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Design and Evaluation of ARIN-561: An Educational Game for Youth Artificial Intelligence Education

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Abstract: Artificial Intelligence (AI) is increasingly vital to our everyday lives. Future generations will not only consume AI, but work with AI-driven tools and contribute to the development of AI. As such, students will need exposure to AI knowledge at a younger age. Despite this need, relatively little is currently known about how to most effectively provide AI education to K-12 (kindergarten through 12th grade) students. In this paper, we discuss the design of an educational game for high-school AI education called ARIN-561. The game centered around two agents – a player character and a companion robot, as the story and learning experience unfold through conversations between the two agents and explorations that bond the two agents A series of studies were carried out at high schools in the United States to evaluate the efficacy of the game. Results indicate the potential of ARIN-561 to build AI knowledge, especially when students spend more time in the game.

Keywords: Youth AI education, K-12 AI education, Educational games

1. Introduction

Artificial Intelligence (AI) is a foundational technology that has experienced rapid development in the design and implementation of its systems in recent years. This has led to AI permeating and taking an ever-expanding role in society (Makridakis & Spyros, 2017). The workforce is no exception, where some of today's youth will become a part of future AI development, and many more will utilize AI in their careers. Even for those whose careers do not involve AI, they will still become end-users, such as consumers of AI (Gardner-McCune, Touretzky, Martin, & Seehorn, 2019). There is a critical need to prepare future generations with basic knowledge of AI, not just through higher education, but beginning with childhood learning. This need has been well documented, as the AI4K12 working group has reported the demands and progress from educational practitioners around the world for curricula and guidelines to help their youth learn AI (Gardner-McCune et al, 2019). In the United States, efforts are underway to develop national strategies for research and development in AI, as well as to establish guidelines for K-12 (Kindergarten through 12th grade) AI education. Globally, many countries have piloted curriculum and learning activities of AI education for pre-college aged learners (see Section 2 for review).

Despite these developments, there has been little research into how students, especially pre-college aged students, construct an understanding of and gain practice with core ideas in the field (Wang, Lester, & Basu, 2021). As a result, there is yet little possibility of grounding the design of learning experiences in evidence-based accounts of how youth learn AI concepts, how understanding progresses across concepts, or what concepts are most appropriate for what age-levels. Given the packed course schedule of K-12 students, being able to connect AI learning to existing Science, technology, engineering and mathematics (STEM) subjects becomes a more realistic approach to embed AI education in K-12 classrooms. On the other hand, AI is built on a foundation of philosophy, psychology, and mathematics, and centers around using algorithms to solve real-world problems, which can make building an evidence base for age-appropriate curricula difficult (Russell & Norvig, 2016). Despite this challenge, AI offers a rich context to learn scientific and mathematical concepts already taught in K-12

(Wang & Johnson, 2019) and to apply them to problem-solving. For example, by illustrating how math concepts can be used in powerful AI tools to solve problems, learning math through AI can be a motivational vehicle to illustrate the pathway from K-12 STEM education, to post-secondary STEM education, and later to STEM careers.

Digital game-based learning (DGBL) is a technology-based approach to teaching that has already shown promise in K-12 STEM education, with evidence pointing to its efficacy since the early 2000s (Plass, Mayer, & Homer, 2020), particularly of problem-solving skills (e.g., Spires, Rowe, Mott, & Lester, 2011). There is also a wealth of literature on designing in-game activities that integrate with learning objectives (Arnab et al, 2015, Habgood & Ainsworth, 2011) and out-game teacher's guidance to support students learning in the games (Ke, 2008) to achieve measurable learning outcomes (All, et al, 2016). Despite this, the lack of research into using game-based learning for youth AI education offers a great opportunity to both build on and contribute to the existing knowledge of how to integrate math and AI education in K-12 classrooms through the design of AI game-based learning environments (Lee et al, 2021).

In this paper, we will discuss the design and evaluation of an educational game, called ARIN-561, for teaching high-school students about AI. We conducted a series of evaluation studies at high schools in the United States. Results indicate the potential of ARIN-561 to build AI knowledge, especially when students spend more time in the game.

2. Related Work

While AI education has been absent from K-12 schools, work on integrating it into the curriculum has recently taken shape. For example, in 2018 the AI4K12 Initiative began developing curriculum and guidelines for AI education for K-12 students (Gardner-McCune et al, 2019). The MIT AI Education Initiative designed a DAILy curriculum that centers around helping youth learn about AI in daily life and future workplaces (MIT, 2021). Researchers in human-computer interaction have come up with a concrete definition of AI literacy with the AI competencies users need in order to effectively interact with AI in mind, while providing recommendations for designing learner-centered AI technologies that foster increased user understanding (Long & Magerko, 2020).

Researchers are also beginning to experiment with teaching AI to younger populations, including machine learning (Rodríguez-García et al, 2021; Zhou et al, 2021), ethics (Forsyth et al., 202), and dance (Payne et al, 2021). Youth AI education is also being pursued within the context of computational thinking (Ritter et al., 2019), as well as through conversational agents (Lin et al., 2020) and game-based learning (Lee et al, 2021). The latter project, PRIMARYAI, integrates AI knowledge with life-science topics and teaches AI to middle-school students (Lee et al., 2021), utilizing problem-based learning targeting small groups of students. This aims to motivate them to work collaboratively to solve problems and explore the game world, bringing them in contact with scenarios that prompt AI learning.

Discussions on youth AI education are heating up in Europe (Kandlhofer et al, 2019; AI Plus, 2021), China (Peterson, Goode, & Gehlhaus, 2021), and around the world (Xiong, Wang, & Huang, 2019; Chen & Tang, 2019), with an elementary school AI curriculum under development in Israel (Shamir & Levin, 2020). Meanwhile, researchers in Thailand have designed an agricultural AI game to teach middle-school students machine learning processes (Sakulkueakulsuk et al, 2018), using RapidMiner (Hofmann & Klinkenberg, 2016) to build machine learning models to classify ripe or unripe mangoes. In Australia, researchers have designed and implemented classroom activities for teaching fundamental concepts of AI to Year 6 students to demystify AI through activities such as an unplugged activity on facial recognition and a simple robotic exercise that introduces the concept of machine learning (Ho et al., 2019).

The work presented here aims to uncover how to design an educational game to meet the challenges of teaching AI to K-12 students, particularly building upon work investigating how high school students approach AI concepts and how to guide them through the subject (Greenwald, Leitner, & Wang, 2021), as well as work investigating how to appropriately link high school math concepts to AI knowledge (Wang & Johnson, 2019). Work investigating the learning of computational thinking (Lee et al, 2011; Rich, Yadav, & Zhu, 2019), as well as seminal research into comprehension of mathematical representations (e.g., Curcio, 1987; Friel, Curcio, & Bright, 2001) and statistics (e.g., Batanero et al, 1994) are all also fundamental to the work presented here.

3. ARIN-561

The educational game we have developed, ARIN-561, involves students playing the role of a scientist who sets out to carry out a scientific expedition, but unfortunately crash-lands on an alien planet. In order to survive and uncover the mystery of the planet, students solve problems by learning and applying AI knowledge. ARIN-561is designed to teach high school students AI concepts and algorithms, then prompting them to connect and apply their existing math knowledge to this AI material, and ultimately develop their AI problem-solving skills.

3.1 Design Principles

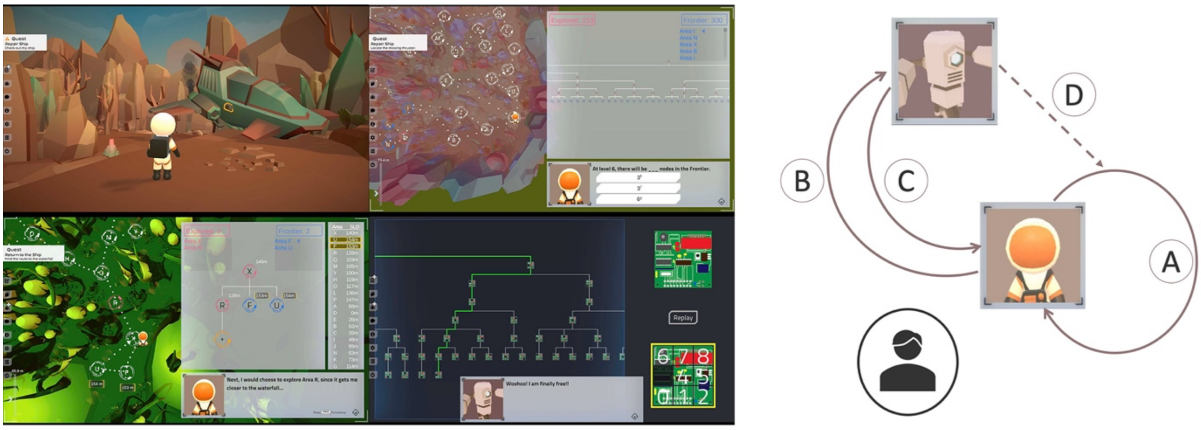
Current implementation of the ARIN-561 game focuses on developing concepts around classical search algorithms (e.g., Breadth First Search, Greedy Search, etc.) Classical search algorithms provide an accessible path to introducing essential concepts for algorithmic analysis, such as space and time complexity, which are vital to evaluating and understanding AI. Classical search as a topic also lends opportunities to connect math knowledge familiar to high school students with AI concepts that are usually taught in higher education. By integrating application of students' existing math knowledge with the introduction of AI algorithms, ARIN-561 provides tools for students to properly evaluate the AI algorithms they are being presented with as they progress through the learning goals.

Within the K-12 AI education research community, students' relationships to AI are widely discussed and roughly fall into three categories (e.g., Gardner-McCune et al, 2019). While the terminologies may be different, students can be categorized as those who will be AI end-users and use AI technology at workplaces, students who will be AI implementer and take existing AI technology to apply cross the society and economy, and students who will be AI researchers and advance AI algorithms. Activities in ARIN-561 aim to achieve learning goals designed to serve the students' learning needs based on the relationship they have and will have with AI. For example, the most important take away for AI consumers will be knowledge of how AI is used in everyday life. Thus, the first goal of ARIN-561 is for students to understand how AI algorithms are used to solve problems in the real world, which we address by designing AI problem-solving in the game that mirrors real-world AI applications. For example, route-planning on a map and cracking a computer password are real-world applications of search algorithms. We therefore included these tasks in the game world of ARIN-561. The second goal is for students to learn how to weight the strengths and weaknesses of different AI algorithms in order to choose between them when attempting to use AI to solve a problem, a task that is imperative to AI implementers. This is addressed by the order in which algorithms are introduced, as well as how they are framed in reference to previously learned algorithms. After being introduced to an algorithm, a task is presented that the algorithm fails to optimally complete, and in turn a new AI algorithm is introduced as excelling at said task. Once all three search algorithms have been introduced, students are tasked with choosing which algorithm would be most suitable for the task the game presents them with. The third goal is for the students to learn somewhat in-depth how each AI algorithm works, which is especially important for AI Developers. For each search algorithm, the students are first provided with a tutorial task that teaches them how the algorithm works and walks them through the task step by step. Students are then presented with a transfer task of increased difficulty in a different domain, with less tutorial support.

3.2 Gameplay in ARIN-561

ARIN-561 is a 3D role-playing game built on Unity, a cross-platform game engine developed by Unity Technologies. In the game, students play as a space-faring scientist crash landed on an alien planet, appropriately named ARIN-561 (Figure 1a). In order to safely return home, the scientist begin exploring the planet to gather resources needed to repair the broken ship while uncovering the mystery of the planet. Students carry out tasks in game that are centered around survival and exploration, which naturally involves tasks such as searching for lost parts and cracking passwords that mirror real world search tasks.

The current implementation of the game covers three classical search algorithms: breadth-first search, depth-first search, and greedy search. Each topic consists of two modules: a tutorial module (e.g., Figure 1a bottom left) and a transfer module (e.g., Figure 1a bottom right) all of which are situated within the game's narrative of surviving on ARIN-561 and solving the mystery behind the crash landing. Completed modules can be revisited through an in-game menu, and students can also explore the game environment for "off-task" activities (Sabourin, Rowe, Mott, & Lester, 2011), such as gathering minerals around the planet.



(a) (b)

Figure 1. (a) Screen capture from the ARIN-561 game. Top-left: The player character (i.e., the student) just crash landed on a foreign planet. Top-right: student is presented with a quiz question, embedded in the game narrative, about estimating the complexity of search algorithm. Bottom left: student is "self-scaffolded" through the greedy search algorithm by their own player character. Bottom-right: the player character solved an 8-sliding puzzle using one of the search algorithms to fix their companion robot's circuit board. (b) Pedagogical agents dialogue in ARIN-561. A: internal dialogue or monologue or think-aloud of the player character; D: robot interjection; B & C: dialogue between robot and the player character.

Tutorial modules begin with a practical problem that the player character has encountered, such as planning a route to retrieve a piece of the spaceship that fell off during the crash landing. Through the player character's internal monologue and their dialogue with the companion robot, students are scaffolded through the abstraction, automation, and analysis process (Coulter, Lee, & Martin, 2010), which are key to computational thinking (Lee et al., 2011). In the abstraction phase, the students are guided to create an abstract representation of the practical problem, in this case representing locations on a physical map and routes through them as the expansion of a search tree (e.g., Figure 1a bottom left). This abstract representation is also presented alongside the original problem representation, in order to ease the transition from abstraction to automation and analysis. Additional guidance is initially provided through the narrative, but gradually fades as students are asked to demonstrate their understanding by continuing to build and expand the search tree by themselves. If students make a mistake, no hints are immediately given, as the interface itself provides enough feedback on possible corrections (e.g., alternative path on a map). A hint will only be given on how to continue after a certain period of time has passed without finding a correct path. However, students will be provided with the option to automate the process after correctly expanding enough levels of the search tree to demonstrate sufficient understanding. In the automation phase, students can watch the search tree expand automatically on the same interface – but can also pause and step through the tree expansion one step at a time to examine the process closely. The automated expansion animations help illustrate the characteristics of the search algorithms, e.g., expanding in a breadth-first or depth-first fashion. In the analysis phase, students are guided by the game narrative to examine the solution (e.g., the route found) and to evaluate the process through which the solution is generated (e.g., time and space complexity of the search algorithm).

Quiz questions are embedded as a part of the in-game dialogue to help students pause and self-assess. These questions are aligned with the narrative to avoid breaking immersion as much as possible. For example, students are presented with a quiz question to think about possible computer memory needed to perform the search (Figure 1a top right). The game pauses as the students answer the quiz question and continues when a correct answer is recorded.

3.3 Agent Dialogue

ARIN-561 features two main characters, the player and the companion robot, who are both pedagogical agents. Pedagogical agents are embodied virtual agents designed to facilitate learning (Johnson, Rickel, & Lester, 2000), and have been the subject of increased research in recent decades. They can fulfil a number of roles to better facilitate student learning, making them incredibly versatile. Pedagogical agents can be virtual tutors to the students (VanLehn et al., 2005; Ritter et al., 2007), virtual tutees (Walker, Rummel, & Koedinger, 2014} or teachable agents (Leelawong & Biswas, 2008) vis a vis peer tutoring, or all of the above. This opens up the possibility for each student to participate in a "trilogue" between a conversational virtual tutor and a virtual simulated student (Graesser, Forsyth, & Lehman, 2017). In educational games, while pedagogical agents can fill the role of tutors, most of the agents working collectively as in-game characters, part of the narrative in a simulated environment, to help students learning by doing (e.g., Rowe et al, 2009). The player character and the companion robot follow this model of pedagogical agents in ARIN-561, taking characters that serve the game narrative and designing them to fulfill cognitive and meta-cognitive function through dialogue. Looking to Figure 1b, we can see this play out in a variety of ways. Dialogue A is essentially an internal dialogue, designed to guide the students through problem-solving and self-reflection while empowering them. Such dialogues allow students to progress to a correct understanding "on their own" but are also used to make explicit their potential misunderstandings. This provides the robot companion opportunities to interject such as in Dialogue D, to prompt students or the player character to re-examine their mental process. Dialogues such as B and C that involve a back and forth between the player character and the robot are then left to serve the function of carrying the game's narrative.

4. Evaluation

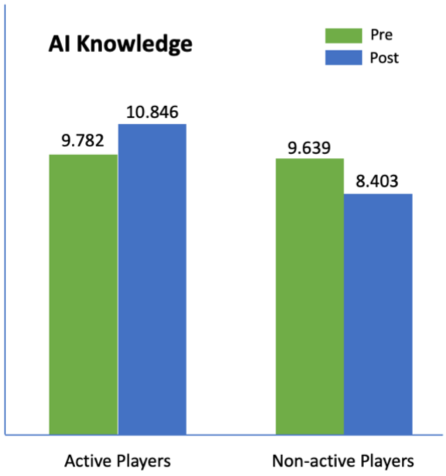
4.1 Recruitment

To assess how ARIN-561 impacts AI learning for high school students, we carried out a series of pilot studies. The studies were carried out at three high schools in a western state in the United States. A total of four teachers were recruited for the study. While the research team reached out both computers science class and math class teachers, all participating teachers are from computer science classes. Thus, all the study sessions are carried out in computers science classrooms. Of the three participating schools, one is a private high school that is among the top 10 art schools in the state where it is located. The second school is a charter school, a recipient of U.S. federal Title 1 funds, due to the large number of socio-economically disadvantaged students in attendance. The third school is among the top-3 high schools in the state where it is located. Student participation to the study was voluntary and not part of the course requirements.

4.2 Procedure

The study is designed to be carried out in 3 to 4 class sessions, each lasting 45-55 minutes long. A few weeks before each study started, students were given an online parental consent form and a youth assent form. During the first session, participating students were first assigned IDs to protect their identity throughout the study. students completed an online pre-survey about their demographic background, existing understanding of AI, etc. Students then logged into the ARIN-561 game online via a web browser. Any technical difficulties encountered were addressed during the first session, via the support from the research team. During the second and third session, students continued to interact with ARIN-

561 at their own pace. During the fourth session, students completed a post-survey about their opinion of the game, their attitude and knowledge about AI, etc.



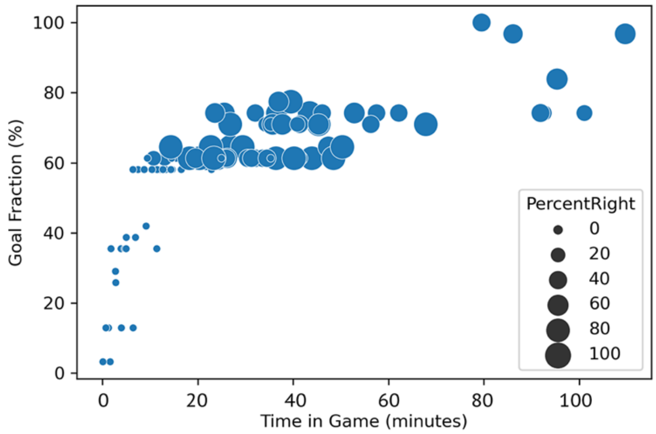


Figure 2. (a) Left: Mean scores on AI knowledge assessments (15 questions/points total) from pre- to post- interaction with ARIN-561. The active players completed half or more modules of the game (3 or more of the 6 modules), while the non-active players completed less than half of the game modules. (b) Right: Fraction of the game explored, as a function of time. Point size indicates the percent of the in-game questions answered correctly on the first attempt.

4.3 Measures

The pre-survey consisted of items about students' demographic background, AI Use Type, Interest in AI, AI Knowledge (15 questions), Math Self-efficacy (Liu & Koirala, 2009), and Math Knowledge. All scales except the Math Self-efficacy were developed by the research team. The AI Use Type included items such as "When I think about how I'd like to interact with AI in the future, I expect that: I will use AI systems in my everyday life as a consumer, and I expect to USE AI systems as a part of my job." The Interest in AI scale included questions such as "Outside of school I try to learn a lot about AI." The assessment of AI knowledge and math knowledge specifically focused on the content covered in ARIN-561, in the format of multiple-choice questions. The AI questions are set in the context of AI problem-solving similar to those encountered in the game, and assess students' understanding of, for example, pros and cons of the search algorithms, search algorithms most applicable to specific types of problems, etc. In the post-survey, same items on interest in AI and AI knowledge from the pre-survey were included. In addition to the surveys, game logs from ARIN-561 were collected. The logs included the in-game click-stream data and responses to in-game quizzes.

5. Results

5.1 Demographic Background

A total of 125 students from three schools participated in the studies, with 15 from the top art private high school, 57 from the charter school, and 53 from the top public high school. The participants' average age is 16.1, with 46% 12th graders, 28% 11th graders, 14% 10th graders, and 12% 6-9th graders. A total of 73% of the students were male, 21% were female and 6% identified as other categories or prefer not to disclose. The participants reported high levels of gaming experiences, with 30% reported playing video games more than 9 hours per week, 40% reported playing games 3-8 hours per week, 16% playing 1-2 hours per week. Only 15% of the participants reported that they do not play video games.

With restricted access to school campus due to COVID-19, the study was carried out entirely by the participating teachers. The research team did not participate in the data collection. Additionally, since students are not required to answer all the questions on the pre- and post-survey, responses to some pre- or post- survey questions were missing from a large portion of the students. For example, 60 out of the 125 students did not complete the assessment of AI knowledge on either pre- or post-survey. While 47 students did not complete the assessment of AI interest. As a result, missing data were excluded from the corresponding analysis.

5.2 Learning AI Knowledge

We hypothesized that interacting with ARIN-561 would help students gain knowledge in AI. To evaluate this hypothesis, we conducted a paired-sample t-test to analyze the changes in AI Knowledge from pre- to post-survey. There was a total of 15 questions on AI knowledge. Thus students can receive a maximum of 15 points on AI knowledge on pre- or post- assessment. Data from all the students who completed both AI knowledge assessment portion of the pre- and post-survey ($N=65$) showed a positive, though not statistically significant increase of AI knowledge from pre- to post- administrations of the assessment ($M=0.427$, $SD=2.819$, $t(64)=1.221$, $p=.227$).

Given the varied completion rate of pre- and post-survey, we further examined the game logs from ARIN-561. Although the students were not supposed to begin filling out the post-survey unless they have completed all the components of the game, the game logs indicated that many students moved onto the post-survey without completing the game. Thus, we created a filter to exclude students who completed very little of the game modules. In particular, students who completed less than half of the game modules (2 or fewer of 6 modules) were then excluded before we repeated the paired-sample t-test on the group of students who completed half or more of the game modules ($N=47$). Results indicated that, the group of students who completed at least half of the game demonstrated a statistically significant ($M=1.0638$, $SD=2.637$, $t(46)=2.765$, $p=.008$, Figure 2a) positive change in AI knowledge, with a mean difference of 1.0638 and a medium effect size ($d=0.403$).

While the game supports additional gameplay or “off-task” activities such as collecting minerals on the alien planet, the six game modules are the core “learning” modules that cover the three classical search algorithms. Thus, students who completed more game modules should out-perform those who completed fewer game modules on AI knowledge. A one-way ANOVA revealed a statistically significant difference in the changes in AI knowledge between the two groups ($F(1, 61) = [11.737]$, $p = .001$) with students who completed half or more modules ($N=47$) demonstrating significantly higher learning gains ($M=1.0638$) compared to those students who completed less than half game modules ($M=-1.5469$). This means that there is a significant group-level differences in AI learning between the group of “active players” (students who completed half or more modules) completing at least half of the game compared with the smaller group of those who did not (Figure 2a).

5.3 Interest in AI

While the interaction with ARIN-561 is relatively brief based on the study design (e.g., two 45-55 minute long class periods), we nevertheless hypothesized that learning AI through fun and interactive game activities in ARIN-561 can positively impact the students interest in AI. Paired-sample t-test on all the students who completed this portion of the survey indicates that there was no significant change in interest in AI after interacting with the game ($M=-0.1282$, $SD=2.0409$, $t(77)=-0.555$, $p=0.581$). Even among the “active players”, those who completed half or more game modules, changes in AI interest is not statistically significant ($M=0.0577$, $SD=1.9037$, $t(51)=0.219$, $p=0.828$).

5.4 Individual differences

Based on students' self-reports of demographic background, we performed additional analysis on the variance in changes of AI knowledge along gender, grade level, math confidence, and interest in AI. Results showed no significant group level differences along any of these factors.

5.5 In-game Behavior

On average, students spent 51 minutes in the six learning modules of the game (*SD=36.4*, not including the time spent in other parts of the game). To understand how variation in game play may be associated with differences in performance, we created a scatter plot using student game log data to plot in-game time (in minutes) against a completion metric (number of game goals/objectives completed), with variation in students' scores (as percent correct) on in-game quizzes represented by the size of the dots. As Figure 2b shows, students who played the game for less than ~10 minutes completed less than half of the game objectives/goals and answered very few the in-game questions that they encountered correctly. Overall, time spend in the game is significantly correlated with increase of AI knowledge (*r=.314, p=.0129*) but not correlated with changes in interest in AI.

6. Discussion

As the field of AI education continues to mature, it is important to ground the design of learning experiences in the field's emerging understanding of best practices for AI education, game-based learning, and longstanding scholarship on effective learning design with related subjects such as math and science. This paper presents our approach to designing an educational game for AI for high school aged youth and presents evidence for how the game may be contributing to AI learning among players. Toward that end, we observed statistically significant learning gains among those high school aged students who completed at least half of the game, while students who completed less than half of the game demonstrated no gain on the measure of AI knowledge. Beyond this difference between the group of active players and the group of those who played less than half of the game, we saw no statistically significant variation in AI knowledge changes along variables for gender-identification, grade level, math confidence, and AI interest prior to playing the game. Overall, time spent in the game is significantly correlated with increase in AI knowledge.

In this study, we hypothesized that learning AI through a guided, fun and interactive environment such as DGBL can stimulate students' interest in AI. We did not find any support for this hypothesis in our data. However, the AI interest scale included items such as "I interact with a lot of AI-related videos and websites" and "Outside of school I try to learn a lot about AI". While such items can be good indicators of interest in AI, they do so based on estimation of past behaviors. Thus, it is less likely to see changes in response to these items. As a follow-up, we created sub-scales of AI interest that only include items such as "I am interested in learning more about Artificial Intelligence (AI)'". However, the data still did not indicate any significant correlations between time spent in the game and changes in interest in AI.

One of the limitations of the study is the relatively small sample size. Efforts are underway for large scale data collection at multiple schools with measures to improve data collection remotely. Data from a larger sample can support fine-grained investigations into how in-game activities, such as different paths in the game, or types of modules completed, on student learning. The assessment of AI knowledge is through an instrument designed by the research team. Data gathered through this pilot study can help validate the instruments. However, the instruments mainly consist of multiple-choice questions. To better assess students' AI knowledge, stealth assessment (Shute, 2001) – assessment of AI learning through additional problem-solving inside the game, can be experimented.

In this pilot assessment, the ARIN-561 educational game demonstrated its potential to support AI learning for high school aged youth across grade levels, gender identities, and prior interest levels in AI. Additionally, in order to realize these potential gains, youth should complete at least half of the game. Given the stark difference between outcomes for those students who completed at least half of the game compared to those who did not, further analyses of student game log data are needed to better understand how in-game behaviors may be contributing to learning gains, beyond the dosage effect reported here.

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