and are aligned with their strengths, understand the occupational implications of the advancement of AI, and outline resources and barriers along their paths to their future dream jobs. Importantly, youth will recognize their AI career-related skills and resources, and develop their capacity to internalize these skills as they formulate future career ideas.

3.4 The Curriculum

The DAILy curriculum interweaves teaching of AI concepts, raising awareness of AI adoption in future jobs, and the investigation of ethical issues in AI. Learning activities include hands-on games, discussions, and building projects that integrate AI capabilities into a custom Scratch-based toolkit. Students learned key AI concepts such as Logic systems, Machine Learning, and Generative Adversarial Networks (GANS) and were engaged in working with both classification and generative uses of AI to develop a fundamental yet holistic view of AI.

The 30-hour curriculum features (1) an Introduction to AI, (2) logic systems (e.g., decision trees constructed by humans), (3) supervised learning (e.g., concepts, processes, and bias) with Google's Teachable Machine, (4) neural networks through a participatory simulation game, and (5) Generative Adversarial Networks or GANs. Within each unit students investigate the existence and causes of algorithmic bias, its societal and ethical implications and ways to mitigate bias; and also gain awareness of AI related careers, recognize their own strengths and interests for future jobs, and realize the importance of technical skills development and the ongoing nature of change and adaptation in today's job world. The detailed curriculum can be found at **aieducation.mit.edu/daily** [2].

Below we describe the connections made between AI concepts, ethics, and career awareness in unit 6. In this unit, we begin by introducing generative machine learning through a color generation activity called “Classifier vs. Generator”. Since these students have already completed a lesson on classification using Supervised Learning, we introduce the process of generation through the creation of new media, and contrast it with the process of classification in which existing media are arranged into categories. Students experience the processes of generation and classification by mixing colors in an online platform called “TryColors” [4]. During the generation stage, students observe that even with a few input colors, they can create a varied palette of colors. Next, in the classification stage, students arrange their generated colors into existing color buckets.

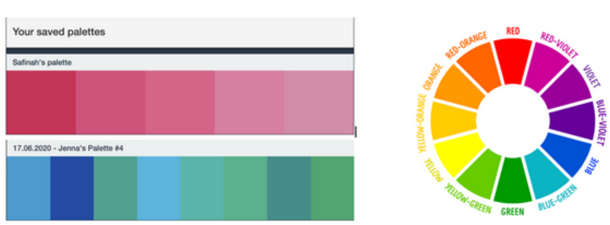

Figure 1: TryColor activity: students generate color palettes using a few starting colors (left), then they classify their generated colors into color wheel buckets (right).

Through this activity, students grasp the difference between algorithms that classify and those that generate. Students then learn about examples of AI systems that perform classification and generation and practice distinguishing between the two. Next, we introduce Generative Adversarial Networks (or GANs) as a type of AI that can generate media after being trained on datasets of media samples. Awareness of GANS in daily life is raised as students learn to distinguish GAN-produced media from human produced media and practice searching for tell-tale signs of algorithmically generated media in an activity called “GANs or not”. We conclude the unit by connecting the core concepts to ethical considerations and career futures. After examining different works of art generated by GANs, we discuss the ethics of GANs (with prompts like “Who should get credit as the artist?”). Then we watch a video about an artist who uses AI as a tool for creative expression, and engaged students in ideating about how AI is utilized in artistic creation and what they would like to generate with GANs.

3.4.1 Conversion of Activities for Online Settings. We adapted the DAILy curriculum for remote synchronous online instruction in preparation for the online summer workshop. This entailed the conversion of several in-person classroom lessons to online activities. For instance, Unit 1 consisted of an *AI or Not* activity, in which students sorted physical cards with pictures of common technology (such as Alexa) as *AI* or *Not AI*. For the online adaptation, we made use of Google Drawing, and digital cards that students could drag into an *AI* side and a *Not AI* side. Each student was provided with their own copy of the Google Drawing with all the cards initially in the middle. They were tasked with sorting the cards individually into the two categories.

3.5 The AI Workshop

The AI workshop was offered in Summer 2020, in partnership with a youth serving community organization. Due to the COVID-19 pandemic, the course was taught virtually. Students met online, on Zoom, for three hours per day each weekday over two weeks. The course was taught by a team of researchers and educators. Each session typically started with the instructor introducing the unit's topic, followed by a whole-class activity, a small group or individual activity, a discussion relating to ethical implications, and connections to AI careers. Participants were grouped by age into three groups of 10 or 11 individuals for small group discussions and hands-on activities.

4 IMPLEMENTATION EXPERIENCES AND CHALLENGES

4.1 Student Participation and Engagement

Classroom observations revealed that the enactment of the DAILy curriculum was successful overall. Students completed all curricular activities outlined in Table 1 with high attendance rates (85 to 95% of all participants attended each day). They actively participated in almost all activities, including the technology explorations, interactive lecturing, embedded assessments, class discussions, daily reflections, and final projects. However, the percentages of students who submitted the completed work for each individual activity ranged from 80% to 30%. One reason for the varied submission

Table 1: The DAILy curriculum: interweaving of AI concepts, ethics, awareness, and careers

Unit	AI Concepts	Ethics	Awareness	Careers
Unit 1	What is AI?	Best PB&J and Ethical Matrix	AI or not AI?	
Unit 2	What are Decision Trees? Pasta-Land	Investigating Bias in AI	Examples of Bias in AI	What will your future career be?
Unit 3	What is Supervised Learning? Explore Teachable Machine	Algorithmic bias. Examples of algorithmic bias.	Supervised Learning in your life - AI Bingo activity	Inventory of me
Unit 4	What is a Neural Network? NN game	Where bias might be embedded in NNs.	Examples of where NN are used	Work personality and matched occupations
Unit 5	How to train a Supervised Learning model in Teachable Machine.	How accurate is your model? What is the potential for bias?	Image classification in your life	Planting seeds of STEM/AI careers
Unit 6	Classifier vs Generator. What are GANS?	Ethics of GANs	GANS or not	People working in AI fields. Creativity in STEM/AI careers
Unit 7	How do GANs work? Generator vs Discriminator game	Art & Ownership discussion	GANs in your life. Engage with various applications of GANs	AI's impact on my future field of work? People working in AI
Unit 8	What are Deepfakes?	Deepfakes and Misinformation	Deepfakes in your life. How misinformation spreads	People working in AI related fields continued.
Unit 9	What is Text Generation? Make a text generator	Best Ethics of text generation	Text generation in your life. Examples of text generation	People working in AI related fields continued.
Unit 10	Ethical Design of AI. Redesign YouTube	Ethical issues in AI (recap)	Stakeholders have different goals for AI	My Career Roadmap

rates may be related to the degree of interactivity with peers in the activities. For example, in the "Investigating bias" activity, students participated in impassioned discussions on examples of bias they noticed in everyday life, commented on each other's examples, and searched online to uncover new examples of biases (such as results of Google image searches). In contrast, submission rate for the corresponding assignment, that of documenting a search for bias, was low despite the high engagement of students.

Based on these findings, we posit that students preferred live exchange of their thoughts and ideas with peers to writing them down, when exploring bias and other ethics-related issues. In the "TryColor" activity, the low submission rate may be related to the gamified approach employed in the activity. Over half of the students spent almost all the allocated time on the game of generating their own colors and replicating others' colors. Many of them ended up with insufficient time to complete the assignment. In addition, we postulate that the low submission rate of assignments may be related to the Google Classroom we used to manage the enactment of the workshop. While this tool helped deliver the workshop activities in a well-structured way, it made the experience resemble school-based ones, which did not resonate well among youth in the out-of-school setting. It is understandable that students in this by-choice summer program felt reluctant to submit multiple assignments every day as they would in school.

4.2 Student Experiences with Activities

We examined students' daily reflections and interviews to reveal more detailed information about their experiences during the DAILy workshop.

4.2.1 Ethics in AI activities. The findings show that students mostly enjoyed ethics-related activities of Unanticipated Consequences (Unit 8) and Investigating bias in AI (Unit 2). 10 out of the 11 students who volunteered to be interviewed after the workshop thought these activities were their favorites. The "Unanticipated Consequences of Technology" activity engaged students in working in small groups to first brainstorm one consequence of a technology (e.g., Lady GAN is a new pop star whose music is created completely by generated music and lyrics to match the style of Lady Gaga). The group then sent their consequence to other groups for the attendant consequences. Finally, the first group reviewed and reflected on the resulting consequences. Students expressed their excitement when working on this activity in the interview, e.g., *"That [activity] was hilarious because a lot of the consequences my group came up with totally turned the tables. Some of them made it much worse and some of them just made it much better, but it was total opposite from what the first consequence with Amelia [pseudonym of a student in the group] was."* During the post-interview, students were also able to internalize what they had experienced and to connect to ethical implications of technology design, *"because if people who make the AIs don't think enough through it, they can have hard consequences and bad consequences. People can get sued if they don't check over or people can get in like a lot of trouble and damage if they don't check over. But it [this activity] was funny, but it's realistic."*

4.2.2 Investigating bias. Similarly, students actively participated in the "Investigating bias in AI" activity where they learned about case studies of bias in AI systems, conducted investigations (searching images of physicists online, etc.) to explore bias present in common technologies, and discussed the implications. In the post-activity discussion, students were surprised to recognize that bias has been existent in many daily technologies, e.g., *"when we typically think of Google, we think it's objective, it's always right, but it's not always represented in the right way"*. We noticed that female students from underrepresented groups were particularly active in the investigation and ensuing discussion. They talked about fairness, how to provide everyone with equitable instead of equal opportunities, and what sexism and stereotyping mean. In a classroom discussion, one female African-American student concluded that *"My takeaway is that AIs like Google and facial recognition, haven't been updated in a long time because you can clearly see the bias in that. And even though we think that these things are very... very smart, but I never understood or considered that they might have been really bias until going over these things."* These findings are consistent with the literature that women and underrepresented minorities are often interested in issues that address societal and ethical concerns [37].

4.2.3 Design and build experiences. The technology exploration and creation activities supported students in making sense of the underlying AI concepts. Students in total spent approximately five hours on a series of activities using Google's Teachable Machine (in Units 3 and 5). They first learned and explored how to use the tool to train a supervised learning model to recognize faces, gestures, and voices. Then they experimented with training a model on a biased dataset (one with more pictures of dogs than cats), observed the results, and brainstormed and attempted to fix the bias. As a final activity they explored integrating the supervised learning model they trained using Teachable Machine into Scratch animations (e.g., when the model recognized certain voices, the sprite would wave hands). Our observations showed that although students had challenges in the last activity due to limited Scratch skills or computing power of their computers, students in general developed a solid understanding of supervised learning and how to mitigate potential biases in supervised learning systems. Further this experience of training an AI model enabled some students to develop a sense of control over technologies as one student reflected in their post-interview, *"I feel like we could do it,...so teachable machine is, we're in control, but we're teaching the teachable machine how to do something."* This sense of agency or control over technology has been long recognized as a key factor in impacting peoples' interactions with and perceptions of technology [27]. It may have helped the participating youth become more interested in and less anxious about AI.

4.2.4 Participatory simulations. Leveraging a participatory simulation approach [24], the Neural Network game engaged students in playing the role of nodes in training of a network. Students captioned a mystery image by passing on information through different "layers" of the network and experienced how nodes, links, and layers worked to train the network. Students found the analogy between feed-forward mechanism and the "telephone game" helpful in helping make sense of the progression of information.

4.2.5 Generative AI activities. Activities around generative AI were engaging yet difficult for students. For instance, the "colors" activity (see an earlier description of the detailed activity) was frustrating as one student mentioned in her interview *"because there was a little too much of one and too much of the other. Even if you got like, at least like a 96% close to it, for me, it still didn't allow me to pass... Sometimes I did give up."* Despite the frustration, the student still found it interesting because she could *"see how people would mix up the colors and all."* Another example is the "Deepfakes" activity in which students reviewed videos, images, and texts and determined whether they were generated by AI. Students were astonished to find out that all the files were generated by AI. Many students admitted that even after receiving instructions on how to detect Deepfakes, they still had difficulties.

4.2.6 Career development activities. The career training sessions immersed students in exploring their future jobs. In the "Inventory of Me" activity students discovered their work personalities and found jobs that match them. Students were surprised to find their matched job options as sometimes they had never heard of them. The exploration of how AI has been and may be adopted in different jobs sparked their interest in AI. In the post-interview, one girl thought that AI will impact her future job *"because when we were doing the job career search, a lot of the jobs that popped up were jobs that I was interested in and it was connected to AIs. So I feel like that definitely shows that a job that I want will be connected to AI in some way."*

4.3 Implementation Challenges

Remote synchronous online instruction due to COVID-19 presented Several implementation challenges. In online versions of unplugged activities, the benefits of working with physical materials and embedding activities in a physical space were lost. For example, in the "PastaLand" activity, students' ability to identify key features of the pasta was limited by the graphical representation we chose. The relative sizes of the different pasta as well as the textures could not be accurately portrayed. Similarly, the online environment limited the use of a project-based learning approach. The difficulties encountered with supporting students' collaboration online limited opportunities to help students apply theoretical knowledge to constructing tangible artifacts.

The online environment also shifted interactions with peers and instructors from semi-private to public. For instance, in an online environment, we found that collaboration while debugging moved from an intimate (semi-private) interaction to an interaction shared with the entire classroom. Discussions were central to several of our activities since the curriculum focused on not just teaching AI concepts but also discussing ethical issues associated with AI. Lack of access to a microphone or video camera, or background noise hindered effortless conversation in these discussions, and at times we had to rely on chat. Student engagement was challenging to maintain and track, since unlike in-classroom learning, we had limited access to visual cues and emotional responses from students.

Another implementation challenge pertained to discussing algorithmic bias, as well as its implications in AI, and its societal implications such as unanticipated discrimination against under-represented minority groups with students from these group. While central to the curriculum, we aimed to present these concepts with sensitivity to the audience. With guidance from the community partner, we discussed how the AI industry was seeking to address these biases and how they, as future AI engineers, can help to identify and mitigate some of these biases. While it is important to discuss the existence and implications of algorithmic bias, we refrained from framing the discussions of bias with students from under-represented groups such that we put the onus on them for fixing a problem in AI that they did not create. Hence, instead of framing the discussion as how they can solve the problem of bias in AI, we framed it as how the AI community can solve it. Lastly, while we discuss several negative implications of AI technologies such as bias, generation of fake media, and misinformation, we notice a need to include more positive examples of AI technologies, such as applications in healthcare, education, and art.

5 LEARNING OUTCOMES

The learning outcomes were mainly evaluated using two instruments administered before and after the workshop: (1) the AI Concept Inventory that assesses youths' knowledge and skills in AI through three validated sub-scales: AI general concepts, logic systems, and machine learning, and (2) the Attitudes toward AI and AI careers survey that explores youths' interest in AI and related careers, AI career awareness, and career adaptability. All questions were drawn and modified from validated instruments, e.g., the career adaptability includes 10 items based on the revised Career Futures Inventory [35, 41]. Detailed information of the two instruments can be found in Lee et al. 2021 (in press) [**?**].

We found a statistically significant increase in youths' AI concept inventory scores from pre- to post-test (t(17)=-2.09, $p< .05$, d = .54). The subscale with the largest increase in scores was machine learning (including both unsupervised and supervised learning). Students on average had a score increase of 1.58 —meaning that over half of the students correctly answered at least two more questions about machine learning concepts and processes on the post-test. We also found significant increase in AI career awareness (t(18)= 3.58, $p < .01$, d = 1.00) and career adaptability skills (t(18) =1.013, $p<.001$, d = 1.40) after the workshop. Students also increased their interest in AI after the intervention, yet the increase was not statistically significant. One reason may be the ceiling effect. Participating youth were highly interested in AI before the workshop (Mean=3.59 out of 5) and maintained their interest level on the post-test (Mean=3.71).

6 CONCLUSIONS

Preparing youth to become knowledgeable citizens and workers in the age of AI is essential for training the next generation of the workforce. This paper reports the design and implementation of an AI workshop among middle school aged youth because middle school years are an important time to develop their interest in and shape their views of AI and related jobs. This workshop aims to develop AI literacy through an integration of AI concepts, ethical and societal implications of AI, and the adoption of AI in future jobs. The workshop also aims to provide a low-barrier to entry for learners with no pre-requisite computing resources or knowledge of computing systems, thereby enabling learners with no CS background to gain a foundational knowledge of AI concepts. We pilot tested this workshop among 31 middle school youths from groups underrepresented in STEM and Computing in a self-selected summer program. We found significant increases in students' conceptual understanding of AI, knowledge of potential bias of AI, and ability to adapt to future AI-empowered jobs. This indicates that the approach of combining AI, ethics, and careers to develop AI literacy is feasible and suitable for middle school youth.

Consistent with previous AI ethics curricula, we have found middle school students were highly engaged in discussions of ethics, in the context of fairness and bias in AI. Students were capable of reflecting on their own behaviors and its impacts on others, and can extend this reflection to encompass how various stakeholders in AI systems can design systems based on their values and needs. Students could identify how and why AI applications can be unfair to themselves and others. For instance, in the post-test interview, one student said, *"I think that bias [in AI] could be harmful for us because a lot of people aren't fairly represented, so they wouldn't be able to use it as much."*

Further, we found that the youths talked with their family members about AI. A student in his post-test exit interview told us that *"I asked my mom that day when we were talking about [..] if AI could probably take our jobs. I asked her, "Are you scared if AI takes your job?" She's like, "Yes, but I know I'll have another job." So, it's really cool what AI could do and make new things for other people."* Through the conversation with his mom, the student was active in leveraging existing familial and aspirational capital [17] to make sense of the potential impact of AI and to inform and refine his existing understanding and perceptions of AI. Meanwhile, this quote provides further evidence that our approach may have sparked high interest among students such that AI arises during family conversations. Research on science learning has suggested that conversations about science topics are not typical occurrences for all youth, especially for those from underrepresented groups in STEM [18, 34].

7 FUTURE WORK

Based on our pilots and findings, we aim to further revise our curriculum and assessment methods. First, we plan to add more discussions around positive application areas of AI such as healthcare and education. We will frame the mitigation of bias in AI conversation such that the onus of fixing the problem does not lie on students from under represented minority groups. Second, we aim to include more project-based activities where students can apply their own interests, and ethical considerations to an AI-enabled project. For instance, we plan to include a generative modeling activity, where students pick their own training datasets, and then generate and share synthetic data such as text, visual art or music, while reflecting on the ethical implications of the generative media they choose. This may necessitate being co-located in classrooms and having computing capability to train large models. Another final project could entail redesigning recommender systems while keeping in mind stakeholders and their values, and checking for inherent biases in the system. Lastly, we aim to scale this curriculum to teachers and students across the country for wider access. We aim to work with educators to explore the efficacy of the DAILy curriculum both in formal middle school curricula and informal settings, such as after-school or summer programs. Once we collect and analyze data from the additional deployments of the DAILy curriculum, we plan to develop an AI literacy competency model to further contribute to the field of AI Education.

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