Supporting Upper Elementary Students in Learning AI Concepts with Story-Driven Game-Based Learning

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Abstract

Artificial intelligence (AI) is quickly finding broad application in every sector of society. This rapid expansion of AI has increased the need to cultivate an AI-literate workforce, and it calls for introducing AI education into K-12 classrooms to foster students' awareness and interest in AI. With rich narratives and opportunities for situated problem solving, story-driven game-based learning offers a promising approach for creating engaging and effective K-12 AI learning experiences. In this paper, we present our ongoing work to iteratively design, develop, and evaluate a story-driven game-based learning environment focused on AI education for upper elementary students (ages 8 to 11). The game features a science inquiry problem centering on an endangered species and incorporates a Use-Modify-Create scaffolding framework to promote student learning. We present findings from an analysis of data collected from 16 students playing the game's quest focused on AI planning. Results suggest that the scaffolding framework provided students with the knowledge they needed to advance through the quest and that overall, students experienced positive learning outcomes.

Introduction

Artificial intelligence (AI) is gaining widespread adoption in every sector of society (Manyika et al. 2017). With swift advancements in diverse capabilities such as machine learning, computer vision, and automated reasoning, AI has emerged as an essential tool for enabling innovation (Lee 2018). This rapid expansion of AI has heightened the need to foster an AI-literate workforce, and it calls for the integration of AI education into K-12 classrooms (Touretzky et al. 2019b; Wang and Lester 2023).

Researchers, policymakers, and practitioners are acknowledging the need to cultivate K-12 students' interest in and awareness of AI (Touretzky et al. 2019b; Cardona et al. 2023; Wang and Lester 2023). Recognizing this critical need, initiatives are actively working on integrating AI education into primary and secondary education (Leitner et al. 2023; Ottenbreit-Leftwich et al. 2023; Williams et al. 2022), as well as formulating AI education guidelines for the K-12 grade levels (Touretzky et al. 2019c). Because early educational experiences can have a substantial influence on students' academic and career trajectories in STEM (DeJarnette 2012), crafting captivating AI learning experiences for elementary school learners is of great importance.

Game-based learning, which offers a promising approach for engaging elementary school students in complex topics and problem solving, is seeing increased adoption because of its potential for producing improved learning outcomes (Clark, Tanner-Smith, and Killingsworth 2016; Hussein et al. 2019b). Story-driven educational games offer substantial support for enhancing student learning while simultaneously fostering student engagement (Rowe et al. 2011). Leveraging rich interactive narratives, these games embed learning experiences within immersive storyworlds featuring situated problem solving (Min et al. 2020). By harnessing the innate abilities of children for understanding narratives, these games aid students in developing problem-solving abilities and inquiry skills (Mawasi, Nagy, and Wylie 2020). As a result, researchers are actively investigating the use of story-driven game-based learning to foster effective and engaging AI learning experiences in K-12 settings (Voulgari et al. 2021; Leitner et al. 2023).

PRIMARYAI is a story-driven game-based learning environment featuring AI-infused inquiry learning for elementary students aged 8 to 11. In this paper, we present our ongoing efforts to iteratively design, develop, and evaluate PRIMARYAI. In the game, students explore why the population of penguins along the rugged coastline of a volcanic island is declining. As students play the game, they solve challenges leveraging AI concepts and tools, while being supported by a Use-Modify-Create scaffolding framework. This framework starts with students "using" pre-built solutions, then "modifying" these solutions for specific tasks, and ultimately "creating" their own solutions using the target concepts (Lee et al. 2011). To investigate the effectiveness of the game, we examine two key questions:

1. Does the game actively engage students and what challenges are encountered during gameplay?
2. Does the Use-Modify-Create scaffolding framework support learning and where is further support needed?

To explore these questions, we use data collected during a classroom implementation with 16 elementary school students playing the game's quest focused on AI planning. Results suggest that students exhibited significant learning gains and that overall the scaffolding framework effectively supported students as they progressed through the game.

Background

Our work is conducted at the intersection of research on AI education in elementary school, game-based learning, and AI-focused game-based learning. Each of these is discussed in turn.

AI Education in Elementary School

As AI technology proliferates, there is growing importance in teaching students AI concepts and skills (Long and Magerko 2020; Touretzky et al. 2019a; Yang 2022). Although incorporating AI learning into K-12 education is in its infancy, explorations are underway to create curriculum and tools for students to develop understandings of AI (Ho et al. 2019; Chai et al. 2021). Some elementary schools have started to introduce AI-focused pedagogical strategies and AI tools to cultivate students' AI awareness and interest. For example, Ng et al. (2022) proposed an inquiry-based learning approach using digital storytelling as an effective way of developing students' AI literacy. Vartiainen et al. (2020) explored using a pedagogical framework of participatory learning and learning-by-teaching to provide young learners with educational experiences focused on machine learning. They examined six students using Google's Teachable Machine to train models using facial or bodily expressions. Shamir and Levin (2022) explored having students participate in a learning-by-design or learning-by-teaching unit to develop machine learning skills and computational thinking competencies. Efforts are also in progress to create AI tools and platforms to support AI education for elementary students. The Zhorai conversational AI platform is being used to design curriculum for elementary students to learn concepts in machine learning (Lin et al. 2020). The Cognimates AI platform allows students to learn about machine learning by creating their own AI models for image classification, sentiment analysis, and speech recognition (Druga and Ko 2021). Teachable Machine by Google is a web-based tool that enables students to generate their own models using machine learning (Carney et al. 2020). PlushPal empowers students to train models to recognize custom designed gestures for their stuffed animal to respond to (Tseng et al. 2021).

Game-Based Learning

Game-based learning holds great potential for supporting students with engaging and effective learning experiences, particularly for elementary grade students (Chen, Lu, and Lien 2021). Recent research shows that using educational games significantly improved elementary students' critical thinking skills (Hussein et al. 2019a), helped students learn spelling and understand new vocabulary (Javora et al. 2021), and motivated students to complete learning activities (Cai et al. 2022). A story-driven game-based learning environment has also been investigated for improving students' content knowledge and problem solving in the context of elementary science education. In the game, a series of quests provides students with opportunities to learn new science concepts (Syal and Nietfeld 2020). In addition, research has examined non-digital game-based learning's effectiveness in classroom settings to promote student learning and engagement without the use of technology (Hosseini, Hartt, and Mostafapour 2019; Hosseini and Perweiler 2019).

Game-based learning can also play an important role in enhancing computer science (CS) education and computational thinking (CT) skills in elementary school students (Hsu, Chang, and Hung 2018; Moreno Guerrero et al. 2022). The engagement benefits of game-based learning, motivates students and helps them develop CT skills while solving game-based challenges (del Olmo-Muñoz, Cózar-Gutiérrez, and González-Calero 2020; Asbell-Clarke et al. 2021). For example, AutoThinking (Hooshyar et al. 2021) is designed to foster elementary students' CS and CT skills. In the game students write programs to locate cheese in a maze, but at the same time need to avoid two cats. Zoombini (Rowe et al. 2021) is a puzzle game for elementary students to develop mathematical skills by applying programming concepts. The game requires students to identify solutions by applying pattern recognition, deductive and inductive reasoning, and spatial arrangement. Minerva (Lindberg and Laine 2018), which allows students to navigate puzzles using a robot to repair a damaged ship, requires students to apply and learn different programming concepts to successfully accomplish tasks. InfuseCS (Smith et al. 2021) is a narrative-centered game-based learning environment for upper elementary students that integrates computational thinking and physical science through the creation of interactive narratives.

AI-Focused Game-Based Learning

To respond to the growing need for students to access engaging and effective AI learning experiences, efforts are underway to leverage game-based learning to teach AI concepts. For example, Wang and Johnson (2019) have investigated integrating search and reasoning with high school math, Henry et al. (2021) targeted introducing 10-14 years old students to machine learning concepts using a role-playing game, Leitner et al. (2022) explored teaching search algorithms to high school students with the ARIN-561 educational game, and Vandenberg et al. (2022) examined introducing AI learning experiences through interactive game-design activities for middle grades students. Using game-based learning for AI literacy at the elementary grade levels is also underway. Adisa et al. (2023) introduced Solving Problems Of Tomorrow (S.P.O.T), a role-playing game that helps students understand AI and machine learning. In the game, students interact with two embedded applications, which are modified versions of Scratch and Teachable Machine. The game's narrative allows students to collect data, train their own models, and use their models to construct AI applications. Voulgari et al. (2021) developed the ArtBot game, which is part of the LearnML educational toolbox. ArtBot was designed for teaching machine learning concepts, including supervised learning and reinforcement learning as well as understanding their societal impact.

PRIMARYAI Learning Environment

PRIMARYAI is a story-driven game-based learning environment that engages upper elementary students in situated AI-

Figure 1: PRIMARYAI game-based learning environment.

infused life-science problem solving (Figure 1). The integrated AI and science instruction provides the advantage of reaching a broad range of students, including those who might not otherwise choose to explore AI. The classroom-friendly game is intended for use in educational settings, accompanied by a curriculum that features “unplugged” AI learning activities. These unplugged activities serve to introduce AI topics to students prior to them engaging with the topics in the game. PRIMARYAI has been developed with the Unity® cross-platform game engine that supports WebGL deployments of the game running in modern web browsers such as Chrome, Edge, Firefox, and Safari. This approach allows the game to run on Chromebooks, which are an increasingly popular hardware platform found in schools across the United States.

PRIMARYAI enables students to acquire knowledge about AI through immersive gameplay, in which students tackle life science challenges leveraging AI tools embedded within the game. In this virtual world, students delve into investigating the decline of the population of yellow-eyed penguins on New Zealand’s South Island. As students journey through the game, they engage in challenges centered around AI, aiding them in collecting data and assessing hypotheses regarding the wildlife on the island. The PRIMARYAI curriculum aligns with the Next Generation Science Standards (National Research Council 2013), including connections to core ideas in life sciences such as “LS4.C: Adaptation – For any particular environment, some kinds of organisms survive well, some survive less well, and some cannot survive at all” and “LS4.D: Biodiversity and Humans – Populations live in a variety of habitats, and change in those habitats affects the organisms living there.”

Game Design

The design of PRIMARYAI features a series of quests covering key AI concepts, including *AI Planning*, *Machine Learning*, and *Computer Vision* that align with four of the five big ideas in AI: *Representation and Reasoning*, *Perception*, *Learning*, and *Societal Impact* (Touretzky et al. 2019b). At the onset of the game, students discover that yellow-eyed penguins exhibit shyness towards humans and are tasked with gathering data using a robot cleverly camouflaged as a penguin (a “RoboPenguin”). Using an in-game block-based interface, students learn how to craft planning tasks. This helps students engage with *Representation and Reasoning* by representing the environment and actions in the planning interface while reasoning about the robot’s actions to capture wildlife photos from specific locations on the island. In a later quest, students examine the accumulated photos and assign labels to each image. This introduces the concept of *Perception*, as students learn about image input, pixel representation, and feature extraction while examining and labeling the images captured by the robot. The image labeling process aids in training the robot to accurately categorize wildlife photos as either penguins, stoats, or other types of wildlife. In the final quest, students delve into *Learning* where they use computer vision to expand their understanding and leverage these methods to further enhance the robot’s capabilities. The central problem involves identifying diseased penguins on the island, teaching students about

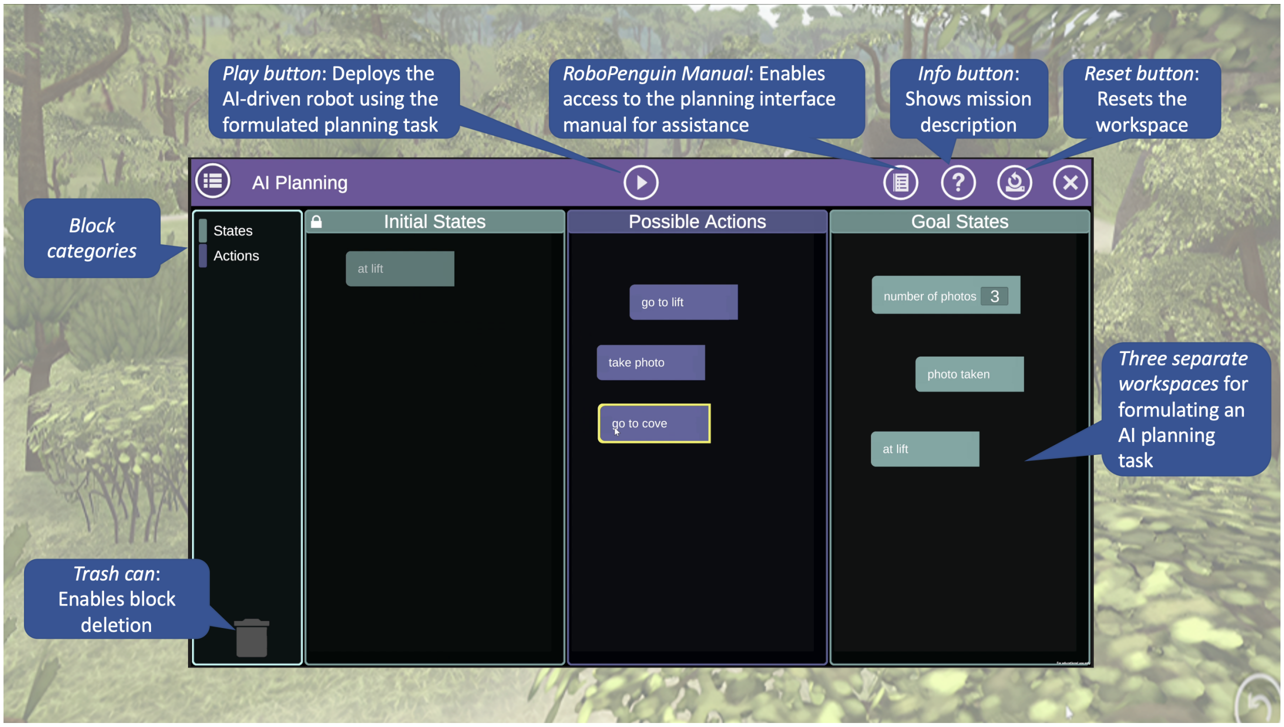

Figure 2: Block-based interface for formulating planning tasks.

Societal Impact of AI using ethical data collection methods to avoid disturbing the shy yellow-eyed penguins. To foster a deeper understanding of the AI concepts introduced in the game, the quests leverage a scaffolding progression based on the Use-Modify-Create framework (Lee et al. 2011). The version of PRIMARYAI used in this study focused on AI planning; the other quests are under development.

AI Planning Quest

PRIMARYAI's AI planning quest features a block-based interface for crafting planning tasks (Figure 2). Using this interface students can formulate planning tasks by manipulating *Initial States*, *Possible Actions*, and *Goal States*. After crafting their planning task, students have the opportunity to see how each element contributes to generating plans that influence the robot's actions in the game. There are three main areas of the block-based interface: the *Control Panel*, which allows students to launch the robot using the planning task they crafted; the *Block Panel*, which allows students to select new blocks to add to their planning task; and the *AI Planning Panel*, which occupies most of the interface and enables students to manipulate the elements of the planning task.

The AI Planning quest uses a Use-Modify-Create scaffolding framework consisting of five missions. The first mission focuses on the *Use* phase of the framework. At the outset of the mission, students are given a pre-designed planning task within the block-based interface. This approach is intended to assist students in familiarizing themselves with both the interface and the nature of the planning tasks they will encounter during the quest. The next three missions, focus on the *Modify* phase of the framework. In Mission 2, students are asked to make a simple modification to the planning task so that the robot will take multiple photos instead of a single photo. In Mission 3, students are asked to make a more substantial modification to the formulated planning task (Figure 3). This is the first mission where students are required to delete and add new blocks to their formulated planning task (Figure 4) and results in the robot exploring another part of the beach (Figure 5). Mission 4 concludes the *Modify* phase of the framework where students are asked to modify the goals of the robot. Finally, the *Create* phase of the framework consists of Mission 5 where students are tasked with formulating a planning task from the ground up for the robot.

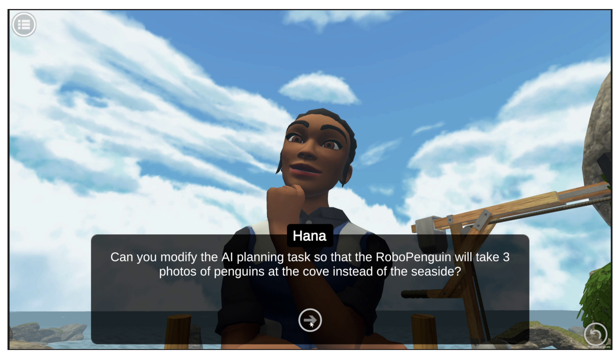

Figure 3: Mission 3 briefing.

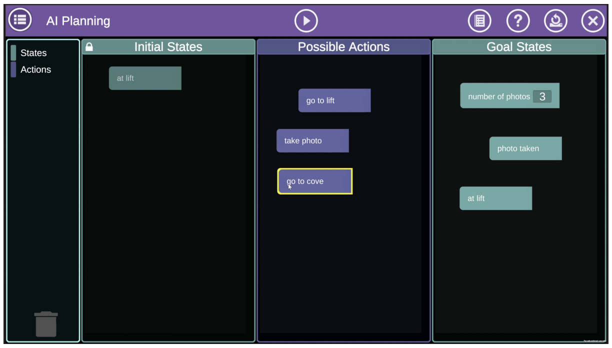

Figure 4: Modifying planning task in Mission 3.

Figure 5: Robot executing plan in Mission 3.

Classroom Implementation

To investigate our research questions, we use data collected during a classroom implementation of PRIMARYAI conducted during Spring 2023.

Participants

In partnership with two teachers from rural school districts in the Midwestern United States, the PRIMARYAI program was implemented with a total of 32 consented students in fourth and fifth grade classrooms in two schools over a span of three weeks (Figure 6). The curriculum consists of four units covering life science and AI concepts:

- Unit 1: Ecosystems and Population Study
- Unit 2: Computer Vision
- Unit 3: Machine Learning
- Unit 4: AI Planning

In this paper, our analysis focuses on data collected from the fourth grade class (n=16), since networking issues prevented the fifth grade class at the other school from being able to complete the game. We focus in particular on students engaging in the unit on AI Planning for which gameplay trace log data was available (n=16). Two students did not complete either the pre-test or the post-test, so they are excluded from the learning gain analysis (n=14).

Procedure

The AI Planning unit started with the students taking a pre-test, consisting of 11 multiple-choice questions targeting AI planning concepts, with questions, such as *"What do you think initial states are?"* and *"Select the best option for the robot's goal state."* After completing the pre-test, students engaged in an unplugged activity on AI planning where they were introduced to concepts such as "initial states," "goal states," and "possible actions" as well as "pre-conditions" and "post-conditions." Students then collaborated in small groups to formulate a planning task for visiting a county fair. The following two days were dedicated to playing the game, during which students attempted to complete all five missions associated with the AI Planning quest in PRIMARYAI. The unit concluded with a post-test, which featured the same set of 11 questions as the pre-test. We collected video recordings of the classroom activities throughout the implementation.

Analysis

Paired t-tests were used to detect reliable changes between the pre- and post-test results using both p-values and 95% confidence intervals. Additionally, they were employed to assess significant differences in the time spent on each mission. We also conducted a qualitative analysis of approximately one hour of video data capturing students' engagement with the PRIMARYAI game during the implementation. This analysis aimed to investigate how students actively engaged with the game.

Results and Discussion

Findings from the study revealed that students demonstrated significant learning on the AI planning content knowledge assessment as evidenced by the significant difference between their post-test (M = 5.43, SD = 1.87) and pre-test scores (M = 4.36, SD = 1.98). A matched pair t-test comparing pre-test and post-test scores showed that there were significant learning gains, $t(13) = 3.51$, $p < .01$.

To explore the question of student engagement with the game, we conducted a qualitative analysis of approximately one hour of video recorded during the implementation to examine student behavior during gameplay. We analyzed videos of students playing PRIMARYAI and found many instances of students actively engaging with the game. The video featured the consenting students playing the game, accompanied by their teacher and an on-site researcher who provided technical support when needed. While most students played individually, they also communicated with each other upon completing missions or when they had questions. The teacher and researcher were available to assist the students.

We noted several student reactions during gameplay, such as "Mission completed!," "I am the penguin now," "Did you find the cove?," and "Find the seaside," that point to their active engagement with the game. When the teacher inquired how many students had completed all the missions, we observed 8 students raising their hands. Additionally, a checklist students completed at the end of the game helped us track the progress of each student. Sometimes, students encountered technical issues due to networking issues stemming from the remote location of the school. This occasionally

Figure 6: Students playing PRIMARYAI.

led to students having to restart the game, with comments, such as "I got logged out" or "I had to start over." However, students could resume from where they left off and continue playing. The video camera was strategically placed to capture the students' laptop screens, allowing us to monitor their behavior as well as their progress throughout the game. In summary, we observed students engaged in playing the game, progressing one mission at a time as they worked to complete all five missions; however, some technical issues were encountered from time-to-time.

To examine the question of the Use-Modify-Create scaffolding framework's effectiveness, we conducted an analysis of the trace data logged during student gameplay to examine the characteristics of students' interaction with the game. The AI Planning quest consists of 5 missions. The *Use* phase is represented by Mission 1. Subsequently, Missions 2, 3, and 4 collectively constituted the *Modify* phase, while Mission 5 constituted the final *Create* phase, focusing on the creation of a planning task from scratch. Previously, the framework consisted of only three missions, with each mission representing a single phase of the Use-Modify-Create framework; however, results from a previous pilot indicated that students struggled when transitioning from the *Modify* phase to the *Create* phase (Park et al. 2022). This insight prompted revisions to the game to augment the *Modify* phase with two additional missions to help students ease into the *Create* phase of the quest.

In terms of progress, 93.75% of the students successfully completed the *Use* phase. Among students who accomplished this phase, 66.67% managed to successfully navigate the missions in the *Modify* phase, and 60% of the students who completed the *Modify* missions were able to successfully complete the *Create* phase, which was the most challenging phase of the quest. These results suggest that even though the students might have found the transition between phases to be challenging, most of the students who mastered preceding phases of the quest were able to successfully complete the next phase of the quest (Table 1).

Table 1: Number of students who attempted and successfully completed each mission.

Mission	Attempted	Completed
Mission 1	16	15
Mission 2	14	14
Mission 3	14	14
Mission 4	13	10
Mission 5	7	6

With regard to the results from the transition between the *Use* and *Modify* phases of the quest, we observe that there is a high positive correlation between students' game time for Mission 1 and Mission 2 (Pearson's r=0.72) (see Table 2). Mission 1 involves no changes to the block-based programming interface, while Mission 2 involves changing a single parameter in one of the blocks, and did not require the addition or deletion of blocks in the planning interface. This might indicate that students who found the interface easy to use in the *Use* phase did not require much time to familiarize themselves with Mission 2 in the *Modify* phase. Conversely,

Table 2: Time spent by students on each mission (seconds).

Mission	Min	Median	Max	Mean
Mission 1	87.20	144.63	7152.01	1147.20
Mission 2	85.73	113.66	247.01	124.09
Mission 3	179.17	314.69	2243.96	542.53
Mission 4	79.26	287.88	1347.43	404.72
Mission 5	127.67	370.05	127.67	306.94

students who took more time on Mission 2 despite spending enough time on Mission 1 might have found the interface difficult to interpret and use. However, we find that 93.33% of students who completed Mission 1 were able to successfully complete Mission 2 as well, indicating that the understanding of the interface that students acquired in the *Use* phase helped them easily transition to the *Modify* phase.

These results are consistent with the results from the trace data analysis conducted on the interaction logs collected from studies with the previous version of the game where we saw that students found it easier to transition to Mission 2 after having accomplished Mission 1 (Park et al. 2022). Interestingly, all students who completed Mission 2 were also able to successfully complete Mission 3. However, students took significantly longer to complete Mission 3, as compared to Mission 2 ($p < .01$). We also observe a negative correlation between game time taken for Missions 2 and 3 (Pearson's r=-0.34), indicating students who spent more time working on Mission 2 might have found it easier to solve Mission 3. This might be because this is the first mission where students were required to add or delete blocks using the planning interface. We did not find any significant difference between the time taken by students to complete Missions 3 and 4, but only 71.43% of students who completed Mission 3 were able to successfully complete Mission 4. While the modifications required in Mission 4 were distinct from those required in Mission 3, this mission also required students to move blocks in the planning interface.

Students who successfully completed Mission 4 had to attempt the mission at least 2 times on average, while students who attempted Mission 4 but were unable to solve it successfully only attempted the mission once. This might imply that students who persisted overcame the challenge of completing Mission 4 after mastering Mission 3. For students who struggled with Mission 4, it will be helpful to provide targeted assistance. Upon failing the mission, providing hints during subsequent attempts of the mission might mitigate potential frustration and deter premature abandonment.

In Missions 1 and 2, moving blocks was not necessary for successfully solving the mission (Table 3 and Table 4). Interestingly, in Mission 1, students attempted to move around 10 blocks on average. This suggests that during Mission 1, where students encounter the block-based planning interface for the first time, they tended to explore by moving blocks, even though no changes were required to complete the mission. This behavior might stem from curiosity to understand the interface. However, it is also possible that students did not realize that in Mission 1 the planning task was already configured for them and assumed they needed to adjust something in the formulation of the planning task to solve the mission. In Mission 2, students moved only around 2 blocks on average, which might imply that they felt more confident about what they were required to do after completing Mission 1.

In summary, these findings suggest that the Use-Modify-Create framework was generally successful in providing students the knowledge they needed to progress to the next mission in the quest. While the overall generalizability of the analyses needs to be explored further, they point to areas for instructional refinement, suggesting the importance of adding additional tutorial and adaptive hints to the game to further promote student learning and engagement.

Table 3: Number of blocks moved by students in each mission (across all students).

Mission	Min	Median	Max	Mean
Mission 1	0	3	57	9.17
Mission 2	0	0	15	1.76
Mission 3	0	17	35	15.65
Mission 4	0	2	20	4.94
Mission 5	0	4	19	7.44

Table 4: Number of blocks moved by students in each mission (only students who successfully solved the mission).

Mission	Min	Median	Max	Mean
Mission 1	0	3	57	10.93
Mission 2	0	0	9	1.57
Mission 3	5	17	35	15.79
Mission 4	1	4	16	4.20
Mission 5	4	6	19	8.83

Conclusion and Future Work

Rapid advances in AI call for introducing AI education to K-12 students. In this work, we presented an overview of our efforts to design, develop, and evaluate a story-driven game-based learning environment for AI education that targets upper elementary students. To investigate the effectiveness of the learning environment, we analyzed data collected during a unit on AI Planning from a classroom implementation with fourth grade students. Overall, results indicated that students exhibited significant learning gains on an AI planning content knowledge assessment as measured from pre-test to post-test. A qualitative analysis of video recording from the implementation revealed that students actively engaged with the game, although technical issues forced students to close and restart the game at times. A quantitative analysis of trace log data from the implementation showed that the game's Use-Modify-Create scaffolding framework helped students learn about AI planning. This analysis also offered insights into the challenges students faced when moving between missions and highlighted the significance of each mission in relation to the successful completion of preceding ones.

As K-12 AI education continues to expand, it will be important to explore how story-driven game-based learning can support learning a broad array of AI concepts for a wide range of grade levels. It will also be important to examine patterns and validate our analyses across gender and demographic factors as broader populations utilize these learning environments. A promising avenue for future work is exploring how AI-driven adaptive learning methods can best support AI education by delivering tailored feedback to assist students. It will also important to conduct large-scale classroom studies aimed at understanding the impact of story-driven game-based learning on students' understanding of AI and their interest in AI.

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