmed that making and constructing technology can be a generative fairway for exploring key concepts in computer science in a highly meaningful and contextualized fashion (e.g. Blikstein, 2013; Krajcik & Blumenfeld, 2006; Seitamaa-Hakkarainen et al., 2010; Vartiainen & Tedre & Valtonen, 2020). It can also help the students develop a better understanding of the tools that afford human action, as well as skills necessary for operating them.

While the results of the study showed advancements in students' understanding of the basic ML concepts, workflows, and limitations, the quality of students' ML explanations varied. Moreover, the analysis of students' interface designs, post-task illustrations, and explanations in the final interviews indicated that evolving conceptual knowledge was typically contextual, strongly linked with their own applications and the ML tool (GTM2) that was used. On the one hand, this may indicate students' engagement in the shared design task, but on the other hand, it may also indicate that the internalized ML concepts were tool-dependent. While GTM2 allows the creation and testing of ML models without classical or block-based programming, it also completely hides the neural network operations. Interacting with black-boxed AI may also lead children to develop oversimplified notional machines, which can be difficult to change once formed (Hitron, Orlev, Wald, Shamir, Erel, & Zuckerman, 2019) Accordingly, there is an evident need for explainable AI (XAI) for K-12 (Toivonen, 2020).

The results of the study further confirmed that students are surrounded by various kinds of ML-based applications in their everyday interactions, but apparently, they generate personal data with little understanding of where, how, or why the data are being collected and processed (Lupton & Williamson, 2017; Pangrazio & Selwyn, 2019; Tedre et al., 2020). While this short intervention was successful in engaging children to co-design their own ML applications that also supported their understanding of the basic concepts and mechanism of ML, it was less successful in raising children's critical stance toward ML-driven services and data-driven practices of their everyday life. There again, the final interviews showed signs of recognition that computers can learn from data, including one's own data (see Druga, 2018). The act of designing and creating one's own ML applications may represent one pathway for making technology more transparent by revealing what underpins data-intensive applications of everyday life.

5.1. Limitations, future studies and implications

While combining several data sources for qualitative content analysis allowed us to explore students' evolving design ideas and explanations of ML, quantifying the introductory task-post task could have increased the reliability of the analysis. However, the target group was small and statistical explanations were not the focus of this exploratory study; the study focused on rich data on students' evolving ideas and explanations in tool-mediated actions. Further methodological development and collection of data across diverse contexts and target groups are certainly needed for understanding student progress in ML. Results from several different contexts and from different age groups would also provide more insight on the best practices for teaching ML in K-12 education. Moreover, an interesting future step would be to connect data-driven design with material making, and studying whether that can improve children's understanding of embedded technologies as well as how ML gathers data and how it interfaces with the material world (Long & Magerko, 2020; Touretzky et al., 2019).

Given the paucity of research on the educational opportunities of machine learning technologies in K-12 education, this experiment advances the field by providing core pedagogical insights together with some early results and first-hand experience with a low-threshold ML tool. The theoretical and pedagogical grounding as well as their example application in tool-mediated action provide intermediate-level knowledge (see Barendregt, Torgersson, Eriksson, & Börjesson, 2017) that could be used as a starting point for future research in a pursuit of equitable and inclusive AI education. Data-driven design that builds on children's prior knowledge and interests, hands-on learning, embodied interaction and students active agency (e.g. Krajcik & Blumenfeld, 2006; Resnick, 2017; Seitamaa-Hakkarainen et al., 2010; Vartiainen & Tedre & Valtonen, 2020) maybe, for example, integrated with the regular curricular activity of schools through integrative STEAM projects as well as in elective courses. Design-oriented pedagogy combined with visual, auditory and bodily modes of interactions with a computer fit STEAM education especially in those cases where generic laws and rules may not be readily available. Because not all teachers are already skilled in ML-based technologies, we emphasize the importance of participatory methods (Druin, 2002; Fails et al., 2012) and cross-boundary collaboration that will assist expanding culturally relevant approaches across schools and teacher education as well.

Moreover, the results show preliminary insights for developing an understanding of ML and its role in their everyday practices. We see these results as highly important, as the students were able to name the phenomena they had previously encountered when using, for example social media, and realized that the machine learns from the data produced by the users, in this case the students themselves. We believe that projects like this are needed in order to help children build their data agency: their ability and volition to be an active player and contributing member in the data-driven society.

6. Selection and participation

The present study was guided by the ethical principles of research in the humanities and the social and behavioral sciences, provided by the Finnish Advisory Board on Research Integrity (2009). The aims, research methods used, and publication plans were explained to the participants and participation was voluntary.The guardians of all the participating children gave informed consent to conduct the research and consent was also asked from teachers and school administrators.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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