A Socially Relevant Focused AI Curriculum Designed for Female High School Students

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Abstract

Historically, female students have shown low interest in the field of computer science. Previous computer science curricula have failed to address the lack of female-centered computer science activities, such as socially relevant and real-life applications. Our new summer camp curriculum introduces the topics of artificial intelligence (AI), machine learning (ML) and other real-world subjects to engage high school girls in computing by connecting lessons to relevant and cutting edge technologies. Topics range from social media bots, sentiment of natural language in different media, and the role of AI in criminal justice, and focus on programming activities in the NetsBlox and Python programming languages. Summer camp teachers were prepared in a week-long pedagogy and peer-teaching centered professional development program where they concurrently learned and practiced teaching the curriculum to one another. Then, pairs of teachers led students in learning through hands-on AI and ML activities in a half-day, two-week summer camp. In this paper, we discuss the curriculum development and implementation, as well as survey feedback from both teachers and students.

Introduction

This paper details the design and initial testing process of our artificial intelligence (AI) and machine learning (ML) module of the CS Frontiers (CSF) curriculum. The CSF project focuses on curriculum development of a new high school course designed to introduce students who have completed the U.S. College Board's Advanced Placement Computer Science Principles course to cutting-edge computing technologies and applications (Broll et al. 2021). Due to the decreasing trend of female students showing interest in the field of computer science over the last several decades, the CSF curriculum focuses on engaging female students (Seneviratne 2017). To increase female interest, curricular activities are focused on interdisciplinary and socially relevant connections between computer science and other disciplines, such as social media and criminal justice (Lédeczi et al. 2021), that female students have shown interest in (Fisher and Margolis 2002). The activities in the CSF AI and ML module connect advanced computer science concepts with other domains, such as criminal justice, natural language processing, the environment, and more. To teach novice high school students advanced topics, the curriculum leverages NetsBlox, the block-based programming language, which supports advanced programming techniques and connects to several Application Programming Interfaces (APIs) to enable interdisciplinary projects and access to online datasets (Broll et al. 2017). Introducing students to AI and ML using a block-based language helps novice students focus on learning computing concepts rather than syntax of a text-based language (Resnick et al. 2009).

In this paper, we explain the design process we used to create a 35-hour abridged camp curriculum, how teachers learn to use it, and how students and teachers perceived the materials. We will describe the pre and post surveys we used during the summer camp to determine female engagement and confidence, and the results of these surveys. In conclusion, we will discuss the significance of our findings and how our future work with this curriculum will proceed based on these discoveries. The investigation of the AI and ML module has shown that the curriculum positively impacts females' confidence and sense of belonging in computer science.

Background & Related Works

There has been a decline in female interest in computer science and computer science topics over the past several years (Seneviratne 2017). Considering how the gender disparity in Tech has a statistically even distribution across race, ethnicity, and socioeconomic status levels, it can be deduced that the factors influencing the gender gap are not the same as those impacting the systemic connections between race, ethnicity, and income (Wang and Hejazi Moghadam 2017). Therefore, this problem is not only about access, but it is also compounded with social barriers and perceptions (Wang and Hejazi Moghadam 2017). Research has shown that female interest in computer science changes in early high school, where first career choices occur (Microsoft Corporation 2017). For this reason, we want to introduce advanced topics to females early in high school, to show the possibilities of computer science that are not usually explored until late in a college computer science degree. Research suggests that bridging the gender gap in computing requires presenting computer science as a variety of perspec-

tives and possibilities (Khan and Luxton-Reilly 2016) and making connections to other subjects (Fisher and Margolis 2002). For instance, women (in general) prefer "people-oriented fields" that involve caring for communities and improving quality of life (Kirk et al. 2012), while men prefer "thing-oriented fields" (Ceci et al. 2014), which helps explain why women are more prevalent in careers with a clear social purpose, such as healthcare, social work, and education. Socially-relevant projects have shown to be engaging for female and underrepresented students (Fisher and Margolis 2003; Papastergiou 2008; Ceci et al. 2014). Connecting real world experiences that make an impact with diverse female experts for support and inspiration can provide girls with authentic STEM opportunities that promote sustained engagement (Chapman and Vivian 2017). Some existing advanced topic curricula, following this goal of engaging young women in the field of computer science, are based on the subjects of Distributed Computing and the Internet of Things (Grover et al. 2020), (Broll et al. 2021). For our curriculum framework, we wanted to implement an AI and ML module with the same goal. We believe introducing students to these socially-relevant topics early in their exposure to computer science fields will allow females to connect and engage, while still learning novice computing topics.

Curriculum Development Pipeline

Curriculum Curation

This section reviews how the curricula was initially developed and the preparation provided to camp teachers. The development and curation of the camp activities took place in several stages. First, we found relevant and open source AI and ML materials to teach K-12 students. Understanding that the curriculum is intended to fit a 35- to 40-hour summer camp or course-based 9-week schedule, we curated topics that would be suited for an abridged camp implementation and a typical high school classroom. We adapted the AI4K12 grade-band progression charts as learning objectives for this curriculum. AI4K12 is a developed, national curriculum for AI topics in classrooms ranging from kindergarten to 12th grade (Touretzky et al. 2019). Topics range from domain knowledge to search algorithms to machine learning concepts depending on the targeted age group. We specifically used the AI4K12 Big Idea 3 progression chart, as it had high school level objectives specifically relating to machine learning algorithms, neural networks, and datasets. The key insights of these learning objectives (Touretzky et al. 2019) are:

1. Machine learning allows a computer to acquire behaviors without people explicitly programming those behaviors.
2. Learning new behaviors results from changes the learning algorithm makes to the internal representations of a reasoning model, such as a decision tree or a neural network.
3. Large amounts of training data are required to narrow down the learning algorithm's choices when the reasoning model is capable of a great variety of behaviors.

4. The reasoning model constructed by the machine learning algorithm can be applied to new data to solve problems or make decisions.

Once these learning objectives were solidified, our team consisting of 6 female researchers (4 White women and 2 Latinx women) selected the activities which they thought would be most engaging. For learning objectives where resources were not found, we developed activities, such as our NetsBlox Twitter bot detection activity (See Table 1). In conjunction with the selected activities, we also used presentations prepared by AI4All, an online computer science curriculum promoting AI exposure to all students, from their AI Bytes units (Judd 2020). The AI4All AI Bytes units are slide decks introducing areas of research and pre-made tools that students are able to tinker with to explore a topic. The presentations connected AI and ML concepts to real world applications and people. Examples of these presentations are AI & Environment, AI & Drawing, and AI & Facial Recognition. These presentations gave students exposure to how AI can connect to other disciplines they may be interested in and exposure to a diverse range computer scientists.

To assess the open source and developed activities and presentations, we had two high school interns (a female Asian high school student and a male Asian high school student), and one undergraduate researcher (a male Asian computer science undergraduate), complete and evaluate the activities in relation to interest level for female high school students and complexity based on prior computer science knowledge needed to complete the activities. The undergraduate researcher and interns all had differing levels of block-based and text-based programming knowledge to accurately evaluate these activities from different points of view. The undergraduate researcher and interns recorded the time it took for them to complete the activities independently, their perceived complexity of the activity, and if they found it engaging or interesting. After the activities were evaluated, they were paired with the related learning objectives (see Table 1) and arranged into the camp schedule.

Teacher Preparation

In order to achieve our goal, we elected to have secondary education teachers, with experience teaching the Advanced Placement Computer Science Principles course, act as camp instructors, facilitating the curriculum to the camp participants, and simulating a classroom environment (Kick and Trees 2015). To prepare the educators, our team facilitated a week of professional development (PD) that leveraged the Teacher-Learner-Observer (TLO) model developed by Goode, Margolis, and Chapman (Goode, Margolis, and Chapman 2014). In the TLO model, participants spend time playing the roles of teacher and learner while the PD facilitators observe and guide a structured reflection after each TLO session (Cateté et al. 2020). The goal of this PD was for the educators to co-design and critique our developed curriculum, similar to the purpose of the PD in (Grover et al. 2020). At the end of each day during the PD, participants completed a debrief survey where they answered questions about how their TLO sessions went overall, suggested changes to the activities, and any concerns about the curricular materials.

Activity Title	Learning Objective(s)
Twitter Bot NetsBlox Activity	AI4K12 3 - A - v: Describe how various types of machine learning algorithms learn by adjusting their internal representations.
Sentiment analysis using NetsBlox and Python	AI4K12 3 - A - v: Describe how various types of machine learning algorithms learn by adjusting their internal representations.
Introduction to Python Syntax	Understand Python syntax and introductory computational concepts (lists, libraries, objects) in Python
AI4All AI & Environment	Understand the different types of careers and applications to the AI and ML and the environment
AI4All AI & Drawing	Understand the different types of careers and applications to the AI and ML and the arts
AI4All AI & Criminal Justice	Understand the different types of careers and applications to the AI and ML and criminal justice system
Final project using APIs and sentiment analysis of a chosen media type (music lyrics, tweets, or NYT article summaries)	AI4K12 3 - A - v: Describe how various types of machine learning algorithms learn by adjusting their internal representations. AI4K12 3 - A - iii: Use either a supervised or unsupervised learning algorithm to train a model on real world data, then evaluate the results.

Table 1. Selected camp activities (in order that they were presented) and their related AI4K12 learning objective.

Study Implementation & Context

Camp Context

To test our learning objectives in a controlled environment, we condensed our curriculum into a two-week summer camp in conjunction with our university's camp infrastructure (Bottomley 2015). There were two camp implementation types: Camp A which included both NetsBlox and Python activities and Camp B which only included Python activities. Each camp had approximately 35 hours of contact time with participants. Camp A was online 4 hours a day over the course of 10 weekdays. Camp B was online 8 hours a day over the course of 5 weekdays. We had two instances of both Camp A and Camp B each. The online platform used for synchronous activities was Zoom due to its video and audio recording, screen-sharing, breakout room capabilities, and chat features. Breakout room capabilities were particularly important to facilitate collaboration amongst participants, since collaboration is a key computational thinking and computer science practice to better engage female learners (Denner et al. 2005). In each camp's Zoom classrooms, we had two teacher facilitators, one computer science graduate student, and an undergraduate camp counselor.

Gender	Native American	Asian	Black	Multi-Racial	White (non-Hispanic)
Female	1	4	0	1	4
Male	0	10	1	2	1

Table 2. Gender, Race, and Ethnicity demographics of the 24 camp participants included in our analysis.

The gender and racial and ethnic demographics of the 10 female and 14 male high school participants who consented to participate in this research study are displayed in Table 2. We distributed the pre and post surveys via Google Forms. At the beginning of the first day of camp, the participants completed the pre survey and on the last day, the post survey was completed. The surveys were adapted from the NCWIT Computing Interest-Confidence-Perception Survey (National Center for Women & Information Technology 2021) and the Development of the STEM Career Interest Survey (Kier et al. 2014). The survey topics covered were confidence, perception, interest in computing, interest in computing careers, and curriculum content knowledge.

Abridged Curriculum

The AI concepts addressed in the camp were natural language processing, sentiment analysis on textual data, bias in datasets, computing ethics, AI connections to social media, and AI in real world applications. The expected learning outcomes of the summer camps were 1) describe how various types of machine learning algorithms learn, 2) use either a supervised or unsupervised learning algorithm to train a model on real world data, then evaluate the results, 3) understand introductory computational concepts (lists, libraries, objects) and syntax in Python, and 4) understand the different types of careers and applications of AI and ML to the criminal justice system, the environment, and the arts. The activities that taught each learning objective are presented in Table 1.

While we also prompted the participants on completion and difficulty feedback, the focus of our AI and ML summer camp was on engagement and interest with the materials presented. To account for the density of material in the short two-week camp and to account for difference in computing backgrounds, our team scaffolded activities to help novice participants connect to the programming faster and added extensions to challenge advanced participants. In the summer camp implementation, there was limited time to engage in each activity, so we prepared starter code for participants to offset the reduced time. For example, for novice participants, the penultimate activity provides adaptable starter code usable for the final project, and for more advanced participants, they could choose to pick a new API to work with as a challenge.

The intention for each activity was to have participants think of the impact and larger applications of the concepts they were learning. For assignments, the participants were asked to think beyond their small batch activities to larger implications. For example, if we look at the final project, it had the option of three APIs Genius Lyrics, Twitter, and the

New York Times (NYT). From these options, the participant groups chose and devised a research question they hoped to begin to answer with their final project. One group's final project compared the sentiment analysis on the lyrics of a few songs from 5 short haired artists to 5 long haired artists. The participants were then asked to explain what their results meant and to come to the conclusion that their results utilized a small amount of data but with more they could make stronger claims. Implementing the curriculum through a summer camp served as a way to pilot the materials and receive initial feedback from participants and teachers.

Results and Analysis

Participant Survey Results

Using a statistical software package, SPSS, an independent-samples t-test was conducted on the pre and post camp surveys to compare female and male participant confidence before and after attending the 2021 summer camps. The pre and post survey entails 52 Likert type questions in the following subcategories: confidence, perception, interest in computing, interest in computing careers, and curriculum content knowledge. Questions 1-41 were on a 4 point scale, with 4 indicating stronger agreement, and questions 42-52 were on a 5 point scale with 5 indicating strongest agreement with the statement. Bonferroni correction was applied to correct for the large number of tests, so significance requires $p \leq \alpha = 0.018$.

In Table 3 we share a set of selected questions and their results that measure confidence on items related to AI and ML content, career identity, and self efficacy in computer science.

Questions 15 and 19 of the survey were concerned with confidence in understanding relevant computing concepts presented in the camp. Questions 36-38, asked how much they knew about computer scientists and what their job responsibilities look like. In the final part of the survey, questions 42-51, respondents were asked to rank on a Likert scale how true they felt each question related to their self efficacy. Below we highlight and discuss questions 15, 36, 37, 38, and 42 as those items measure confidence in career identity and general computer science.

There was a significant difference, t(9) = 3.28, p= 0.01, in confidence regarding Q.15 for female participants increasing from M=2.0, σ= 1.05 to M=2.7, σ = 1.05 in Likert value. Effect size was calculated as Cohen's D = 0.68, indicating a medium effect on increasing female participants' confidence in their ability to represent data (and images).

For Q. 36, there was a significant difference, t(9) = 3.28, p= 0.01, in confidence in understanding computer scientists' jobs for female participants increasing from M= 2.20, σ = .63 to M = 2.90, σ = 0.57. Effect size was calculated as Cohen's D = 0.68 indicating a medium effect, suggesting that the camp helped female participants become more confident in knowing the jobs that computer scientists have. The next question of interest is Q. 37 where data shows that female participants felt more confidence in knowledge of computer scientist's job responsibilities (M = 2.20, σ = .92 to M = 3.0, σ = .67) from pre to post. Using the Bonferroni correction,

however, this trend is not quite significant, t(9) = 2.45, p= 0.04. Although overall the camp helped female participants become more confident in understanding what computer scientists do in their jobs.

The fourth highlighted question is Q. 38. There was a significant difference, t(9) = 3.86, p< 0.01, from pre (M=1.40, σ=0.70) to post (M=2.30, σ=0.82 with an increase in confidence in how much participants know about building AI applications for female participants. Effect size was calculated as Cohen's D = 0.74, indicating a medium effect on helping female participants become more confident in knowing how to build AI applications. This result shows support for our hypothesis that a more socially relevant and applied curriculum would be more engaging for female participants. The last question of interest for the in-group analysis is Q. 42. There was a significant difference, t(9) = 2.45, p= 0.04, from pre (M=2.90, σ= 0.99) to post (M=3.70, σ= 0.95) with an increase in confidence in completing computer science activities for female participants. Cohen's D = 1.03 indicating a large effect, regarding the camp helping female participants become more confident that they would be successful in activities that involved computer science. Together these results suggest that the female participant efficacy increased after the completion of our summer camp.

Furthermore, we highlight the results of questions 38, 42, and 51 in comparison to our male participants because they reflect each of the survey section topics: confidence in AI and ML content, self efficacy in computer science, and career identity. The first question of interest helps serve as a baseline for the cross group analysis, Q. 38 shows that female and male participants did not show a significant difference from each other in their change of understanding regarding AI.

The second question of interest is Q. 42. There was a significant difference, t(22) = -2.54, p= 0.02, in increase in confidence in completing computer science activities for female attitudes (MD=0.80, σ= 1.03) compared to male attitudes (MD= -0.14, σ= 0.66). With Cohen's D = 0.83 indicating a large effect, these results suggest that female participants gained more confidence in their ability to do well in computer science activities when compared to male participants. The last question of interest for the cross group analysis is Q. 51. There was a significant difference, t(22) = -3.03, p< 0.01, in increase in confidence in talking with computer scientists for female attitudes (MD=0.70, σ= 0.82) compared to male attitudes (MD= -0.14, σ= 0.36). With Cohen's D = 0.60 indicating a medium effect, these results suggest that female participants gained more when compared to male participants, in becoming more comfortable talking to people who are computer scientists.

Participant Feedback

To gain perspectives from our female participants, we look at open-ended questions from the post-survey on participants' experience in the camp and their interest in a career in computer science. The female participant data showed the overall response to the question "What other feedback, comments, or suggestions do you have after your experience with the [CSF] Camp?" was very positive. One female

Survey Question	Pretest Mean	Post Mean	MD	σ	t	p
Q.15: Right now, how confident are you in your ability to understand how computers present data and images?	2.00	2.70	0.70	0.68	3.28	0.01*
Q.19: Right now, how confident are you in your ability to program computers to create new apps (in other words, writing code)?	2.00	2.60	0.60	0.69	2.71	0.02
Q.36: How much do you know about jobs computer scientists have?	2.20	2.90	0.70	0.68	3.28	0.01*
Q.37: How much do you know about what computer scientists do in their jobs?	2.20	3.00	0.80	1.03	2.45	0.04
Q.38: How much do you know about how to build artificial intelligence applications?	1.40	2.30	0.90	0.74	3.86	<0.01*
Q.42: I am able to do well in activities that involve computer science.	2.90	3.70	0.80	1.03	2.45	0.04
Q.51: I would feel comfortable talking to people who are computer scientists.	3.30	4.00	0.70	0.82	2.69	0.03

Table 3. t-Test results showing the mean difference in female participant confidence from pre/post surveys ($\alpha = 0.018$) (N=10).

Survey Question	F M	Pretest Mean	Post Mean	MD	σ	t	p
Q.38: How much do you know about how to build artificial intelligence applications.	10	1.40	2.30	0.90	0.74	2.76	0.78
	14	1.64	2.64	1.00	0.96		
Q.42: I am able to do well in activities that involve computer science.	10	2.90	3.70	0.80	1.03	-2.54	0.02
	14	4.50	4.36	-0.14	0.66		
Q.51: I would feel comfortable talking to people who are computer scientists.	10	3.30	4.00	0.70	0.82	-3.03	<0.01
	14	4.50	4.36	-0.14	0.36		

Table 4. Independent samples t-Test results showing mean differences in female (F) versus male (M) participant change in confidence from pre/post-survey.

participant commented on recommending the program, "I learned a lot and would recommend it to others." Others included, "I like how they were trying to make the students very energetic and more involving with the lesson' and 'I had fun at this camp." Four female participants commented on the impact of the facilitators on their experience which is another factor for female participant engagement (Fisher and Margolis 2002). Additional feedback illustrates how facilitation is a valuable aspect of curriculum development and the importance of the facilitator(s) impact on the participants. A female participant commented, "I really enjoyed the camp and the support my teachers provided", "The information was very thorough and I really liked the step by step coding instructions. The Genius API activity was also something I've never seen before (in a good way).", "I liked how knowledgeable all the counselors were and the amount of effort that was put into the presentations and activity planning was evident".

Our results indicated that while the participants were challenged, they were not discouraged by the difficulty or the new concepts they were learning as represented in the following comment "I really enjoyed this camp! A few of the assignments towards the end of the week were confusing but once we worked through them it felt good that we could understand it."

In the final part of the survey, respondents were asked "Do you think you could be a computer scientist?" 6 female participants answered yes and 4 answered maybe (due to being interested in other STEM areas, which was specified in the survey). The results of this question, coupled with the Likert scale survey questions, is interesting to our research goals because it indicates that the participants left more confident in knowing what being a computer scientist is like and whether they could visualize themselves as one. With female representation in computer science being 25% nationally (National Center for Women & Information Technology 2021), career identity of school age females is important to investigate to help further understand the barriers and obstacles to female students entering computer science (Google Inc. 2014).

In summary, the results of the pre/post surveys informed us about female self efficacy levels after the camp and how it compared to male participant data including changes in confidence, content knowledge, and career interest. The female participants had positive responses to building AI applications and how computers present images and data, and reported some improvements to their self efficacy in computing and AI concepts. In comparison to the male group, the female participants had a significantly greater increase in AI and ML content, self efficacy in computer science, and career identity after attending the camp. Between the two groups, we regard both male and especially female participants positively engaging with the curriculum as we are moving in a positive direction toward the CSF project goals

of broadening participation in computer science and engaging more young women in advanced computing topics.

Teacher Feedback

Sentiment of teacher feedback received from educators who facilitated the abridged camp curriculum changed over time, as the teachers became more familiar with the materials and gained confidence in teaching more advanced computer science topics. Initially during the PD, one educator felt there was a sense that the "big picture" of AI was disregarded with the introduction of Python. This view was directly stated in a statement by the facilitator, "Make sure campers understand the bigger picture – anticipate that they'll wonder why we introduced Python". When asked about how they felt about Python fitting into the curriculum, multiple educators explained it would be more beneficial for participants to be exposed to Python; perhaps by comparing NetsBlox and Python code, but not to learn Python syntax in the course, because the main goal of the curriculum is to engage participants in the overall topic of AI and ML, not programming. Additionally, in anticipation of problem areas, the educators suggested more detailed explanations of the AI and ML concepts in activities' instructional guides to better support teachers in leading the materials and answering participant questions. Overall, prior to leading the summer camps, the teachers felt comfortable with the provided materials.

Each day after each camp session, we debriefed with the teachers to get their perspectives on trying out the materials with participants. In all cases, the facilitators reported a positive view of the curriculum and disclosed that participants were engaged in the activities. Conversations with the PD facilitators expressed some types of activities were more successful than others. Successful activities included the NetsBlox activities, the AI4ALL AI Bytes units, and the final project presentations. Teachers stated that the NetsBlox activities (Twitter Bot Classification and Sentiment Analysis) allowed participants to focus on the AI concepts being discussed without participants being concerned with optimal coding concepts. As the participants began the Python activities, a facilitator commented "Students seemed to enjoy working in Python. My students even said that it was fun." We also received positive comments about the AI4ALL AI Bytes presentations and the topics discussed. One teacher said, " [I] really really appreciated the absolutely excellent slide shows!", and another said, "Campers had some good insights about some of the issues with facial recognition AI, as well as some of the potential beneficial uses". This statement also expresses that participants were not only learning about the subject of AI and ML, but engaging in the subject matter.

Finally, the culmination of the camps was the paired/group final projects and presentations. The day before the final presentation showcase (where parents were able to attend with their children to view the final project demos) a facilitator remarked "All groups made excellent progress on their projects today. More than half the groups were able to finish and think about extensions to their projects. The other groups are confident that they'll be able to finish in time tomorrow." Despite the differences in programming backgrounds, all participants completed a final project and presented a slide presentation on them with a demo of their Python code.

Other feedback wasn't necessarily related to the curriculum but suggested time adaptations such as more time for teacher preparation between the school year, PD, and beginning of the camp (since the PD and camps were in consecutive weeks. Given the geographically dispersed nature of the team, some teachers had been out of school for multiple weeks, while another had just finished a few days prior. With time commitments and the obstacles of virtual learning, we plan to adjust for these challenges in coming seasons.

Discussion

Participant Perceptions

The 2021 summer camps served as a pilot test for a controlled virtual classroom setting, and provided valuable feedback from the participants and facilitators. The results of the surveys suggest that the abridged version of the full 9 week AI and ML module curriculum was successful in engaging the female participants in the summer camp and improving their self efficacy and confidence in computing. The female participants had positive responses to computing concepts and reported improvements to their self efficacy in computing and career connections. Specifically, in comparison to the male participants, the female participants had a significantly greater increase in AI and ML content, confidence in computer science, and career interest after attending the camp. It's interesting to note the negative correlation in the difference in means for the male participants given the overall positive growth in mean. We theorize the male participants had a preexisting misconception about how much they knew prior to the camp given their high scores on the pre-survey. Then after participating in the camp, they had a more realistic perception of the computing topics. Therefore, we don't believe the male participants learned less than the female participants given the data findings. Looking at the data further may expose deeper correlations or individual student characteristics that may confound or explain the data, although that is currently outside the scope of this report.

We conjecture that the female participants were more impacted by the abridged camp curriculum than the male participants due to female representation in the camp facilitation, female representation in the camp curriculum, socially relevant applications, and intentional group pairings. In the open-ended response questions, 4 female participants commented on the impact their camp facilitators had on their experience. In the camps, only 2 of the 11 instructors and computer science teaching assistants from across both Camps A and B were male, demonstrating higher female representation in computer science. The AI4ALL AI Bytes units also showed diverse computer scientists and highlighted inclusivity in the field. Furthermore, we reduced the amount of technical jargon and focused on a more applied people-focused computing lens versus "things-focused" programming and syntax (Kirk et al. 2012). As we had some student participants in the summer camp that were new to computing, we find that the combination of inclusive representa-

tion in the curricular materials, and socially relevant applications helped make the curriculum relevant to a range of students with different backgrounds. We also believe this lowered the barrier of knowledge to participate in group discussions. Considering imposter syndrome has a greater prevalence in computer science students than other disciplines and a greater prevalence in female students than male students, the teachers helped further facilitate more engagement in discussions by intentionally pairing female participants together to ensure that they were not the only female participants in all male groups (Rosenstein, Raghu, and Porter 2020). These same discussion group tactics were also applied to picking final projects and joining breakout rooms.

Furthermore, a relationship exists between including interdisciplinary frameworks to make traditional computational thinking more inclusive and broadening the participation of underrepresented students in computer science (Kafai, Proctor, and Lui 2020). The camp's curriculum connected computational thinking to interdisciplinary perspectives by including creativity in brainstorming sessions and application to other real world applications (i.e. music, art, social media, nature, and equity).

Teacher Perceptions

Although student perceptions and experiences of the camp were positive, PD teachers were initially hesitant to try to fit all of the different activities into the two week camp, specifically teaching two languages in a limited time frame as it might take away from the content. When leading the camp sessions, however, the teachers realized that the participants didn't struggle as much as anticipated and that they were eager to learn the new materials. To alleviate future potential discomfort, our goal is to include more NetsBlox and Python interconnected activities to ensure that students are transitioning smoothly between the two languages, and understanding how the computing concepts are represented in both a block-based and text-based language. In the end, the teachers worked in pairs as they delivered the materials and were able to include each of the main activities into their camp programs.

Limitations

Several limitations were imposed by COVID-19 restrictions including virtual learning obstacles, population size, and time constraints. The online virtual learning setting included internet, video, or audio connection problems, which as the camp progressed led participants to be less inclined to have their cameras on and deterred from the typical social experience of a camp or classroom. To combat this, one teacher used "chat cascades" which began with a question prompt to the group to have them type, but not send their response until told to do so. Once prompted, all participants would send their response at once in the text chat and the participants could see all of the responses filter in as a cascade. Additional limitations may impact the findings of this report, such as the self-selection bias of camp participants and the different computing background experiences of the instructors. To mitigate the diversity in teacher backgrounds, teachers were given the same preparation materials, and each teacher

pair included a teacher with a python programming background. Lastly, to account for the large number of tests, we conducted a Bonferroni correction when needed.

Conclusions and Future Work

The aim of the present evaluation was to examine how well the AI and ML curriculum engaged high school students, specifically the 10 female survey participants in the summer camps. Given the limitations of this preliminary study, our pre and post survey results and teacher and student feedback support our extended curriculum goals of engaging female high school students in advanced computing topics. This study's results support previous research that female students engage well with socially relevant topics like contextually situated AI and Machine learning (Fisher and Margolis 2002). Specifically, our results suggest that there was a positive increase in female participant confidence and self efficacy in confidence in AI and ML content, self efficacy in computer science, and career identity after attending the camp that situated AI and ML concepts around socially relevant topics like social media, environment, criminal justice and the arts.

In our future work, we plan to address the remaining feedback from students and teachers by providing additional support and guidance. We intend to run another summer camp with the adapted AI/ML curriculum to evaluate and continue refining the curriculum and to get another round of feedback before solidifying the module into the full 2022-2023 academic year curriculum. This designing, testing, and implementation pipeline ensures several rounds of active feedback from teachers and participants before the full curriculum is deployed for in-class testing and evaluation (Könings, Seidel, and van Merriënboer 2014). The teachers who were involved in the facilitator PD have committed to implementing selected activities in their classrooms during the spring 2022 semester, so we expect to receive more feedback and data from authentic classroom environments.

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