Towards an AI-Infused Interdisciplinary Curriculum for Middle-Grade Classrooms

Bita Akram, Spencer Yoder, Cansu Tatar, Sankalp Boorugu, Ifeoluwa Aderemi, Shiyan Jiang
North Carolina State University
bakram@ncsu.edu, smyoder@ncsu.com, ctatar@ncsu.edu, sboorug@ncsu.edu, sboorug@ncsu.edu, iwaderem@ncsu.edu, sjiang24@ncsu.edu

Abstract

As AI becomes more widely used across a variety of disciplines, it is increasingly important to teach AI concepts to K-12 students in order to prepare them for an AI-driven future workforce. Hence, educators and researchers have been working to develop curricula that make these concepts accessible to K-12 students. We are designing and developing a comprehensive AI curriculum delivered through a series of carefully crafted activities in an adapted *Snap!* environment for middle-grade students. In this work, we lay out the proposed content of our curriculum and present the design, development, and implementation results of the first unit of our curriculum that focuses on teaching the breadth-first search algorithm. The activities in this unit have been revised after being piloted with a single high-school student. They were further refined after a group of K-12 teachers examined and critiqued them during a two-week professional development workshop. Our teachers created a lesson plan around the activities and implemented that lesson in a summer workshop with 14 middle school students. Our results demonstrated that our activities were successful in helping many of the students in understanding and implementing the algorithm through block-based programming while extra supplementary material was needed to assist some other students. In this paper, we explain our curriculum and technology, the results of implementing the first unit of our curriculum in a summer camp, and lessons learned for future developments.

Introduction

In recent years, AI has started to play an increasingly essential role in daily technology usage and decision-making. It is also becoming a domineering aspect of the future STEM workforce [Bughin et al. 2018] as Advances in AI systems are replacing more traditional methods in scientific research and STEM occupations with AI-based modeling and problem solving [Gapinski 2017]. Thus, it is imperative for our new generation to gain a fundamental understanding of AI mechanisms and also their potential to perpetuate biases and unfairness through automated decision-making. The inevitable spur of AI in our future economy and ways of living has caused the integration of AI into the K-12 curriculum to gain significant momentum [Touretzky et al. 2019; Williams et al. 2019; Zimmermann-Niefield et al. 2019].

Our goal is to design a comprehensive AI curriculum for middle grade science classrooms to engage students with the most fundamental ideas of AI in the context of interdisciplinary, real-world problem solving. Approaching AI education from an interdisciplinary standpoint is crucial for building a diverse, competent STEM workforce. It is imperative for all students to develop the requisite skills needed for AI-infused problem-solving in STEM subjects to more closely match what current workforce need [Silapachote and Srisuphab 2016]. The work to integrate science and AI instruction for authentic problem-solving in K-12 education is under development [Wan et al. 2020] .

In this paper, we present the layout of a curriculum that integrates four of the most fundamental and prominent AI concepts: search, knowledge-representations systems, machine learning, and natural language processing, with the four core disciplinary ideas specified by next generation science standards (NGSS): Life Sciences, Physical Sciences, Earth Sciences, and Engineering Technology and Application of Science. Our activity design follows NGSS practices, including but not limited to: Developing and Using Models, Analyzing and Interpreting Data, and Using Mathematics and Computational Thinking. We emphasize concepts related to AI ethics and social impacts throughout the whole curriculum. The layout of the proposed curriculum is specified in the Technology-enhanced AI Learning Environment section. Our curricular modules aim to foster competency, interest, and career aspirations towards AI-infused science problem-solving for a diverse range of students.

We also present the design, development and implementation results of the first unit of our proposed curriculum that teaches the breadth-first search (BFS) algorithm to students. Our unit includes a series of activities to teach students the basics of the BFS algorithm contextualized within a real-world problem-solving scenario: path finding. It then presents students with a real-world problem-solving scenario in life-sciences in which students need to complete a contact tracing application for COVID-19 using BFS. Our curriculum is delivered through an innovative learning environment that is specifically adapted to facilitate integrated science and AI problem-solving. Our learning environment builds on the affordances of block-based programming environments by taking advantage of their potential for creating abstract representations of higher-level computer science concepts including AI at varying levels of granularity. For this curricular module, we created an extension of *Snap!* to facilitate students' engagement with our AI-focused learning activities.

The first draft of our curricular module was piloted with a high-school student and the results were presented at a computer science education focused workshop [Yoder et al. 2020]. We then revised our activities based on the results of the pilot study and worked with a group of K-12 teachers to further refine the curriculum. We then implemented our revised curricular module in a summer camp with 14 middle school students. Data is collected through video recording, think aloud protocol [Charters 2003], and log data from students' interactions with the learning environment. We further present the results of analyzing this data to evaluate the effectiveness of the curriculum and to identify necessary improvements and design implications for designing a comprehensive AI curriculum and effective learning environment.

Related Work

AI has gained rapid momentum and become a hot topic of debate in every aspect of our daily lives. Therefore, scholarly attention has turned into examining AI literacy in K-12 [Williams et al. 2019; Zimmermann-Niefield et al. 2019]. In particular, as an example, Lee et al. (2021) designed an AI workshop for underrepresented middle school students to investigate the learning challenges and opportunities in their AI curriculum modules. Similarly, Williams (2021) also designed a curriculum for middle school students to introduce machine learning (ML) concepts through a block-based programming environment. Another work by Zimmermann-Niefield and colleagues (2019) provided an embodied learning experience for youth to create ML models for recognizing their own physical activities [Zimmermann-Niefield et al. 2019]. They found that youth developed an understanding of how ML models learned patterns of body movements and this could contribute to the understanding of the iterative process of ML. In addition, Google developed web-based tools (e.g., Teachable Machine) to make ML accessible to the public, including youth [Charters 2003]. These studies stressed the cultivation of data literacy among youth as modeling data as a core concept in ML and helped to understand how middle school students comprehend ML concepts through extracurricular activities. While many effective AI curricula have been made for K-12 [Estevez, Garate, and Graña 2019; Sabuncuoglu 2020; Williams et al. 2019], few of them go beyond the concepts involved in machine learning. Examples of such curricula for high-school students are mentioned in [Burgsteiner, Kandlhofer, and Steinbauer 2016; Kandlhofer et al. 2019]. In this work, we present a curricular module that teaches a core AI idea, search, with the goal of expanding our curriculum to encompass other crucial AI ideas and techniques that are through students' engagement with authentic problem-solving scenarios.

Figure 1: West, the character to guide students through the exercises.

Technology-enhanced AI Learning Environment

Curricular Modules

Each module of our curriculum integrates an AI core concept and a science core disciplinary area. Our AI core concepts are selected based on our review of relevant literature and authors' experience in teaching AI at the K-12 and college levels. Our science core disciplinary areas are selected based on NGSS standards for grades 6-8. Furthermore, our activity design is informed by evidence-based educational theories and NGSS practices for middle-grade students.

Search & Life sciences Search algorithms are among the most fundamental approaches in AI-based problem solving. Today, search algorithms are being used for many applications including path finding and game play. In this module we discuss the main idea behind search along with some of the basic but important search algorithms including breadth-first search, uniform-cost search, and adversarial search in the context of scientific real-world applications. We integrate this module with life sciences to design project-based activities where students have to design and implement AI-based solutions for real-world life science problems. As an example, as part of this module we ask students to implement a contact tracing app that finds the shortest distance between a selected person and the closest infected person in their social network to decide whether they should self quarantine. In the following sections, we explain the results of integrating this activity in a summer camp for middle-school students.

Knowledge-representation systems & Physical sciences Knowledge-representation systems are systems that maintain knowledge and are capable of generating new information using inference. Understanding the basics of these systems demystifies how computers reason. It also emphasizes how biased background knowledge and rules results in biased decision-making. This module will be presented in conjunction with the physical sciences module where students will use this opportunity to build a knowledge-representations system for representing models of physical aspects of the world which can reason based on the integrated background knowledge and rules. For example, while interacting with this module, students build a small knowledge representation system containing facts and rules about mass and gravity, which can reason about the direction of the

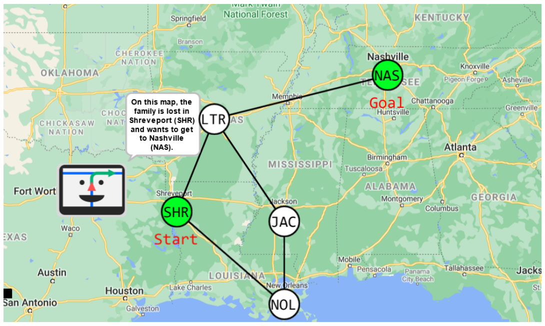


Figure 2: West and an exemplary city map used in activities

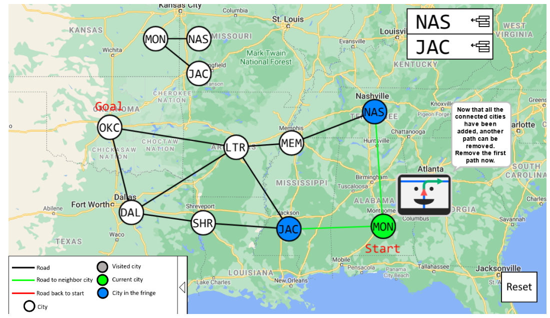


Figure 3: The graphical interface students interact with to perform BFS. (Bottom-left) The legend, which explains to students how the different states for nodes and transitions are displayed. (Middle) The graph representing a city map. (Right) The fringe.

gravity force given masses of two objects. This strategy has been used in Betty's brain [Alexandra et al. 2019] to help students gain a better understanding of the concept being learned and has shown effectiveness in improving students' learning of the content knowledge [Zhang et al. 2020].

Machine Learning & Earth sciences Machine learning is undoubtedly the most adopted AI technology by STEM fields. Gaining a solid understanding of machine learning and its applications is fundamental in preparing students for an AI-driven STEM career. In fact, many curricula have been created to introduce machine learning applications and, in some cases, techniques [Estevez, Garate, and Graña 2019; Hitron et al. 2019; Williams et al. 2019] to K-12 students. We build on these efforts by introducing machine learning as part of the general AI scheme. We help students build simple machine learning models on their own which enables them to gain an in-depth understanding of the mechanisms involved in data-driven decision making. Furthermore, we integrate these activities with real-world scientific problem-solving scenarios to give them an authentic experience. For the science component, we focus on the earth science module as part one of the NGSS core disciplinary areas. The abundance of data in this field lends itself well to data-driven decision making. For example, students can identify features important in prediction of natural catastrophes by analyzing relevant data and make predictions about the next upcoming catastrophe based on the identified features.

Natural Language Processing & Engineering Technology and Application of Science Similar to machine learning, natural language processing is becoming a substantial part of today's industry and students' daily interactions including conversations with virtual agents and searching information on web-based search engines. Thus, it is essential for them to get familiarized with the fundamental ideas that make natural language processing possible in addition to its applications in STEM fields. We integrated this module with the engineering, technology, and application of science module where students can use NLP to automatically analyze written solutions to a specific problem and automatically identify features contributing to the effectiveness of different solutions.

AI Ethics and Social Impact No AI curriculum is effective and complete without a thorough discussion of AI ethics and their social impacts. This module will be an integrated component of all of the previous modules to emphasize the importance of ethics among all applications of AI and the contexts in which they are applied. At the end of each module, students will have a discussion about aspects of AI ethics that are relevant to the presented AI technology. We cover concepts such as bias, fairness, automation and employment, privacy, etc. For example, after the contract tracing exercise students discuss matters related to privacy of contact tracing app users.

Each module ends with project-based design learning practice. Students pick a real-world problem that is properly scaled for the scope of their class with the help of their teachers, carefully investigate its requirements and constraints, and design, implement and test solutions drawn from the variety of techniques they have learned in that module. The agency given to students to pick the context of their activity paves the way for underrepresented students to pick projects that matter to them and thus, increase their engagement and motivation. On the very last day of this curriculum, students pick their favorite project and present the process of problem formulation, requirement analysis, designing, implementation, and testing for the project to the class. By getting engaged with our activities students will experience the following specified NGSS practices for grades 6-8:

- Asking questions (for science) and defining problems (for engineering)
- Developing and using models
- Analyzing and interpreting data
- Using mathematics and computational thinking
- Constructing explanations (for science) and designing solutions (for engineering)
- Obtaining, evaluating, and communicating information

As the first step towards designing a comprehensive and inclusive AI curriculum, we designed, implemented, and evaluated the first unit of our curriculum which is focused on teaching the breadth-first search algorithm to middle-grade students.

Curricular Modules	Core AI Algorithms	NGSS Disciplinary Core Ideas	Activities	Exemplary AI Ethics and Social Impacts
Search/Life Sciences	Breadth-first search Uniform cost search Adversarial search	MS-LS2-2 Ecosystems: Interactions, Energy, and Dynamics	Students build a contact tracing application that utilizes breadth-first search to find the distance between a person and its closest infected connection as specified in a social network graph.	Privacy
Knowledge-Representation Systems/Physical Sciences	Knowledge-based Systems Inference	MS-PS2-4 Motion and Stability: Forces and Interactions	Students build a knowledge representation system containing facts and rules about mass and gravity that can answer simple questions such as "object A has a bigger mass than object B", what is the direction of the gravity force?"	Bias
Machine Learning/ Earth Sciences	Supervised Learning: Decision Trees Unsupervised learning: clustering with K-means	MS-E-SS3-2 Earth and Human Activity	Students utilize supervised and unsupervised approaches to identify earth and climate features that have led to catastrophic events and use these features to predict future events.	Fairness
Natural Language Processing/ Engineering Technology and Application of Science	Information retrieval Feature Extraction (n-grams, bag of words, ...) Feature selection Classification	MS-ETS1-3 Engineering Design	Students receive a corpus containing descriptions of a variety of solutions to a problem. Students use a feature extraction method such as n-grams to build a feature set for each solution. They can use a supervised or unsupervised approach that they have learnt in the previous section to identify the best features of the successful approaches.	Automation and employment

Table 1: Curriculum Modules and Associated NGSS Standards and AI Concepts.

Learning Activities

We developed six activities in UC Berkeley's Snap block-based programming language that introduce and use a simple graphical interface for teaching the breadth-first search algorithm (BFS). The first four activities serve as an introduction to BFS, and feature a character, West, pictured in Figure 1, who guides students through the steps of the algorithm by telling them how to act as a GPS. The last two activities are formatted as programming activities, where students are given incomplete implementations of BFS, and are required to fill in the gaps. The first programming activity uses a path-finding application that helps bridge the gap between understanding the algorithm and implementing it using block-based programming. In the last activity, students implement a contact tracing app, similar to the COVID contact tracing apps, to showcase a real-world application of BFS. Below, we describe each activity in detail.

Activity 1 In activity 1, students are presented with a map of the southeastern United States, with certain cities represented by labeled circles and roads represented by black lines. (Figure 2). West guides students through the task of finding the shortest path between these cities through text-based prompts, and highlighting different parts of the map in response to clicking. First, students must find the shortest path between two cities in the small map shown in Figure 2 to introduce the shortest-path problem, then they must find the shortest path through a much larger map, to illustrate the difficulty of the problem, and finally, they must find the shortest path through a partially hidden map to learn how the search algorithm perceives it. [Anonymized link]

Activity 2 Activity 2 introduces students to the steps of BFS through new interactive components: a list of cities in the fringe and a visualizer showing the possible paths the algorithm is currently considering (Figure 3). Students are first shown a step-by-step description of the algorithm with visual aids, and then perform the steps of the algorithm themselves, guided by West.

Activity 3 In activity 3, students are guided through a complete interactive run-through of the algorithm. West goes through each step and if a mistake is made, it is explained and correction is allowed.

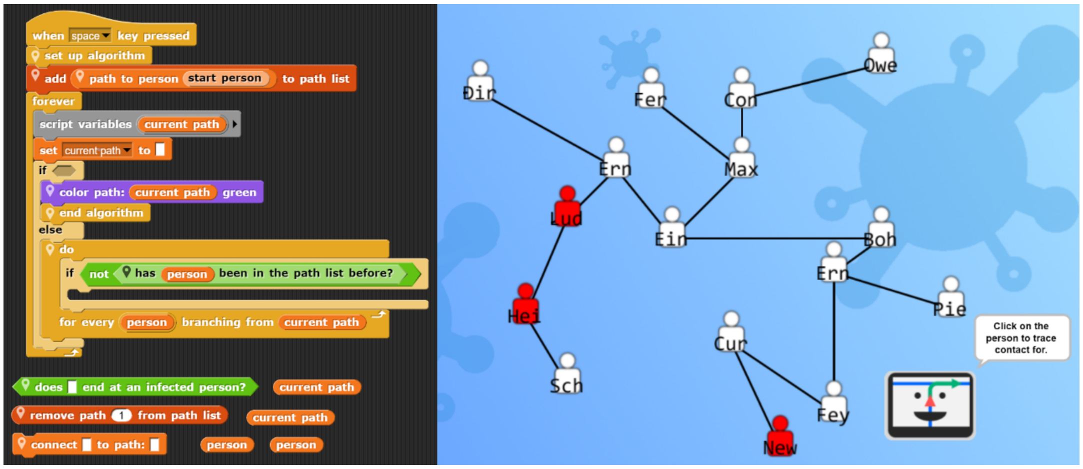


Figure 4: Activity 6. (Left) The incomplete BFS implementation with the missing blocks located under the code . (Right) the graph representing the social network from which the student selects an arbitrary person to trace to the nearest infected person.

Activity 4 Activity 4 is much like activity 3, with the exception that students must use BFS to find the shortest path without step-by-step guidance. West is still available to provide hints when clicked.

Activity 5 This activity serves the purpose of easing students into implementing the BFS algorithm using block-based programming. Once again, they are presented with a map of cities with the goal of finding the shortest path from a beginning city to a goal, but they can only do this through block-based programming. This activity is framed as a Parson's problem where students need to fill in a few gaps in an almost complete BFS algorithm implementation. All necessary blocks are provided on the screen. The gaps are located in strategical places in the algorithm to encourage students to think effectively about the fundamental aspects of the algorithm including how to initialize the fringe, how to choose and explore the next best path on the fringe, and how to add the next potential path to the fringe.

Activity 6 Activity 6 is very similar to activity 5 in that it is a Parson's problem requiring students to complete a partial implementation of BFS in order to find the shortest path between two nodes on the Snap stage. However, this activity re-contextualizes the problem being solved by BFS. Instead of finding the shortest path between two cities, students find the shortest path in a social network between an arbitrary person and someone infected with COVID-19 in the same way that a contact tracer app might. Figure 4 shows the code on the left and the social network on the right.

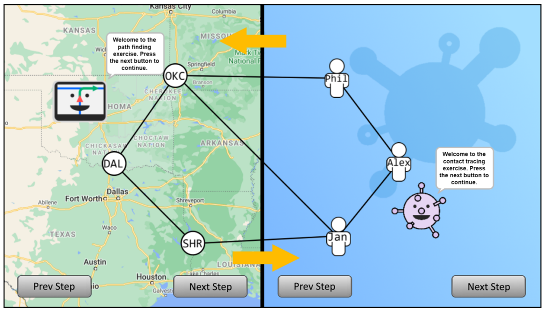
Block-based AI Learning Technology

We adapt the *Snap!* block-based programming environment to deliver our activities. *Snap!*, originally designed for making high-level computer science concepts accessible to novice programmers, provides a flexible framework for abstracting complex concepts with varying levels of granularity, and thus, is a suitable candidate for scaffolding complex AI concepts. In order to enable middle-grade students to implement BFS algorithm, we provide them with custom blocks that abstract the unnecessary and complex implementation details of BFS algorithm and allow them to focus on the crucial aspects of the algorithm. Figure 4 demonstrates the custom blocks created for implementing the BFS algorithm.

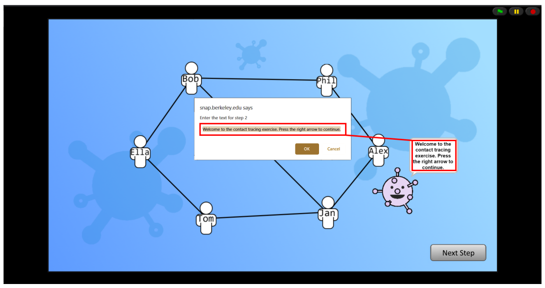
Teacher Dashboard

We further designed a teacher interface that enables teachers to adapt the context of available activities to the context of their choice. This helps teachers to choose contexts that are culturally relevant to their classrooms and are more aligned with students' interests. Using this interface, teachers can adapt both the appearance of an activity and the feedback students receive while engaging with them. An example would be when a teacher decides to turn a navigation search problem into a contact tracing app problem. This teacher can do so by replacing the map in the background with a background related to viruses, and substituting city-shaped nodes with nodes that represent people. She can then use the interface to change the story and feedback communicated to students to match the new context. Figure 5 demonstrates this example. Though we didn't incorporate the teacher interface in the summer camp, we conducted a focus group with teachers which led to design suggestions and improvements that can be applied before an actual study.

Learning Objectives The learning objectives are 1) engaging students in exploring the BFS algorithm and implementing the algorithm through block-based programming; 2) facilitating students' cognitive development in AI-based modeling and problem-solving; and 3) helping students develop interests in AI-empowered careers by introducing the integration of AI in different application fields. To ensure that learning objectives are met, we employed a wide range of design principles, such as using use-modify strategy to help students gain in-depth understanding BFS algorithm and contextualizing learning activities in real-world problem-solving scenarios in which students creatively apply the al-



(a)



(b)

Figure 5: Teacher dashboard. (Top) Teachers can change context. (Bottom) and modify hints and feedback

gorithm in solving problems in application fields (e.g., contact tracing in healthcare).

Implementation

To evaluate our proposed curriculum and learning environment, we created a preliminary version for teaching breadth-first search as part of the search curricular module. This activity was piloted first with one high-school student which led to refinements and improvements to the learning environment and the curriculum itself [Yoder et al. 2020]. Over the course of summer, we worked with three teachers, two computer science teachers and one English Language Arts (ELA) teacher to refine the material for middle school students and to create a lesson plan using the materials. Towards the end of the summer the teachers implemented the refined curriculum in a summer camp for middle grade students. 14 students, grades 5 to 7, participated in this camp. Most of the students attended from Southeastern region of the United States. The implementation was conducted via Zoom (a video conferencing tool) due to COVID-19. We collected data in the format of video recordings, think-aloud protocol, and log data from their interactions with the environment.

The workshop started with a warm-up activity. In this activity, students were directed to a website where they could see candy pictures and made an ordered list of their top five favorite candies. After the warm-up activity, the teachers started a presentation to introduce AI to students. During their introductory presentation, they asked questions (e.g., "How do you define AI in your own words?") to engage students. After the presentation, four breakout rooms opened, each designated to one of the first four activities, and were administered either by a teacher or research staff. Initially, all students were sent to the first breakout room. Students who completed the each activity were directed to the breakout room for the subsequent activity. This setup helped students to work on the activities at their own pace and be with students who were working on the same problem at all times. Students who finished all four activities were grouped into pairs and were sent to a new breakout room to work on the last two activities. A member of the research team explained the pair-programming mechanism and the activities to them. Breakout rooms were often visited by the research team to collect notes and also to help students when needed. Students worked on the activities in two 45-minute sessions with a 15-minute break between them.

Results

Our results demonstrated that the activities were successful in engaging students and creating motivation around the presented subject. In our analysis of their recorded sessions, we found that they had in fact gained a solid understanding of the breadth-first search algorithm and were having constructive arguments on how to correctly complete the implementation of the block-based programming environment to solve science-focused problems. Below, we present insights we obtained from analyzing students' data: think-aloud, video recordings, log data collected from the programming activities; and a post hoc debriefing with teachers.

Student Learning

During the implementation, students worked on the activities at their own pace during a limited time frame. As a result, not every student finished all six activities. Seven of the fourteen students completed the fourth activity and were divided into four groups. During the programming activities, we observed that they made clear connections to what they had learned in the non-programming activities to guide their programming. This demonstrates that our non-programming activities were successful in building a foundational understanding of the BFS algorithm. We also observed that all four groups completed the fifth activity with similar steps and they all faced the same roadblock. Taking a closer look at the source of the common challenge, we realized that one of the involved custom blocks for this step had not been clearly named. This demonstrates the importance of designing effective and clear custom blocks for novice learners. All four teams were comfortable with completing the activity once they overcame the aforementioned challenge. Furthermore, we observed that the first action for three out of the four groups who made it to sixth activity was to correctly incorporate the block that had given them trouble in the last exercise in the partially completed program. These three teams also quickly correctly identified how the new context changes what the "goal" for the algorithm is. In the GPS example, it was the user-selected destination city. In the contact tracer, it was an infected person. All three teams placed the block to test this condition in the correct place very soon after starting. Overall, based on the discussions among students and the commonalities between their approach to tackle the programming exercise, they had a good idea of the breadth-first search algorithm and were able to translate that understanding into code.

Our analysis also revealed that students needed more feedback during their engagement with our activities. This was particularly demonstrated by the fact that though all three teams who made it to sixth activity successfully completed the activity, only one group recognized that their solution was correct. While the graphical interface had the capability of showing the correctness of their solution, they did not utilize this feature. This is most probably due to the inadequacy of our feedback system. Many students did not read the prompts telling them what to click. There was also not much feedback for incorrect solutions. This suggests that students understood the algorithm and how to code it for the sixth activity but our lack of feedback was getting in the way of their completing the exercise. Also, some students ran out of time which shows that the two 45 minutes sessions seems to be too short for some of the students.

Teacher Impression

After the workshop, we conducted a debriefing session to learn more about the teachers' experiences and their feedback on the curriculum. This session started with introducing the Teacher Dashboard. One of the researchers showed a demo of the dashboard and asked the teachers' opinions. All teachers found the dashboard helpful for developing their own activities. Additionally, one of the CS teachers suggested allowing students to use a similar interface for their own practice. Moreover, our qualitative analysis of the debriefing session revealed that all teachers also agreed that the curriculum has a potential to support middle school students' understanding of AI. However, they pointed out a few issues to improve in the curriculum. Firstly, all teachers suggested and agreed on integrating formative feedback into the curriculum. They mentioned that the curriculum should include formative feedback to support students' learning. More specifically, the ELA teacher explained that some students were stuck on the activities and could not move forward. Therefore, she believed these students needed more support from an expert. This confirms our findings from analyzing data collected from students about lack of sufficient feedback. The CS teachers also echoed the same idea. One of the CS teachers suggested building in ''... some supports where it's expected that students may feel a struggle, or that it's not supposed to be something you get right away." Another suggestion, along with formative feedback, was formative assessment. When we asked the teachers to evaluate the students' learning based on their observations, one of the CS teachers explained that they could not have a deep sense of how students understood BFS concepts: "what we needed and didn't have was some sort of formative assessment to ask them, like, I would have perhaps used an exit ticket and asked them to define the concepts." Other teachers also supported her ideas and mentioned using web-based learning environments (e.g. Kahoot or Google Survey) to ask conceptual questions.

Overall, with these improvements, these teachers saw potential to use this curriculum in their classrooms. They were all comfortable with leading the summer camp implementation, including the ELA teacher who had no programming experience. This indicates that the our curricular approach not only helped students to gain an understanding of the BFS algorithm and how to implement it but also helped teachers build self-efficacy in teaching AI.

Discussion

These promising preliminary results indicate that solving real-world problems via block-based programming holds the promise of helping students to develop knowledge in AI problem solving and triggering students' interest in directly applying such knowledge in various areas. In particular, these results highlight the need for introducing AI concepts in the context of real-world applications as opposed to an isolated approach to teaching AI algorithms. Engaging with real-world applications of AI will help students to understand the interdisciplinary nature of AI through the practice of integrating science knowledge and practices, knowledge in application domains (e.g., healthcare), and computer science. More effort should be devoted to promoting AI as an interdisciplinary field so that students can naturally draw connections between application areas of interest and CS, which would broaden the range of students to whom such AI learning environments can appeal.

Conclusion and Future Work

In this paper, we proposed designing a comprehensive interdisciplinary AI curriculum integrated with the middle-grade science curriculum. We further presented the design, development, and implementation results of a unit that teaches BFS from the first module in our curriculum, search. The results obtained from implementing this unit in a summer camp with 14 middle-grade students and three K-12 teachers demonstrate that the curriculum was effective in engaging students with the designed activities and in shaping their understanding of the BFS algorithm.

They also demonstrate that K-12 teachers found this curriculum promising and felt comfortable with implementing it in their own classrooms. In the future, we plan to extend the search module to cover other important algorithms, including uniform-cost and adversarial search methods contextualized within middle-grade life science curriculum. In addition, we plan to add three more fundamental AI modules including knowledge-representation systems, machine learning, and natural language processing integrated with physical sciences, earth sciences, and engineering technology and application of science, accordingly. Furthermore, we will work on expanding our adaptation of the *Snap!* environment to accommodate the new curricular content. We further develop our teacher interface features to make activity design and adaptation accessible to other teachers and educational researchers. Finally, we will utilize data collected from students' interactions with our learning environment to provide them with formative and sumative feedback.

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