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Investigating a visual interface for elementary students to formulate AI planning tasks

Kyungjin Park [a,*], Bradford Mott [a,*], Seung Lee [a], Anisha Gupta [a], Katie Jantaraweragul [b], Krista Glazewski [b], J. Adam Scribner [b], Anne Ottenbreit-Leftwich [b], Cindy E. Hmelo-Silver [b], James Lester [a]

[a] North Carolina State University, Raleigh, NC, USA
[b] Indiana University, Bloomington, IN, USA

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ABSTRACT

Recent years have seen the rapid adoption of artificial intelligence (AI) in every facet of society. The ubiquity of AI has led to an increasing demand to integrate AI learning experiences into K-12 education. Early learning experiences incorporating AI concepts and practices are critical for students to better understand, evaluate, and utilize AI technologies. AI planning is an important class of AI technologies in which an AI-driven agent utilizes the structure of a problem to construct plans of actions to perform a task. Although a growing number of efforts have explored promoting AI education for K-12 learners, limited work has investigated effective and engaging approaches for delivering AI learning experiences to elementary students. In this article, we propose a visual interface to enable upper elementary students (grades 3–5, ages 8–11) to formulate AI planning tasks within a game-based learning environment. We present our approach to designing the visual interface as well as how the AI planning tasks are embedded within narrative-centered gameplay structured around a Use-Modify-Create scaffolding progression. Further, we present results from a study of upper elementary students using the visual interface. We discuss how the Use-Modify-Create approach supported student learning as well as discuss the misconceptions and usability issues students encountered while using the visual interface to formulate AI planning tasks.

1. Introduction

Advances in artificial intelligence (AI) are transforming society and the workplace of the future [1]. With a wide array of capabilities ranging from automated reasoning to machine learning and natural language processing to computer vision, AI is becoming a fundamental tool that people depend on to perform their work and carry out their daily lives [2,3]. Nations around the world are recognizing the importance of AI and taking steps to develop strategies for creating and sustaining their AI research and development workforce (e.g., [4–6]). This has generated a vital need to foster AI literacy among K-12 students to enable them to successfully navigate the future where AI will be ubiquitous [7].

AI literacy centers on enabling individuals to understand and evaluate AI, communicate and collaborate with AI, and effectively use AI [8]. Recognizing that AI literacy is a critical competency for all students, efforts are underway to incorporate AI learning opportunities within K-12 education [9,10], as well as to develop guidelines for K-12 AI education [11]. For example, a working group on AI K-12 education sponsored by the Association for the Advancement of Artificial Intelligence (AAAI) and the Computer Science Teachers Association (CSTA) has identified a set of big ideas in AI that all students should understand through a collaboration between AI experts and K-12 teachers. These big ideas include *Perception, Representation & Reasoning, Learning, Natural Interaction, and Societal Impact* [11]. Given the importance of early learning experiences for fostering students' perceptions and dispositions towards STEM, creating engaging and effective AI learning activities for elementary school students is an important endeavor.

Responding to the growing need to provide K-12 students with AI learning opportunities, researchers have developed tools and curricula that enable K-12 students to interact with and learn about AI technologies and ideas. These include online tutorial lessons and hands-on activities on a range of AI-related topics at various levels [12,13],

* Corresponding authors.
E-mail addresses: kpark8@ncsu.edu (K. Park), bwmott@ncsu.edu (B. Mott), sylee@ncsu.edu (S. Lee), agupta44@ncsu.edu (A. Gupta), katemart@iu.edu (K. Jantaraweragul), glaze@indiana.edu (K. Glazewski), jascrib@iu.edu (J.A. Scribner), aleftwic@indiana.edu (A. Ottenbreit-Leftwich), chmelosi@indiana.edu (C.E. Hmelo-Silver), lester@ncsu.edu (J. Lester).

1 https://www.readyai.org
2 https://code.org/oceans

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2590-1184/

programs to teach big ideas in AI,[1] and interactive visual interfaces for teaching machine learning and AI ethicsI.[2] As visual interfaces, especially block-based programming, have shown promise for teaching introductory computer science and computational skills [14–17], they have been actively employed to support teaching AI concepts and practices as well [18–23]. Well-designed visual interfaces, languages, and tools tailored to specific users are critical to support learning and enable users to effectively express complex computational tasks [24–26]. Students can create their own artifacts (e.g., image or speech recognition models, conversational AI agents) by interacting with these visual interfaces and tools [18,19,27].

In response to the need for engaging AI learning experiences for elementary school students, we are designing and developing PrimaryAI, a game-based learning environment that enables students to gain experience with AI-infused problem solving using in-game visual interfaces [28]. Leveraging the benefits of game-based learning [29], PrimaryAI aims to create effective and engaging AI learning experiences. Prior work has shown that well-designed game-based learning environments enable students to develop problem-solving skills, communicate and collaborate with other students, and actively participate in rich virtual contexts [30,31]. Gameplay in PrimaryAI is structured around overarching quests consisting of a set of missions for students to complete. One of the quests in PrimaryAI focuses on *Representation & Reasoning*, by introducing students to AI planning in the context of using a virtual semi-autonomous robot to gather data on an endangered species. AI planning investigates techniques to enable AI-driven agents, such as robots, to utilize the structure of a problem to construct plans of actions to perform a task [32]. In this article, we present our work to design a visual interface for PrimaryAI to enable upper elementary students (grades 3–5, ages 8–11) to formulate AI planning tasks during gameplay that leverages a Use-Modify-Create scaffolding progression [33].

We investigate three key research questions focused on introducing AI planning to upper elementary students using a visual interface:

- *RQ1: How is the proposed visual interface received by students and what hurdles do they encounter while using it?*
- *RQ2: How does the proposed visual interface, in conjunction with the Use-Modify-Create scaffolding progression, assist students in expressing AI planning tasks?*
- *RQ3: What misunderstandings do students have when formulating AI planning tasks using the proposed visual interface?*

To investigate these questions, we analyze data collected from forty-two upper elementary students using the PrimaryAI game-based learning environment and the proposed visual interface. Qualitative and quantitative analyses of video recordings and trace log data of students using the visual interface, as well as student interview responses, indicate that the proposed visual interface, in combination with the Use-Modify-Create scaffolding progression, has significant potential for effectively supporting students in learning AI planning concepts.

2. Related work

The research presented in this article extends our previous work, which provided a qualitative analysis of students interacting with the proposed visual interface to formulate AI planning tasks [34]. In the current work, we complement our previous analysis with an examination of fine-grained gameplay interaction log data that was recorded as students interacted with PrimaryAI in an additional data collection held in an elementary classroom setting. We conducted a quantitative analysis of the student interaction data in order to extract the latent characteristics of student engagement with the proposed visual interface, which provides additional insight into our research questions. In the remainder of this section, we provide an overview of related work on efforts to bring AI learning experiences to K-12 settings as well as visual interfaces and tools for supporting K-12 Computer Science and AI learning.

2.1. K-12 AI education

As AI has grown in prevalence, it has become increasingly important to educate students to learn and think critically about AI [35,36]. A number of recent efforts have started to explore how to integrate AI into the K-12 curriculum and foster AI literacy among K-12 students. The AI4K12 initiative proposed the Five Big Ideas of what K-12 students should learn about AI [11]. Similarly, researchers have developed K-12 AI literacy resources that include a wide range of hands-on online AI learning activities for K-12 students to learn about AI.[3] For example, ReadyAI[4] is creating pre-configured toolkits, such as AI-in-a-Box, that includes both hardware and software to teach AI courses to K-12 students. Additionally, Curiosity Machine[5] and AI with MIT App Inventor[6] [12,13] are online tools to teach AI concepts and the basics of machine learning to K-12 students. AI for Oceans Code.org[7] provides an AI educational platform that teaches K-12 students about AI and machine learning by allowing them to explore how AI can help with global environmental issues. Work is also underway to develop modules for K-12 students to learn about AI and how to use it responsibly [37]. For instance, researchers have created the AI and Ethics for Middle School curriculum to teach middle school students about ethical issues in AI, such as bias in machine learning algorithms and ethical design principles [10,38]. Bilstrup et al. [39] presents a card-based design workshop by allowing students to explore how ethical and moral choices reflect their own machine learning applications. Our work on PrimaryAI fills a gap in the ongoing work by investigating how game-based learning can be used to integrate AI education into upper elementary classrooms.

2.2. Visual interfaces for K-12 computer science education

Providing a simple and intuitive visual interface for K-12 students who are unfamiliar with expressing computational tasks poses significant challenges. Although there are many text-based programming tools for K-12 students (e.g., Gidget [40], CodeCombat [41], CodeMonkey[8]), researchers are increasingly exploring visual interfaces to help novices learn to program. This is especially appealing for young learners, where tools are supported by intuitive and novice friendly interfaces without considerable guidance or supervision. There are a variety of block-based visual programming languages, such as Blockly [14], Scratch [15], Snap! [16], Tynker,[9] and MIT App Inventor that have been developed and utilized in K-12 classrooms. Smith et al. [42] developed an approach to use block-based programming for interactive storytelling to engage upper elementary students in computational thinking. Bradbury et al. [43] investigated how to effectively design collaborative programming environments for elementary students, where students used a block-based programming language called NetsBlox [44]. Hill et al. [45] introduced *LaPlaya*, a block-based programming language designed specifically for students in grades 4–6. Percival et al. [46] implemented CryptoScratch, a Scratch platform-based framework that allows students to learn how to use cryptographic algorithms such as AES, RSA, and SHA2. Although these works provide friendly and effective interfaces for K-12 students, they do not support elementary students in learning AI concepts. Our approach enables block-based programming to be tightly integrated into gameplay that features AI problem solving within a game-based learning environment. Prior work has also looked at using gameplay to teach programming, such as Blockly Games[10] and Lightbot [47]; however, this work did

3 https://aieducation.mit.edu
4 https://www.readyai.org
5 https://www.curiositymachine.org/lessons/lesson/
6 https://appinventor.mit.edu/
7 https://code.org/oceans
8 https://www.codemonkey.com/
9 https://www.tynker.com/
10 https://blockly.games/

not address learning AI concepts. Our efforts build upon these prior endeavors to design a visual interface for upper elementary students to enable students to formulate AI planning tasks in a game-based learning environment.

2.3. Visual interfaces for K-12 AI education

Efforts are underway to develop visual interfaces, tools, and curricula to support K-12 students to engage with AI tools and learn AI concepts and practices. These visual tools enable students to explore machine learning, computer vision, and other AI technologies by creating opportunities for students to explore and learn about AI on their own. For example, Google's Teachable Machine[11] [18] uses a web-based interface that helps students easily create machine learning models without having any prior experience in coding. It enables students to train and test machine learning models to classify images, poses, and sounds. Similarly, AI Programming for eCraft2Learn[12] is an extension to Snap! [16] that enables students to build their own AI program using block-based programming. AI blocks are used to build custom AI models involving image and speech recognition, and neural network application development. Another example is Cognimates [19], an open-source platform for AI literacy for students between 7–14 years old [15]. Cognimates allows students to participate in creative programming activities that includes building their own AI models to perform image classification, speech recognition, and sentiment analysis. Similarly, other tools also extend block-based programming languages to support building machine learning applications for students unfamiliar with programming. Machine Learning for Kids (ML4Kids) is an extension to Scratch and helps students build simple AI programs by leveraging AI models powered by IBM Watson [20]. ML4Kids provides an easy-to-use environment for building machine learning models to recognize images, text, or sounds. It enables students to train machine learning models and use them in their own projects. PoseBlocks [21] provides a custom block-based programming interface developed on top of Scratch, supporting body, hand, face, and emotion recognitions to help middle school students explore AI concepts. PoseBlocks integrates with Google's Teachable Machine to build custom image, audio, and pose models from body-sensing camera and microphone inputs. In contrast, Scratch Text Classifier [22] helps middle school students become more knowledgeable about how classifiers work, allowing students to create their own project using a custom created text classifier. AI Snap! blocks [23] is an extension to Snap! allowing students to create machine learning applications by utilizing a set of predefined machine learning blocks. Convo [27,48] is a conversational programming interface using Conversational AI in MIT App Inventor, which has been used in K-12 settings to teach students AI concepts as they create their own conversational AI agents. AlpacaML [49] enables students to build ML gesture classifier models to be integrated into Scratch projects. These tools help to systematically create AI curriculum and tools for K-12 students to learn AI concepts. However, most of the prior work has focused on teaching machine learning with either middle or high school students. Little work has investigated effective and engaging approaches for promoting upper elementary students to learn AI concepts. The current research explores a visual interface that allows upper elementary students to formulate AI planning tasks within a game-based learning environment.

3. PrimaryAI game-based learning environment

PrimaryAI is a game-based learning environment that is being designed to support AI education for upper elementary students (Fig. 1). The game is designed to be implemented in classrooms with an associated AI curriculum that incorporates "unplugged" learning activities. The classroom activities help introduce students to AI concepts prior to encountering them in the game. This section provides an overview of the PrimaryAI game-based learning environment as well as discusses the design of the proposed visual interface integrated in the game to support upper elementary students in formulating AI planning tasks.

3.1. Game design

PrimaryAI enables students to learn about AI by engaging in a rich storyworld in which they address life science problems using in-game AI tools. In the game, students investigate the recent declining population of yellow-eyed penguins on New Zealand's South Island. Throughout students' exploration in the game, they complete a series of AI-centric quests that help them gather data and evaluate hypotheses regarding the interactions among wildlife on the island. The learning environment's curricular content is aligned with the Next Generation Science Standards [50] as well as concepts and practices from the K-12 Computer Science Framework [51] oriented towards age-appropriate AI concepts.

PrimaryAI is designed to promote student engagement through four intrinsic motivators as identified in Lepper's classic work on intrinsic motivation in learning: *challenge*, *curiosity*, *control*, and *contextualization* [52].

- *Challenge*: throughout the learning experience, students are presented with a series of game-based challenges that introduce them to AI concepts. Students use visual interfaces, inspired by work in block-based programming, to develop solutions to AI-centric challenges presented in the game.
- *Curiosity*: as students explore the storyworld, their investigation is driven by an overarching mystery—What is causing the recent decline in the native population of yellow-eyed penguins on the island? The learning environment encourages students to solve the mystery by gathering data and analyzing data about the local penguin populations.
- *Control*: as students investigate the mystery, they are free to choose how to navigate the virtual world and interact with the environment. For example, students can create their own solutions to AI planning tasks using the in-game visual interface, which provides them with creative flexibility and a strong sense of choice.
- *Contextualization*: the learning environment uses a narrative context that integrates fantasy elements based around real-world struggles, e.g., declining penguin populations, to contextualize the students' learning activities within. Students utilize a virtual semi-autonomous robot, disguised as a penguin, to navigate around yellow-eyed penguin colonies to collect data. These activities draw on both cognitive and affective aspects of problem solving to motivate students during their learning.

PrimaryAI gameplay features quests that cover key AI concepts: *AI Planning, Machine Learning*, and *Computer Vision*. In one of the quests, students learn that the yellow-eyed penguins are notably shy around humans and are asked to collect data using a robot disguised as a penguin—playfully referred to as RoboPenguin in the game. Students learn to formulate AI planning tasks using our proposed visual interface to control the robot to collect photos of wildlife from designated areas on the island (e.g., beach or nest). In another quest, students are asked to review the collected photos and apply labels to each photo, so that they can train the robot to learn how to correctly classify wildlife photos as either penguins, weasels, or other wildlife. This quest introduces students to supervised machine learning concepts. In the final quest, students learn about and use computer vision techniques to further enhance the robot's capabilities. For example, providing the robot with the ability to accurately recognize predators of the penguins, which might be contributing to the recent decline in the penguin population. The version of PrimaryAI used in the study described in this

[11] https://experiments.withgoogle.com/ai/teachable-machine/
[12] https://ecraft2learn.github.io/ai/

Fig. 1. The PrimaryAI Game-Based Learning Environment.

article, focuses on the AI planning quest, which introduces AI planning concepts; the other quests are under development.

To help students gain a deeper understanding of the AI concepts covered in PrimaryAI, the quests are organized using a Use-Modify-Create (UMC) scaffolding progression, which has shown promise for promoting the acquisition and development of computational thinking skills [33]. For example, PrimaryAI's quest on AI planning uses a UMC scaffolding progression consisting of three missions: (1) *Use*: students are initially provided a fully formulated AI planning task in the visual interface in order to support them in becoming familiar with the interface and the planning tasks being addressed, (2) *Modify*: students are asked to manipulate blocks in a partially formulated AI planning task using the visual interface, (3) *Create*: students are asked to formulate a new AI planning task from scratch using the visual interface. We expect that this UMC approach will help scaffold student learning during the AI planning quest.

3.2. Visual interface for formulating AI planning tasks

The visual interface for formulating AI planning tasks in PrimaryAI is shown in Fig. 2. This interface enables upper elementary students to specify AI planning tasks through *Initial States*, *Possible Actions*, and *Goal States*. The design of the interface was refined through several rounds of iterative feedback and refinement, with the goal of delivering a clear concept of AI planning while interacting with the visual interface. Students can observe how each component in AI planning contributes to generated plans and how different AI planning task constructions affect the AI robot's action in the game. The visual interface consists of three main functional areas: *Control Panel*, *Block Panel*, and *AI Planning Panel*. The Control Panel along the top of the interface enables students to deploy the robot in the virtual storyworld using their formulated AI planning task, revisit the mission briefing describing the task that needs to be accomplished using the robot, and reset the AI Planning Panel to its original configuration for the mission in case the student would like to start over.

The Block Panel on the left side of the interface allows students to select blocks from two different categories: States and Actions. The blocks are color coded based on the part of the AI planning task specification that they correspond with and can only be dropped in the appropriate columns of the AI Planning Panel. For example, students can only move blocks under the *Actions* category into the *Possible Actions* workspace of the AI Planning Panel. The Block Panel also includes a trash can icon, which allows students to delete unwanted blocks from the workspaces by dropping the block onto the icon.

The AI Planning Panel, which occupies most of the interface, consists of three vertically-divided workspaces that represent the key components of the AI planning task specification. The *Initial States* workspace is pre-populated by the game based on the context of the mission (e.g., robot is currently located at the research station on the island), which allows students to understand the starting state for the robot and think about which actions and goals are appropriate for achieving the objective of the mission. The *Possible Actions* workspace allows students to specify which actions should be considered, while creating a plan for achieving the mission objective. Finally, the *Goal States* workspace is used to specify the goals that need to be achieved in order for the mission to be successfully completed. As students drag blocks from the Block Panel to the workspaces, they are highlighted in yellow when the block is over a valid workspace, otherwise the blocks are highlighted in red. When a block is dropped onto an invalid workspace (i.e., highlighted in red), the block snaps back to its original location to help ensure students learn to place blocks correctly.

Using the visual interface, students specify AI planning tasks for the robot penguin. Students drag blocks from the States and Actions block categories to specify the AI planning task based on the mission's

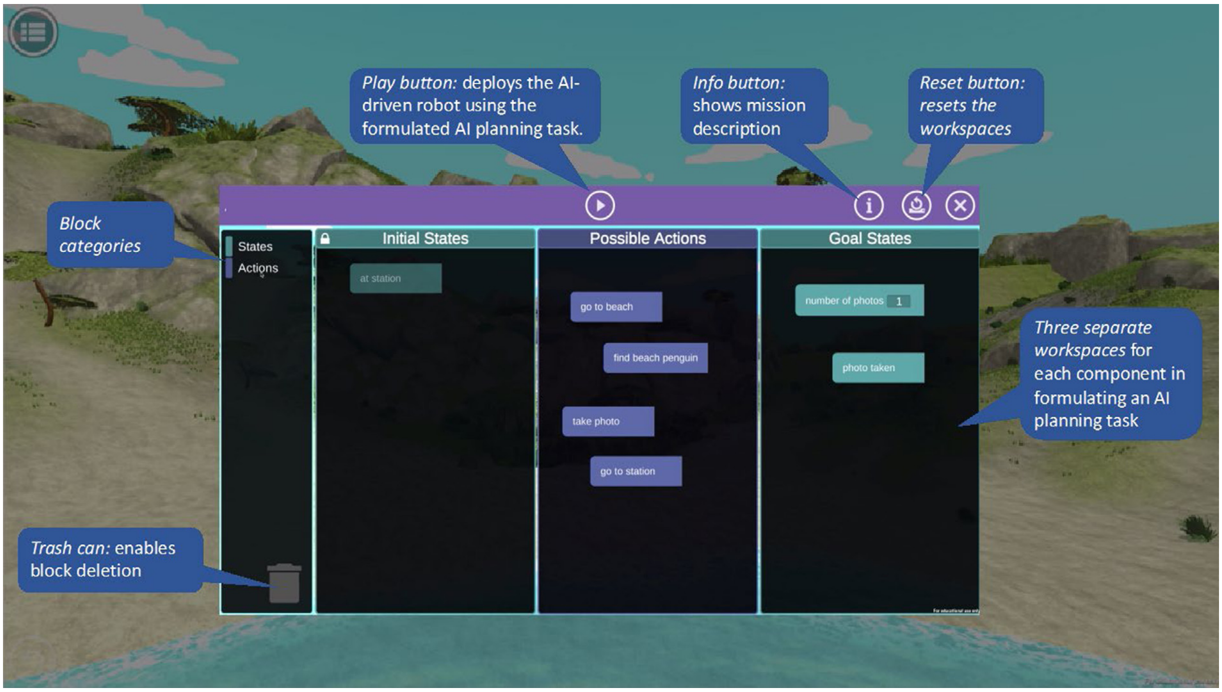

Fig. 2. The visual interface for formatting AI planning tasks.

Fig. 3. In-game screenshot of plan being executed by the robotic penguin based on a formulated AI planning task.

scenario (e.g., "Take three pictures of penguins at the beach and come back to the station"). After specifying the AI planning task using the visual interface, students can watch the robot penguin plan and execute actions to achieve the goals based on their formulated AI planning task. Fig. 3 shows the view of the robot penguin students see as it executes the plan. The AI Dashboard on the left side of the screen shows students aspects of the plan as the robot executes the plan (e.g., goals, current actions). The current action is also presented in a thought bubble above the robot penguin's head to help students follow what action is currently being executed. This indicator is also used to notify the student whether a goal is being achieved by the robot, or if it is unable to create a plan based on the student's AI planning task formulation.

To develop the visual interface for specifying AI planning tasks, we iteratively evaluated several design alternatives with elementary school teachers who have been co-designing the PrimaryAI curriculum with the research team. Early mockups of the interface were created using the Blockly developer toolkit[13] to support design discussions with the teachers (Fig. 4). The first mockup we worked on with teachers is shown in Fig. 4a where a nested block was utilized to represent the AI planning task specification (i.e., initial state, possible actions, and goals) where state and action blocks could be attached to it. This approach had several advantages: (1) students would likely find it easy to manipulate, since it is similar to other block-based programming environments, and (2) we could leverage an existing block-based programming toolkit based on Blockly that was designed specifically to integrate with game-based learning environments [53], which would speed up development.

[13] https://developers.google.com/blockly/guides/create-custom-blocks/blockly-developer-tools

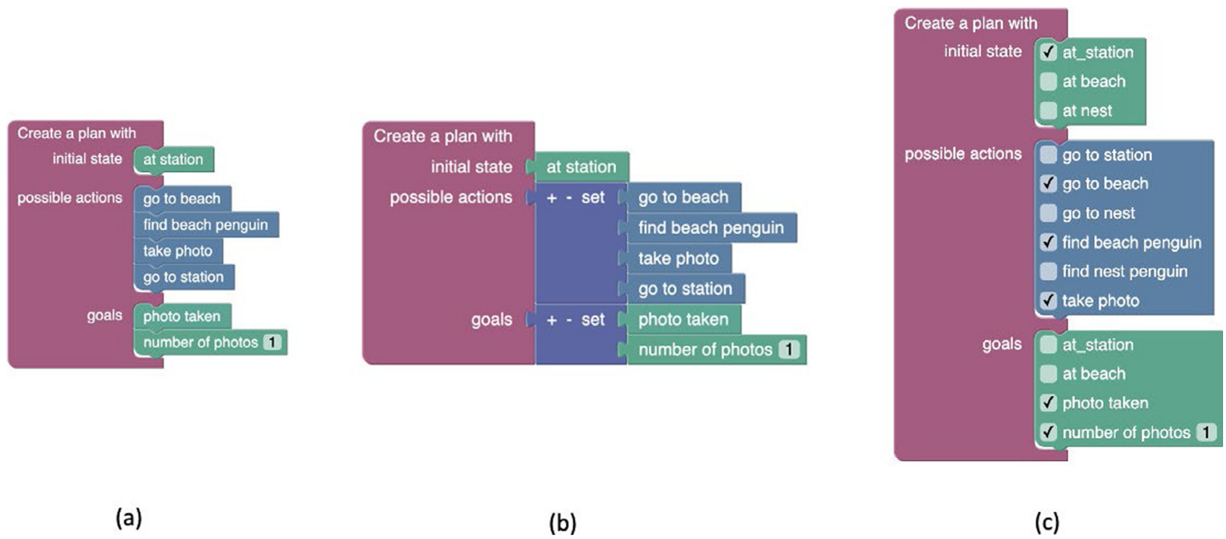

Fig. 4. Three mockup designs for AI planning task formulation from early design iterations. (a) Nested blocks, (b) "Set" blocks, and (c) Checkboxes.

However, after discussing the approach with our partner elementary school teachers, several concerns were identified: (1) stacking the state and action blocks vertically might inadvertently suggest to students that the states and actions are sequential in nature, and (2) using a more traditional block-based programming design might give students the impression that they can program the AI agent directly.

Following the completion of the first mockup, other design options were investigated (Fig. 4b and Fig. 4c). The mockup in Fig. 4b attempts to address the concerns about sequential order by explicitly showing that states and actions are contained in a "set" block where students can manipulate the number of possible actions or states using the "+" and "-" signs on the block; however, this design raised concerns about being overly complex for upper elementary students. The mockup in Fig. 4c explores a different approach to resolving the sequential ordering concern by allowing students to modify and test their AI planning task formulation using checkboxes; however, this design raised concerns about its scalability to larger AI planning tasks with a variety of actions and states. After considering all of the options, we came to the conclusion that, while the sequential ordering issues within the individual components could probably be resolved, the outer nested block posed additional challenges by implying a sequential relationship between initial states, possible actions, and goals. Unlike traditional programming tasks upper elementary students are familiar with, the specification of an AI planning task is less sequential in nature. The AI planning agent considers each of the components in an AI planning task formulation to come up with a plan (i.e., sequence of actions that can achieve the goals). Thus, in the final version of the interface as described above (Fig. 2), we aimed to make the interface as easy to understand as possible for upper elementary students, while addressing the concerns raised by our partner teachers.

4. Method

4.1. Study design

In order to test our visual interface to support upper elementary students in expressing AI planning tasks, we conducted a study in Spring 2021, consisting of data collected at three sites (Site A, Site B, Site C) with forty-two upper elementary grade students (Fig. 5). The description of each site can be found in Table 1. We collected three types of demographic information from each site: (1) gender, (2) race, (3) grade.

- Site A: (1) 3 male and 3 female students, (2) 1 student identified as African American, 1 as Pacific Islander, and 4 as White/Caucasian, and (3) 2 students were third graders, 1 student was a fourth grader, and 3 were fifth graders.
- Site B: (1) 7 male and 8 female students, (2) all 15 students identified as White/Caucasian, and (3) 10 students were third graders, 1 student was a fourth grader, and 4 were fifth graders.
- Site C: (1) 9 male and 12 female students, (2) 7 students identified as African American, 7 as Latinx, and 7 as White/Caucasian, and (3) all 21 students were fifth graders.

All students were native English speakers. Students participated in a pre-survey, and unplugged activities prior to playing the game to gather demographic information and explain the fundamental concepts of AI planning. Students were encouraged to ask questions during the game if they required assistance.

As described in Section 3, we adopted a Use-Modify-Create approach to present the AI planning tasks to students in the game. The mission scenarios we used were as follows:

- *Use*: A non-player character (NPC) in the game, who narrates the missions, adds the appropriate actions and states to the workspaces to specify the AI planning task for the students. Using this formulated AI planning task, the robotic penguin will take a picture of a penguin at the beach and then return to the research station. Students are asked to review the formulated AI planning tasks in the visual interface and deploy the robotic penguin.
- *Modify*: The NPC asks students to revise the formulated AI planning task using the visual interface so that the robotic penguin will take 3 photos of penguins at the beach and then return to the research station.
- *Create*: The NPC informs the student that someone accidentally deleted all the possible actions and states from the formulated AI planning task, so students are asked to specify a new AI planning task to control the robotic penguin using the visual interface.

We collected video recordings of students' computer screens and voice recordings throughout their gameplay for the studies conducted at Site A and Site B. Collecting the video recordings allows us to carefully examine the students' behavior during gameplay and is helpful in capturing students' micro-interactions with the learning environment [54]. At Site C, we collected student game interaction data from 21 students in a classroom setting in order to conduct a quantitative analysis of the inherent characteristics of student interaction with the proposed visual interface captured in trace log data. The trace logging system in the

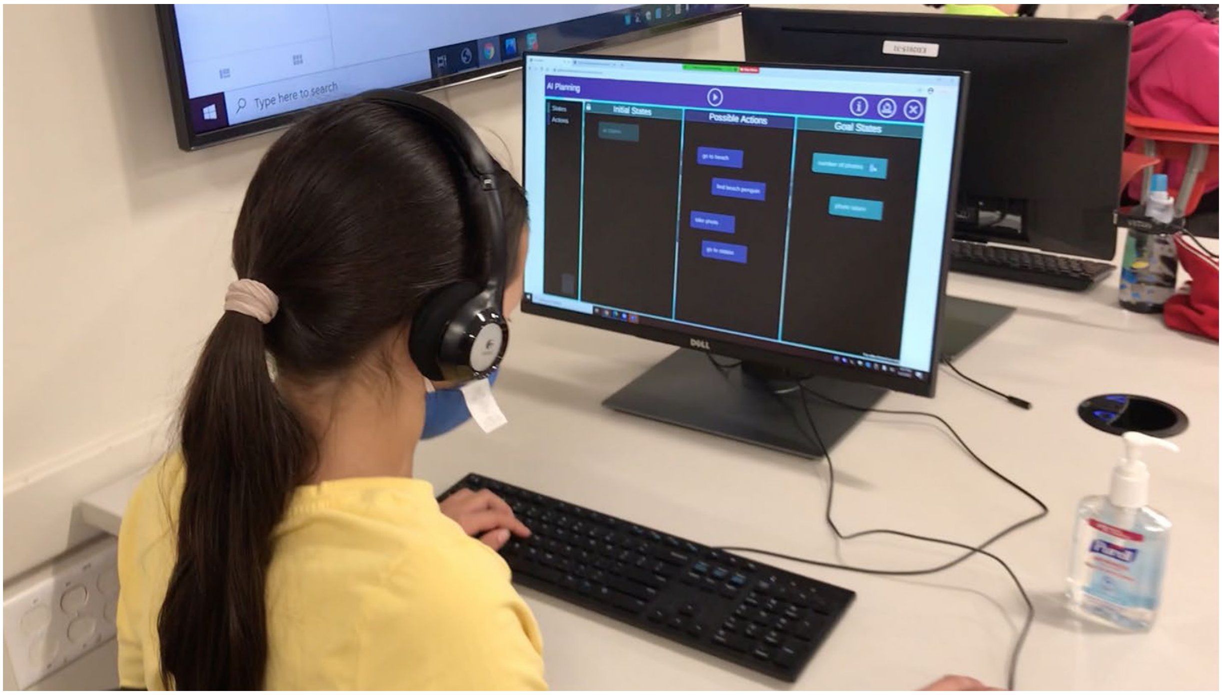

Fig. 5. Student playing PrimaryAI in the study. The student is formulating an AI planning task using the in-game visual interface.

Table 1
PrimaryAI data collections in Spring 2021.

Site	*Description*	*Screen recording*	*Trace sata*	*Number of students*
Site A	University laboratory	Yes	No	6
Site B	After school classroom	Yes	No	15
Site C	Co-design teacher's classroom	No	Yes	21

game records all activities performed by a student during gameplay. This includes what the student observes on their game screen (e.g., pop-up messages, how in-game objects move based on the specified AI planning task, and which part of the game scene they are in), as well as student actions (e.g., type of object they are moving (i.e., blocks) from one panel to another, any component the student clicks on in the visual interface). All of the trace log entries are logged with corresponding time stamps.

In addition to investigating how our visual interface supports upper elementary students in expressing AI planning tasks in order to address our research questions, we also wanted to better understand how students reacted to our proposed visual interface and how effective they thought the interface was for their learning. For this purpose, we conducted a short interview with some of the students where they were asked questions about the game, the visual interface, and what they learned about AI.

4.2. Analysis methodologies

For our qualitative analysis, we analyzed the video recordings from Site A and Site B using Ramey et al.'s qualitative video data analysis methodologies, which emphasize three aspects of video analysis: transcription tensions, defining the unit of analysis, and representing context [55]. We defined the specific aspects of our study that we intended to analyze using the collected data, based on our research questions: (1) How is the proposed visual interface received by students and what hurdles do they encounter while using it? (2) How does the proposed visual interface, in conjunction with the Use-Modify-Create scaffolding progression, assist students in expressing AI planning tasks? (3) What misunderstandings do students have when formulating AI planning tasks using the proposed visual interface? We iteratively transcribed our recordings in order to capture both spoken and non-verbal interactions (i.e., screen-based activity) throughout the gameplay. We drew broad conclusions from the observations of several students in our study.

For our quantitative analysis of students' interaction with the proposed visual interface, we analyzed the trace log data from the 21 students at Site C. Similar to the qualitative analysis with video recordings, we analyze these data with respect to how simple our visual interface is to manipulate the blocks as desired (RQ1), and how our UMC scaffolding progression was accepted by students (RQ2). Metrics for evaluating the effectiveness of our visual interface includes (1) the number of completed missions, (2) game time for each mission, and (3) the correlation between the number of blocks moved and the number of trials for each mission, where the trials were logged when students executed their formulated AI planning task. The micro-interactions, such as where students placed the blocks (e.g., pixel-level coordinates) in the workspaces, were not captured in the trace log data, thus the misconceptions related to RQ3 were not investigated in this quantitative analysis. Qualitative and quantitative analysis findings are discussed in conjunction with each other in Section 5.

5. Results and discussion

We discuss the student behavior observed and reactions during the recordings, as well as student interview responses and design implications from the study observations.

5.1. Observation

Overall, students were very active while playing the game. The recorded data contained many examples of students' verbal reactions of excitement about the game-based learning environment. Also, students seemed to be deeply engaged in the overarching narrative of the game. Considering our target population is upper elementary students, seeing the students engaged in the learning environment was a positive step in delivering the desired learning outcomes. The following excerpts from the recordings demonstrate some of the reactions to the visuals and problem-solving tasks in the game-based learning environment:

- *"Penguins are adorable!"* (While seeing the penguins in the game)
- *"Oh, he came through a bush!"* (Pointing at a penguin)
- *"Go RoboPenguin, go!"* (While seeing the robotic penguin approaching a group of penguins)
- *"Why Ted... why?"* (Reacting in the third mission to one of the engineers, Ted, who accidentally erased the possible actions from the AI planning task formulation)
- *"I want to see the baby penguins in the nest!"* (While dragging action blocks related to taking photos of the penguins)

Related to our proposed visual interface for expressing AI planning tasks, all students effectively formulated the tasks using the proposed visual interface, and the majority of them successfully completed the offered missions. According to our video analysis, none of the students appeared to have difficulty dragging and dropping blocks. We believe this is one of the benefits of our visual interface adopting a look-and-feel similar to block-based programming, as many students will be familiar with it. This advantage was also demonstrated in our quantitative analysis. To verify this, we calculated the correlation between the total number of blocks moved and the total number of trials for each mission. We hypothesized that if they are positively correlated, it indicates that manipulating the blocks in our proposed visual interface is relatively simple (i.e., the increase in the number of blocks moved is mostly because of the additional trials). According to Table 2, there were moderate to strong positive relationships between the number of blocks moved and trials for all missions. The low correlation for mission 3 in comparison to prior missions may indicate that there was more variation among students when they were required to formulate the entire AI planning task from scratch. The distribution of time duration used for moving a block as shown in Fig. 6 also shows that students for the most part moved blocks to their target within a few seconds ($M = 1.82$, $SD = 2.03$), which could indicate that manipulating the blocks in our visual interface was simple and straightforward, even with considering the possibility that there can be some students that are adept at handling the mouse or touch screen. The average number of blocks moved per trial, on the other hand, reveals an intriguing result (Table 3). Although students did not need to manipulate blocks during the first mission (*Use* mission in our UMC progression), because the solution was pre-populated, students moved more blocks on average in mission 1 (*Use*) than in mission 2 (*Modify*). This may indicate that we need to communicate more clearly that all they need to do is examine the formulation of the planning task in order to assist them in focusing more on comprehending the problem than on moving blocks. Another possibility is that this was the first time the students interacted with the interface in the game, so they may have moved more blocks as they were exploring how the interface worked. Additionally, students appeared to comprehend that the robotic penguin performs the actions listed in the Possible Actions workspace. Students did not appear to struggle with the language used in the blocks, indicating that our visual interface is intuitive for upper elementary students; however, because our participants were all native English speakers, additional study with a broader population of upper elementary students is necessary to confirm this. An intuitive visual interface for students to interact with could reduce cognitive burden on students, allowing for a shift in focus from learning how to use the different features in the game to applying AI planning concepts to the game scenario.

We identified certain usability concerns with the visual interface in our qualitative analysis, which may cause students to become disengaged from the learning activities. The trash can icon is present in the lower-left corner (see Fig. 2) to enable for the deletion of blocks from workspaces. This is similar to the functionality found in block-based programming languages such as Blocky, but since we have three workspaces for each component in the AI planning task formulation some of the blocks on the workspaces are rather far away from the trash can icon. This was not an issue for students who used a mouse; however, for some students who used a trackpad or touch screen on their computer, we observed it was difficult for them to drag the blocks to the trash can at times. Also, in the current version of the interface blocks have to be properly aligned over the trash can icon to allow block deletion (i.e., when it is highlighted in yellow) (Fig. 7). Since we expect students will need to iteratively test formulating their AI planning tasks to develop complete solutions, by manipulating the blocks it is critical to enhance the usability of block deletion in our visual interface.

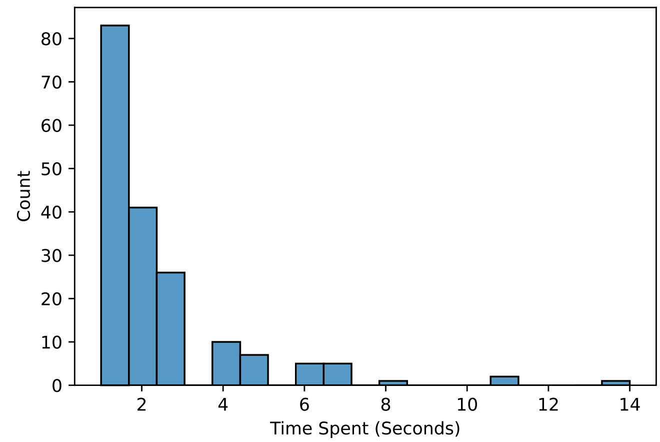

Fig. 6. Histogram of the time spent for block moving. Each bar indicates the total number of blocks in the dataset that were moved within each time window.

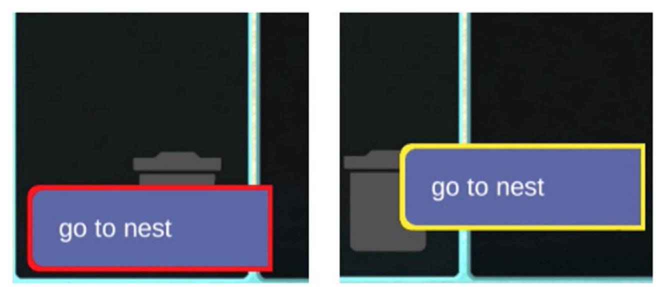

Fig. 7. Observed usability issue when deleting blocks. A block cannot be deleted when it is highlighted in red (Left), and it can only be deleted when highlighted in yellow (Right).

With regard to our Use-Modify-Create scaffolding progression approach (RQ2), we observed from qualitative and quantitative analyses that the majority of students were able to specify the entire AI planning task in the final mission, implying that the UMC scaffolding progression is assisting students in grasping AI planning concepts. Fig. 8 shows the number of completed missions for all students participating in the Site C data collection. Here, we see that 81% of participating students (i.e., 17 out of 21) successfully completed the final mission, which demonstrates our approach is promising; however, we should continue to work on ensuring that the remaining students comprehend the concepts as well. According to Table 4, the median of game time spent marginally increased from Mission 1 (*Use*) to Mission 2 (*Modify*), but greatly increased during Mission 3 (*Create*) ($p = 0.07$). This progression might indicate that most students were prepared for Mission 2 following their experience with Mission 1, but perhaps needed more practice prior to Mission 3. This also implies the need for multiple missions for each

Table 2
Relationships between the number of blocks moved and the number of trials for each mission.

	Pearson Correlation coefficient (r)
Number of blocks moved and trials in Mission 1 (*Use*)	0.806 ($p < 0.01$)
Number of blocks moved and trials in Mission 2 (*Modify*)	0.790 ($p < 0.01$)
Number of blocks moved and trials in Mission 3 (*Create*)	0.437 ($p < 0.1$)

Table 3
Statistics for the number of blocks moved per mission trial.

	Mean	*SD*
Number of blocks moved per trial in Mission 1(*Use*)	3.46	2.12
Number of blocks moved per trial in Mission 2 (*Modify*)	1.24	1.01
Number of blocks moved per trial in Mission 3 (*Create*)	6.93	4.43

Table 4
Statistics of the game time spent on each mission by students at Site C (Minutes).

	Min	*Median*	*Max*
Game time spent on Mission 1 (*Use*)	1.40	2.12	13.45
Game time spent on Mission 2 (*Modify*)	1.78	2.15	3.47
Game time spent on Mission 3 (*Create*)	2.16	4.07	48.23

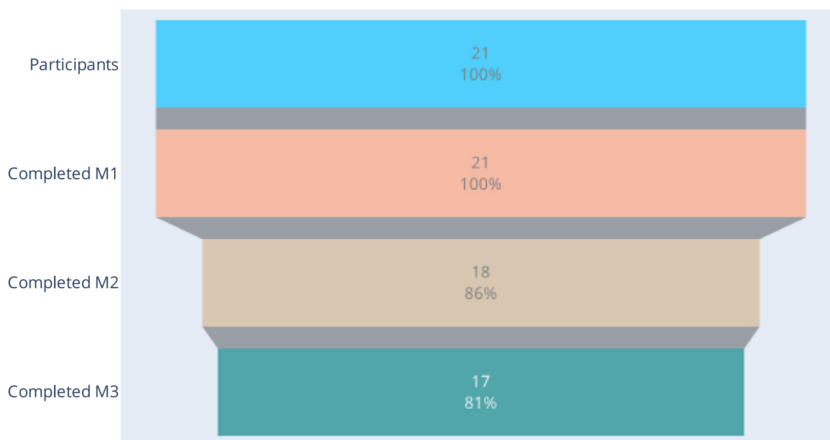

Fig. 8. Funnel chart of the number of students at Site C who completed each mission in PrimaryAI.

step of the UMC scaffolding progression. Additionally, we noticed from the video analysis that some students complained about the repetitive nature of the tasks. This could be because the planning tasks were too easy for the students or because the tasks in each mission should be more varied. This will require additional research to determine the optimal mix of "not too difficult" and "not too easy" task variations, or potentially the development of many task sets that are adjustable to specific students' knowledge competencies as indicated by the large difference between the shortest and longest game time spent in each mission (i.e., the missions were easy for some students, but hard for the other students) (Table 4).

Lastly, we observed a common misunderstanding among many students as they formulated their AI planning tasks (RQ3). While the task formulation does not specify sequential actions and states, it was evident from watching the videos that many students attempted to align the blocks sequentially, as they do in other block-based programming environments. To avoid this misunderstanding, we purposefully arranged the pre-populated blocks in the workspaces during the Use and Modify missions in such a way that they were not aligned; however, this design was insufficient, as students continued to perceive the blocks as sequential actions from top to bottom. While some actions (e.g., "Find beach penguin" and "Take photo") are repeatedly done numerous times in the created plan, the current architecture can nevertheless contribute to this mistake. Additionally, we observed students attempting to organize all other possible actions on the workspace prior to the "Go to station" action, which is always executed at the end of a successful plan but does not have to be at the end of the AI planning task specification (Fig. 9, Left), or attempting to connect blocks by aligning them (Fig. 9, Right).

5.2. Interviews

After playing the game, we conducted interviews with some of the students to get their feedback on the learning environment as well as to understand how the visual interface was being received. The questions along with a set of responses from the students are listed below.

What did you think of the game?

For this general question about the game, students showed how much they liked the visuals (e.g., animations) in the game and how they enjoyed playing it.

- *"It was pretty fun, I liked it".*
- *"I liked the animations".*
- *"I thought it was great. It was really well programmed for people to use the environment. It was pretty impressive".*
- *"It was pretty interesting and it taught me a lot about AI that how simple it can be. I always thought AI is the super complex thing, and it still can be, but also it can be super simple just like planners".*

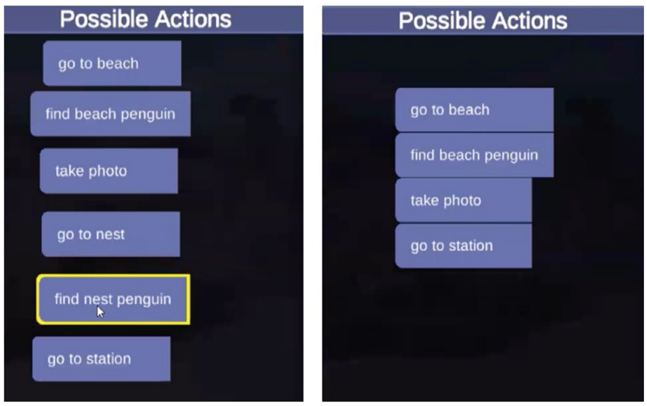

Fig. 9. Student misconception about the sequential order of blocks in formulating an AI planning task. The student is inserting a new block before the "Go to station" block that is always executed at the end of the plan (Left). The students made all blocks left-aligned and attached to one another (Right).

These responses align with what we observed while the students played the game (Section 5.1). Considering our target student level (i.e., upper elementary student), it is critical for a game-based learning environment to grab students' interest from the beginning in order to be successful in delivering the learning objectives. Students also mentioned that they were impressed by their ability to manipulate in-game objects, and enjoyed learning about AI through the game, which they viewed as a complex subject.

What did you like about the visual interface for specifying AI planning tasks?

Regarding the visual interface designed for specifying AI planning tasks, students found it useful and helpful for increasing their engagement with the game, and they liked its interactive design.

- *"I thought [it was] more interactive because if you didn't exactly create [the AI planning task formulations], it would be just you pressing play and watching everything [ ] so I thought [the visual interface] made [the game] a little bit more fun".*
- *"I felt [the visual interface] was very customizable. There were so many things you could do".*
- *"I loved it. I felt like [the game] was very interactive. I really liked the coding part because [the visual interface] puts into initial states, possible actions, and goal states, which I thought it was actually pretty cool".*

These responses suggest that our visual interface was easy to utilize, thus helping students understand the concept of AI planning, in addition to making the game more enjoyable.

How could we make the visual interface for specifying AI planning tasks better?

Regarding future improvements to the current visual interface, it was surprising how detailed students' responses were. For students to better grasp the concepts, students suggested changing some of the wording in blocks, providing more information through additional functionality (i.e., hovering), and using different colors for each component of the AI planning task. Students also suggested a customizable visual interface where one can change the size of the text in the interface.

- *"I would make it a little more detailed, so under [the AI Planning Panel], it tells you [more] about possible actions".*
- *"For the number of photos, you could say how many photos you want to have taken in the end, so that kids know actually what [the block] means. I feel like a lot of kids don't exactly understand and [might] interpret it in a wrong way and something could go wrong".*
- *"I think [a] pop up [with a detailed description] when you hovering over [the components in the interface] would be nice".*
- *"For some students with blurry vision, it might be really hard for them [to read the text in the blocks], so maybe we could increase [the text size] a bit".*
- *"Having a slider that can change the text size would be helpful".*
- *"Initial state color can be a different color [than] the goal states".*

All of these are valuable suggestions that must be carefully considered for the next version of the visual interface in order to target broader student populations.

Students' responses to the following two questions show that they were well engaged in our narrative-centered game-based learning while learning how to specify AI planning tasks using the proposed visual interface.

What did you learn ***about AI?***

- *"I learned how simple AI is and how AI can be used to help study endangered species".*
- *"I learned AI can be used to help people and animals".*

What did you think about using an AI-driven robotic penguin to save the yellow-eyed penguins?

- *"It was a pretty smart idea because it combines science and ingenuity all in one".*
- *"I thought it was really cool how someone engineered up robot penguins to take pictures of real ones".*

Through the experience of playing PrimaryAI, students were not only able to learn about AI, but also learn about how AI techniques can be applied to helping with endangered species issues.

Overall, students' responses show that they were engaged in the game and the ability of manipulating the robotic penguin using our visual interface made the game more interactive. Students' suggestions on the visual interface point to potential improvements to make to the visual interface. Lastly, students were interested in the game's approach of connecting life-science problems with AI learning and started to see AI as a useful tool that is not as complex as one might imagine.

5.3. Design implications

We identified a set of design implications for assisting students' learning based on our study observations. First, the representations of the components of an AI planning task utilized in visual interfaces are critical for student learning. Although we carefully designed the proposed visual interface to avoid potential misunderstandings, further refinement of our representations is required to convey the fact that the actions laid out in the interface are not necessarily sequential and do not need to be connected in order for the AI-driven agent to create a plan successfully. Several options are being considered to address this issue, including the following: (1) better arrangement of the pre-populated blocks so they are distributed both horizontally and vertically, in the Use and Modify missions, to show that the blocks do not need to be sequentially or spatially aligned, and (2) prompt feedback to students whenever they attempt to connect two blocks in a workspace. Second, given the variety of computing platforms used in elementary classrooms, we need to improve the design of our visual interface to make it more compatible with a variety of input devices (e.g., trackpads). As indicated previously, one of the primary usability difficulties highlighted throughout the survey was the inability to eliminate undesired blocks using the trash can symbol. To address this issue, we could potentially try: (1) experimenting with other deletion methods (e.g., right-click and remove), (2) adding a trash can icon in each workspace so that it is closer to the blocks being erased, or (3) highlighting droppable areas in addition to highlighting the blocks in different colors to clearly communicate where the blocks could go.[14] Lastly, based on students' suggestions on the visual interface, we should explore a few areas for improving the usability of the interface: (1) supporting a tooltip-mode where students can click or hover over components in the visual interface (e.g., blocks, icons, terms) and see details on it, (2) introducing a revised color scheme for each of the three components in formulating an AI planning task, and (3) introducing accessibility functions such as resizable text or customizable color schemes.

6. Conclusion

Accelerating advances in artificial intelligence have introduced the need to introduce AI education to K-12 students. In this work, we proposed a visual interface for elementary students to formulate AI planning tasks within a game-based learning environment. Qualitative analysis of video recordings, quantitative analysis of trace log data, and student interviews demonstrated how our visual interface and a Use-Modify-Create scaffolding progression assisted students in learning about AI planning. The analyses also identified student misconceptions while using the visual interface as well as usability issues with the current version of the visual interface. As we continue to develop the PrimaryAI game-based learning environment, it will be critical to refine the visual interface and conduct additional rounds of testing with a broader student population with varying levels of knowledge competency regarding AI, as well as prior block-based programming experience. Adopting rigorous qualitative and quantitative data analyses will be important as we develop and test our environment iteratively. As AI education continues to expand into K-12 settings, it will be important for future work to explore age-appropriate visual interfaces across a wide range of grade levels and AI concepts, including machine learning and computer vision. Co-designing these visual interfaces and tools with elementary school teachers and students will help ensure they are designed to meet the needs of K-12 classrooms. It will also be important to investigate patterns across gender and other demographics variables as broader student populations utilize these learning environments. Although there were differences in gender and racial distributions among the study sites, the overall population size was small to identify different patterns among groups. Another promising area of future work is to explore how AI-driven adaptive learning techniques can tailor the AI problem solving tasks for individual students as well as the feedback provided by visual interfaces supporting student learning to assist a broader population of upper elementary students.

CRediT authorship contribution statement

Kyungjin Park: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. **Bradford Mott:** Conceptualization, Validation, Writing – original draft. **Seung Lee:** Conceptualization, Writing – original draft. **Anisha Gupta:** Data curation, Writing – review & editing. **Katie Jantaraweragul:** Resources, Writing – review & editing. **Krista Glazewski:** Writing – review & editing, Funding acquisition, Project administration. **J. Adam Scribner:** Resources, Writing – review & editing. **Anne Ottenbreit-Leftwich:** Resources, Writing – review & editing, Supervision. **Cindy E. Hmelo-Silver:** Writing – review & editing, Supervision. **James Lester:** Writing – review & editing, Supervision, Funding acquisition, Project administration.

Declaration of competing interest

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

[14] https://www.nngroup.com/articles/drag-drop/

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Kyungjin Park is a fifth-year Ph.D. student in the Department of Computer Science at North Carolina State University. She received her Bachelor's degree in Electronics and Computer Engineering from Hanyang University, Seoul, Korea. Her research is in the area of artificial intelligence and machine learning with a focus on natural language processing application in collaborative game-based learning environments, as well as procedural content generation to support adaptive learning in K-12 computer science game-based learning environments.

Dr. Bradford Mott is a Senior Research Scientist in the Center for Educational Informatics and an Adjunct Assistant Professor in the Department of Computer Science at North Carolina State University. His research is in the areas of artificial intelligence and human–computer interaction with a focus on game-based learning environments, interactive narrative technologies, AI in education, and computer science education.

Dr. Seung Lee is a Research Scientist in the Center for Educational Informatics at North Carolina State University. His research centers on applying artificial intelligence and machine learning to creating adaptive learning environments for applications in education and training with a focus on developing intelligent tutoring systems and multimodal natural language dialogue systems for intelligent narrative-centered learning environments.

Anisha Gupta is a third-year Ph.D. student in the Department of Computer Science at North Carolina State University. She received her Bachelor's degree in Computer Science and Engineering from Heritage Institute of Technology, Kolkata (India). Her research interest is in the application of machine learning techniques to support adaptive learning environments using stealth assessment for student interactions with game-based learning environments.

Katie Jantaraweragul is a fourth-year Ph.D. student in the Department of Instructional Systems Technology at Indiana University. She received her Bachelor's degree in Elementary Education and Master's degree in Educational Leadership from Indiana University. She has over 10 years of experience as a K-12 teacher, instructional coach, and technology coach. Her research interests include problem-based learning, participatory co-design, and computer science education in elementary classrooms.

Dr. Krista Glazewski, a former middle school science teacher, serves as Professor and Department Chair of Instructional Systems Technology at Indiana University exploring means of supporting teachers as they adopt new technological and curricular innovations. Her partnership work has spanned multiple regions in the U.S. to investigate how and under what conditions teachers might adopt and adapt new practices. She currently serves as Editor of the *Interdisciplinary Journal of Problem-Based Learning*, an open-access journal that publishes peer-reviewed articles of research, analysis, or promising practice related to all aspects of problem- or inquiry-based learning.

Dr. J Adam Scribner is the Director of STEM Education Initiatives in the School of Education at Indiana University. He is a certified biology teacher, and the former Manager of STEM Outreach for the Center of Innovation in Engineering and Science Education at Stevens Institute of Technology (NJ). He bridges theory to practice to develop transformative STEM teaching and learning experiences designed to foster the next generation of engineers, scientists, creators, and innovators. His expertise lies in the areas of the design of K-12 STEM curricula as well as teacher education and professional development around the integration of multiple STEM disciplines.

Dr. Anne Ottenbreit-Leftwich is the Barbara B. Jacobs Chair in Education and Technology. She is a Professor and Interim Chair of Instructional Systems Technology within the School of Education and an Adjunct Professor of Computer Science at Indiana University. Dr. Leftwich's expertise lies in the areas of the design of K-12 curriculum resources (particularly focused on technology and computer science), the use of technology to support teacher education, and development/implementation of professional development for teachers and teacher educators. Her research focuses on the adoption and implementation of technology and computer science at the K-12 levels.

Dr. Cindy E. Hmelo-Silver is the Barbara B. Jacobs Chair in Education and Technology, Distinguished Professor of Learning Sciences, and Director of the Center for Research on Learning and Technology in the School of Education of Indiana University. Her research focuses on how people learn about complex phenomena and how technology can help support that learning. She studies problem-based learning, collaborative engagement, and computer supported collaborative learning. Dr. Hmelo-Silver is an International Society for the Learning Sciences inaugural fellow as well as a fellow of the American Educational Research Association and International Society for Design and Development in Education.

Dr. James Lester is Distinguished University Professor of Computer Science and Director of the Center for Educational Informatics at North Carolina State University. He is Director of the National Science Foundation AI Institute for Engaged Learning. His research centers on transforming education with artificial intelligence. His current work ranges from AI-driven narrative learning environments and virtual agents for learning to multimodal learning analytics and sketch-based learning environments.