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Article

AI Odyssey: Designing and Evaluating a Board Game for Family-Based AI Literacy

Lu Ding[1] and Steven A. Holland[2]

[1]Counseling and Instructional Sciences, University of South Alabama, Mobile, Alabama, United States; [2]Division of Research Safety, University of Illinois Urbana-Champaign, Urbana, Illinois, United States
luding@southalabama.edu; shol726@illinois.edu

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Abstract

AI is becoming an increasingly integral part of society and daily life, making AI literacy more essential for the general population. Current research on AI literacy instruction is still in its infancy, primarily focusing on formal learning, and many require digital devices to participate. Moreover, there is a limited number of qualified teachers, and available instructional materials may not always be sufficient. These challenges can have an outsized impact on children and families of lower socioeconomic status, exacerbating the digital divide. Therefore, we created a non-digital board game called AI Odyssey, intended to promote AI literacy by providing an accessible learning experience without requiring a qualified teacher or digital device. This study outlines the process of creating the game and an in-depth analysis of an initial exploratory study. A variety of data, including pre- and post-tests of AI literacy, surveys of self-efficacy, interest, parental support, and career choice, as well as video recordings of playing sessions and interviews, are analyzed. The results paint a positive picture of using AI Odyssey to increase understanding and interest in AI literacy. Lessons learned and future directions are also discussed.

1. Introduction

Artificial Intelligence (AI) will eventually impact many aspects of human life through everyday technologies rather than merely a buzzword constrained to the computer industry, and everyone, including non-technical individuals, should learn AI [1]. While AI has infiltrated everyday life, a lack of knowledge of what AI is and how AI works is ubiquitous across all ages and professions [2]. It is crucial and urgent to provide instruction in AI literacy to those without technical backgrounds [3], [4], [5], [6], [7]. AI literacy can be broadly defined as the ability to understand and navigate AI-enhanced systems effectively and responsibly [4]. AI-literate non-technical individuals do not need to be programmers or engineers; instead, they should be equipped with the knowledge to make warranted judgments about AI-enhanced products and services, be aware of the ethical considerations of AI technologies, comprehend AI-related news and conversations, and effectively interact with AI-driven systems.

While increasing efforts have been spent on teaching AI literacy in K-12, research is still scarce [8]. These studies have investigated the theoretical frameworks and pedagogical strategies for integrating AI literacy into existing STEM courses, resulting in increased engagement, attitudes, awareness, etc. [9]. A few studies focused on teaching AI literacy in informal learning environments. For example, the *Robot Revolution* in the Museum of Science and Industry in Chicago exhibited numerous robotic artifacts and robots demonstrating intelligent features such as reciting Shakespeare [10]. Long and Magerko [11] developed five interactive exhibits in museums to improve public understanding of and interest in AI, and the authors [12] further used these exhibits in a study conducted at participants' homes. Nevertheless, the positive learning outcomes do not come without challenges. The most significant challenge lies in the shortage of qualified teachers and the absence of adequate instructional guidance [13]. Besides, most of the learning activities involve digital devices such as the Cozmo robot and Google's AIY kits, which may worsen the digital divide and disadvantage underrepresented groups [14]. Digital formats can also introduce barriers, including the need for reliable internet, updated software, or multiple devices for group play. In addition, the activities often require students to have prior knowledge of programming, and this prerequisite may inhibit students from participating [12].

To address these challenges, we designed a board game named AI Odyssey to teach AI literacy, particularly for those who do not have a technical background. AI Odyssey is a standalone unplugged (i.e., without the assistance of digital devices) board game that departs from the aforementioned challenges and provides the flexibility of learning AI literacy anytime and anywhere. First, it can be a standalone instructional material without the requirement of a qualified teacher to teach AI literacy. Second, the nature of board games allows for several family members to engage in a playing and learning activity at the same time. Third, since it is an unplugged learning game, it does not require high-tech or multiple digital devices to operate; instead, once produced, the game can be played anytime and anywhere without additional infrastructure. The main focus of this study is to describe AI Odyssey and present an exploratory study to test its effect on families learning AI literacy. In this paper, we first describe the rationale behind the design and development of AI Odyssey. We then provide a family case study on testing AI Odyssey with three families with at least one child (11-14 years old) to provide preliminary results on the effect of using an initial version of AI Odyssey in teaching AI literacy. Finally, we discuss lessons learned from the case study and practical implications. Particularly, this study is guided by the following questions:

1. How does AI Odyssey influence families' understanding of core AI literacy concepts?
2. How does playing AI Odyssey with family members influence children's attitudes toward AI (i.e., self-efficacy, interest, parental support, and career choices)?
3. How do children and parents negotiate and make sense of AI-related concepts during co-play with AI Odyssey?

2. Background

2.1 AI literacy

Many researchers and developers have attempted to define AI. Non-technical individuals see AI as advanced technology that allows computers and other devices to behave intelligently, potentially assist humans in completing their jobs, and reduce human labor [15]. From an expert perspective, Kaplan and Haenlein [16] described AI as a system's ability to correctly interpret external data and apply what it has learned to accomplish particular objectives and tasks through flexible adaptation. Both definitions emphasized that AI is not just automation, but involves intelligent, adaptive behaviors that are trained by data to accomplish certain goals. What differs between automation and an AI-enabled system is that the former usually uses rule-based programming that follows certain steps to accomplish a task, whereas the latter is more adaptive and intelligent in a way that can predict the next steps, adjust to new inputs, and optimize decisions based on patterns in data [17]. Recent researchers proposed *AI literacy* as a term to describe individuals' understanding and perception of AI instead of focusing on the technical facets of AI. Literacy is the ability to read and write [18]. AI literacy encompasses a multifaceted comprehension of the underlying principles, applications, and ethical implications of AI [1]. AI-literate non-technical individuals do not need to be programmers or engineers; instead, they should be equipped with the knowledge to make warranted judgments about AI-enhanced products and services.

Several frameworks of what to teach AI literacy to non-technical individuals have been proposed. Despite various focuses, a consistent theme that emerges from these frameworks is foundational knowledge of *AI mechanisms*, which helps individuals critically evaluate AI applications, recognizing both their potential and limitations in various domains. This knowledge does not necessarily need to be correlated with programming skills; rather, it involves the need for non-technical individuals to understand the underlying principles of how AI works. It includes the basic steps of machine learning (i.e., collecting data, training models, and deploying models) [4], [19], related data literacy, and AI utilizing sensors to perceive the world [4], echoing Touretzky and colleagues' [9] "big five ideas for K-12." As AI continues to integrate into different sectors, equipping individuals with this foundational knowledge becomes increasingly essential for responsible AI adoption and ethical considerations.

In a similar vein, a critical competency is understanding *AI capabilities*, which encompasses several interrelated dimensions. First, recognizing AI applications is fundamental, as it enables individuals to identify where and how AI systems are embedded in daily life [20]. For instance, research has reported misunderstanding rule-based automated technology as AI-enabled machines or, on the contrary, cannot recognize AI-enabled systems [21], [22]. Furthermore, grasping AI strengths and weaknesses is key to developing realistic expectations of its capabilities. While AI excels at pattern recognition, automation, and data-driven decision-making, it also has significant limitations, such as susceptibility to biases, a lack of common-sense reasoning, and difficulty handling ambiguous contexts. Understanding these limitations can help mitigate the risks of over-reliance on AI while promoting a balanced view of its potential [4][23].

Moreover, *sociocultural implications of AI* were also proposed to be a concept that laymen need to learn. Issues such as data privacy, algorithmic bias, job replacement, and the impact on social norms have become focal points that non-technical individuals need to be aware of [7]. With the advancement of generative AI (GenAI) and its increased accessibility, there have been suggestions to consider the ethical implications of the artifacts created by GenAI and their potential to spread misinformation [23]. Researchers have raised the idea of sustainable AI that urges everyone to be aware of the environmental impact that AI can have on society, such as the water consumption of GenAI [24]. Nevertheless, environmental impact appeared not to be a focus of existing AI literacy; however, we believe this awareness is critical in AI literacy education. Lastly, recognizing the imperative role of humans in human-AI collaboration is essential in non-technical individuals' AI literacy repertoire [1], [5].

2.2 Game-based learning

Games can serve as a powerful vehicle for engaging students in learning, sparking students' interest, and boosting their self-efficacy in STEM fields. Game-based learning (GBL) integrates interactive, goal-oriented gameplay into educational settings to enhance engagement, motivation, and knowledge retention. GBL fosters active learning by allowing students to experiment, make decisions, and see the consequences of their actions in a risk-free environment. Whether through digital simulations, board games, or gamified assessments, game-based learning can be adapted to various subjects and skill levels, making it a versatile and effective instructional approach.

Recent meta-reviews have highlighted the effectiveness of using digital games in enhancing students' achievements in STEM [25], [26]. Digital games have also been successfully utilized to foster students' interests and self-efficacy in learning, such as mathematics [27] and sciences [28]. Differing from digital games, board games are typically designed to be played with all the physical pieces unique to the game and on a tabletop in one setting; this makes board games more suitable for players to interact [29]. Bayeck [30] reviewed 44 articles using board games in education and revealed that board games can be used in teaching various topics, including mathematics, physics, CS, etc. Similar to digital games, board games have also been found to be able to boost students' interest and self-efficacy in learning [31].

Gaming as family time is beneficial to both parent-child relationships as well as parents' and children's personal growth. After interviewing 20 families who frequently play games together, Musick and colleagues [32] found that playing digital games together created a "democratized" family life and that technology co-use in gaming can serve as an important relational tool for parents, promoting conversations with their children and segueing into meaningful discussions about important topics. The benefits of playing games as families are not only limited to commercial entertainment games but also extend to educational games. In a study where five parent-child dyads were invited to play Quest Atlantis (QA) in an afterschool program [33], the authors reported that educational games like QA can be used to foster parent-child relationships and learning from early adolescence onward. In addition, researchers have also studied which features of games can make them more acceptable and enjoyable for families to play together. It has been found that the aspect families cared the most about was whether the game was fun, followed by whether the game could be played cooperatively [34].

2.3 Involving parents in learning

The benefits of engaging parents with students' learning include raised achievement, interests, self-efficacy, and aspirations [35], [36]. Parents' educational background is a direct predictor of children's educational achievement because parents are the first teachers of students [37]. According to the social cognitive theory, the role of social influences and self-efficacy in learning is critical in individuals' experiences and learning [38]. As the most immediate and influential social environment in their children's lives, parents not only provide direct support but also serve as important role models, and their involvement can significantly shape children's confidence, interests, and career aspirations in STEM domains. Strong associations were found between parents' and students' literacy levels [39], science belief and knowledge [40], and parents' understanding of AI concepts substantially influenced students' knowledge of AI and students' perception of AI-enabled agents [41]. It has been found that parents' knowledge of STEM is integral to their support of student STEM learning [42]. In a nutshell, parental support positively influences students' career decisions via the mediation of self-efficacy in sciences [43].

Despite these well-established findings, parental involvement in AI literacy remains an underexplored area. Unlike previous parent-student interaction models, where parents traditionally assume roles of authority in scaffolding students' learning by providing explanations or asking questions [40], or adopt a more peripheral role focused on financial support and collaboration with teachers and schools [35], we followed a Co-Play-Learn model (as shown in Figure 1) that takes into accounts several factors that encourage parents and students play and learn together by taking equal roles. This design is particularly relevant for learning AI literacy within families for two reasons. First, awareness and understanding of AI concepts are limited across all age groups and professions, meaning that parents and children alike often begin with little prior knowledge. Second, the inclusive and social nature of board games makes them well-suited for joint learning activities in families, fostering dialogue and mutual discovery.

By positioning parents as co-learners rather than instructors, AI Odyssey can provide opportunities for families to build AI literacy together. Increased parental knowledge of AI is expected to enhance their capacity to support children's learning, while joint gameplay can raise children's AI literacy, self-efficacy, and interest in AI-related careers.

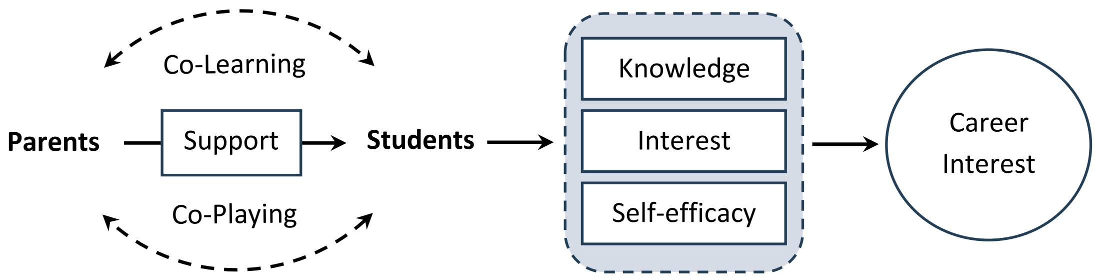


Figure 1. The Co-Play-Learn framework

3. Method and Material

3.1 Design of AI Odyssey

The process of designing AI Odyssey was guided by Hirumi and Stapleton [44], who proposed five steps for designing educational games: conceptualization, design, production, test, and post-production. Since AI Odyssey is still a work in progress, we only report the first three steps in this section and provide a preliminary test study in the next section. The design team was composed of a researcher whose expertise was in AI literacy and game-based learning and a game designer who had extensive experience in playing and designing games, as recommended by Hirumi and Stapleton. Important decisions needed to be made during the conceptualization phase, which included the audiences and the format of the game. Recognizing the imperative of teaching AI literacy and the pivotal role of middle school in fostering youths' affinity for specific academic fields [45], we made the deliberate choice to design AI Odyssey as a game suitable for middle school-aged individuals and beyond. In addition, to bridge the digital divide, AI Odyssey was decided to be made into a low-tech board game to be more accessible to underprivileged individuals. In this phase, another important decision we needed to make was the learning objectives. Informed by the three dimensions of AI literacy, namely AI mechanisms, capabilities, and sociocultural implications, AI Odyssey was designed to address 10 AI literacy competencies proposed by Long and Magerko [7].

While the authors [7] identified 17 competencies of AI literacy, AI Odyssey does not attempt to address all of them. Instead, we focused on a subset of ten competencies that both align with the three overarching dimensions of AI literacy (mechanisms, capabilities, and sociocultural implications) and can be effectively represented in a board game format. Competencies that are highly abstract (e.g., interdisciplinarity, general vs. narrow AI) or that require technical depth (e.g., detailed knowledge representations, advanced decision-making) were excluded from this version of the game (but remain important directions for future iterations). By prioritizing competencies that address common misconceptions and lend themselves to role-based gameplay, we aimed to balance conceptual rigor with accessibility and engagement. The ten competencies chosen for AI Odyssey represent the three dimensions of AI literacy, and the definition of each competence is shown in Table 1.

Table 1. The alignment between AI literacy competencies and how AI Odyssey addresses them

AI Mechanisms
Machine Learning Steps: Understand the steps involved in machine learning: collect data, train model, and deploy the model.
AI Learns from Data: AI systems do not possess innate intelligence but rely on data-driven learning to make predictions or decisions.
Data Literacy: Understand what data is, such as images and voice recordings, and how they can be used for training AI.
Data can be Messy: Understand that data cannot be used for training without preprocessing.
AI Relies on Sensors: Understand what sensors are, recognize that computers perceive the world using sensors, and identify sensors on a variety of devices.
AI Relies on Algorithms: Recognize that algorithms govern how AI systems process data and produce outputs.
AI Capabilities
AI can manifest in Various forms: Recognize that there are many ways to think about and develop "intelligent" machines.
Strengths & Weaknesses: Identify problem types that AI excels at and problems that are more challenging for AI.
AI Ethics
Human is Essential: Recognize that humans play an important role in programming, choosing models, and fine-tuning AI systems.
Ethical Issues: Identify and describe different perspectives on the key ethical issues surrounding AI.

In the design phase, the design team needed to determine a brief game proposal, including the genre, gameplay, prototype, etc. This phase generated numerous handwritten notes and digital copies of design documents that delineated the aforementioned objectives. To determine the game genre, we referenced the game genre map for educational game designers, postulated by Heintz and Law [46]. This genre map is a continuum guide from light to dark that gradually represents the richness of a game. Along this continuum, various game genres are displayed. According to Hirumi and Stapleton [44], the complexity of the game is dependent on the content that the game aims to address. The higher level and the more comprehensive the educational content are, the more complex the game. Given that AI literacy is a multifaceted concept, we traversed the darker side of the genre map and decided to make AI Odyssey an exploration role-play game. Later, the design team brainstormed the storyline, game mechanics, and fundamental game rules.

Another key consideration in our design process was how to integrate AI literacy concepts in a way that maximized engagement and learning. Prior research in game-based learning suggests that embedding educational content directly within gameplay mechanics – a strategy known as endogenous game design – tends to foster deeper learning and engagement [47]. In contrast, exogenous game design, where educational content is layered onto gameplay through external elements (e.g., explanatory text or separate tasks), may not always sustain motivation or conceptual understanding as effectively. With this in mind, AI Odyssey was designed to integrate some AI literacy concepts through endogenous mechanics, such as data collection, algorithm training, and model deployment. An example of endogenous game design in AI Odyssey is the concepts of "AI learns from data" and "AI relies on algorithms." Players must collect data cards and enter specific rooms to level up their algorithms. Because advancing in the game depends on this process, the concept that AI requires data and iterative training is embedded directly into gameplay. From collecting data to train their algorithm, players learn that AI relies on algorithms to function, and AI will need data to train its algorithms. Another example of endogenous design is the representation of Machine Learning Steps. To reach the deployment phase, players need to iteratively collect data and train their algorithms, the three steps in machine learning.

In contrast, certain complex topics, such as AI ethics and societal implications, are currently introduced through event cards that provide scenarios for discussion as exogenous game design. For instance, the importance of transparency in collecting user data is introduced through an event card. Players encounter this concept as explanatory text when the card is drawn, making it an exogenous element that prompts reflection alongside the core gameplay. Some other concepts (e.g., explainability, privacy) fall under ethical and technical issues are also explained similarly on the event cards. Table 2 illustrates how each of the competences is implemented in the game. Finally, a prototype of AI Odyssey was created. Figure 2 shows some design notes (left) and the prototype (right).

Table 2. The alignment between AI literacy competencies and how AI Odyssey addresses them

Competencies	**Implementations**
Machine Learning Steps	Players need to iteratively collect data and train algorithms.
Data Literacy	Data cards provide numerous examples of what could be data sets.
AI Learns from Data	Players need to iteratively collect data to train their AI algorithms.
Data can be Messy	“Messy” data cards require players to clean the data before using them.
AI Relies on Sensors	Players need to collect at least one “Sensor” to deploy their AI.
AI Relies on Algorithms	Players need to iteratively upgrade their AI algorithms.
AI can be in Various Forms	Players can choose different roles (implementations of AI) to play.
Strengths & Weaknesses	Event cards provide examples of challenges that AI can encounter in the real world.
Human is Essential	Players can choose different roles to play.
Ethical Issues	Event cards provide examples of challenges that AI can encounter in the real world.

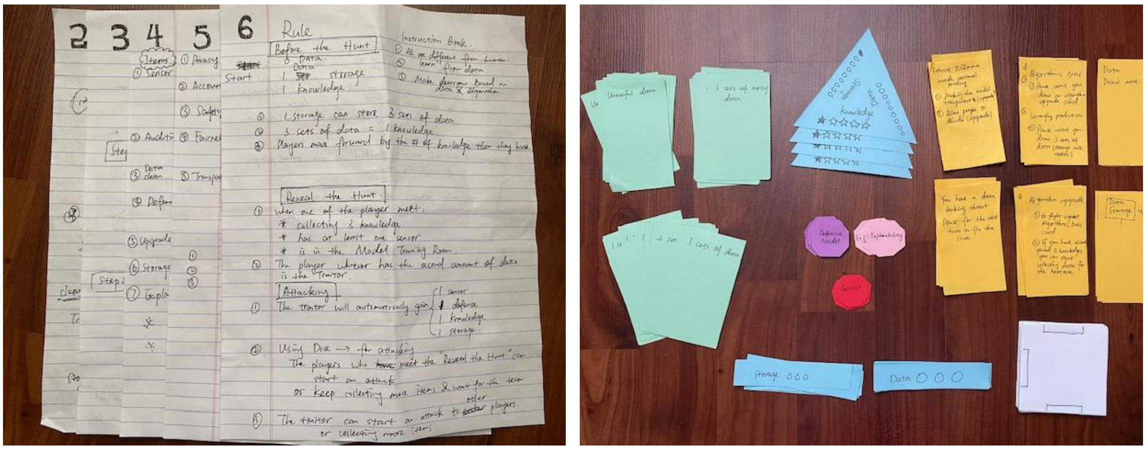


Figure 2. Sample design documents and the prototype

During the Production phase, before a final “Gold” version, Alpha and Beta versions of the game were developed and tested as recommended by Hirumi and Stapleton [44]. The Alpha version (shown in Figure 3) underwent rigorous testing by the developers to ensure its playability and functionality. The design team conducted multiple test plays to evaluate gameplay mechanics, flow, and overall stability. These tests also involved pushing the boundaries of the game rules to explore diverse gameplay possibilities and confirm the game’s resilience. Based on the tests, several modifications were made to AI Odyssey, and a Beta version was created. These modifications included the correction of typos and errors on the cards, the adjustment of the number of cards for each category, the addition of cards for the Rogue AI, the change of the roles, and the separation of cards for two players and 3-4 players.

Figure 3. The Alpha version of AI Odyssey

3.2 The Beta version of AI Odyssey

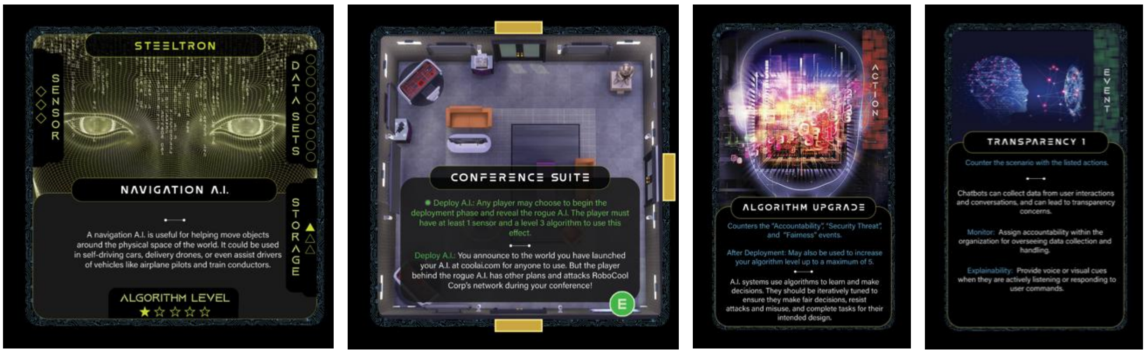
3.2.1 Overview of the Game

AI Odyssey consists of three decks of cards for playing the game: the room deck, the main deck, and the event deck. There is a total of four AI models that players can choose from to develop (Figure 4a shows an example of model cards), and each player starts by taking an AI developer's role (each model matches an AI developer represented as a token). The game starts with the Starting Room card, which consists of three doors (indicated as yellow rectangles) that can lead to other rooms (shown in Figure 4b). Each turn, each player takes turns drawing a card from the main deck to be held in their hand and a card from the room deck to be placed adjacent to the existing room cards on the table, and moves their token to the room. If there is an Event icon on the room card drawn during a player's turn, they will need to draw an event card from the event deck.

The main deck contains three types of cards: *data cards*, *item cards,* and *action cards* (Figure 4c shows an example of the main cards). The *data cards* and *item cards* are used to train their AI models, and the *action cards* are used to counter the event cards. Data cards consist of both regular data cards and "messy" data cards. When players draw a regular data card from the main deck, they may hold it until they collect three cards, which can then be played together to level up their algorithm. If they draw a "messy" data card, however, they must use a data cleaning card before the data can be used for training. Such data cleaning cards, along with sensor cards required for deploying models, are included in the item cards category. The action cards contain solutions that can address the issues on event cards. For example, an action card shows a solution of iteratively tuning the algorithm to ensure that the algorithm is fair in decision-making (the fairness issues presented on an event card).

The event deck contains cards that highlight ethical issues AI may cause in society (Figure 4d shows an example of event cards). For example, fairness issues can appear when an AI hiring system favors one demographic group over another due to biased training data. Privacy issues may arise if a facial recognition system collects and stores personal images without consent, leading to potential data leaks. Accountability issues are illustrated through generative AI, such as when a system produces harmful or misleading content.

The Room cards serve two main purposes in the game. First, they are used to build the game map, enabling players to navigate through different spaces. Second, they provide opportunities for action: some room cards allow players to level up their algorithms, while others trigger events that expose players to ethical challenges AI may pose to society (through event cards). For example, a Research Lab room allows players to upgrade their algorithms, while a Data Center room may trigger an event card about data privacy, illustrating how AI development is tied to societal concerns (when there is an E icon indicating that an event is triggered).



(a) (b) (c) (d)

Figure 4. Example cards from AI Odyssey. (a) *This role card* describes real-world applications of navigation systems such as self-driving cars and drones. (b) *This room card* requires a player to have at least one sensor and a level 3 algorithm, illustrating prerequisites for AI deployment. (c) *This main card* (an action card) emphasizes iterative tuning for fairness, robustness, and accuracy. (d) *This event card* highlights transparency and accountability concerns in conversational AI.

3.2.2 Brief Rules

AI Odyssey can be played with 2-4 players, and each playthrough can last from 30 to 60 minutes. It encourages players to take an AI developer role and is designed to teach non-technical individuals AI literacy as a board game that reflects real-life situations. The story happens in an AI development corporation named *RoboCool*. Players are asked to investigate a rumor that someone is unethically developing an AI at *RoboCool*. The players are asked to interactively collect data, train their AI models, and reveal the person who is developing the unethical AI and destroy the data the unethical AI has collected. During play, the players will encounter AI-related challenges and need to tackle them.

The game is comprised of a Development and a Deployment phase. During the Development phase, players take turns to draw from the main deck. After drawing from the main deck, players can choose to reveal a new room or roll a die to level up their AI algorithm in designated rooms. The goal of this phase is for each player to train their AI model and collect as many main cards as possible to prepare for the Deployment. The first player whose AI reaches level 3 can start the Deployment phase. The AI possessing the second-highest number of data set cards will be designated as the rogue AI.

During the Deployment phase, the ethical AIs will unite to disrupt the rogue AI's training data, ultimately neutralizing the rogue AI. Each player can choose to attack the rogue AI or keep collecting more main cards by following the rules from the Development phase. If a player attacks the rogue AI player, a die will be rolled, and the differences between the two players' rolls, added to their algorithm level, will be taken off as data sets from the player whose added total is less. Ethical AIs win the game when the rogue AI loses all its data sets or vice versa. A statement of how unethically developing AI can be detrimental to society is provided in the game manual for each winning condition. Figure 5 illustrates a full playthrough of the AI Odyssey.

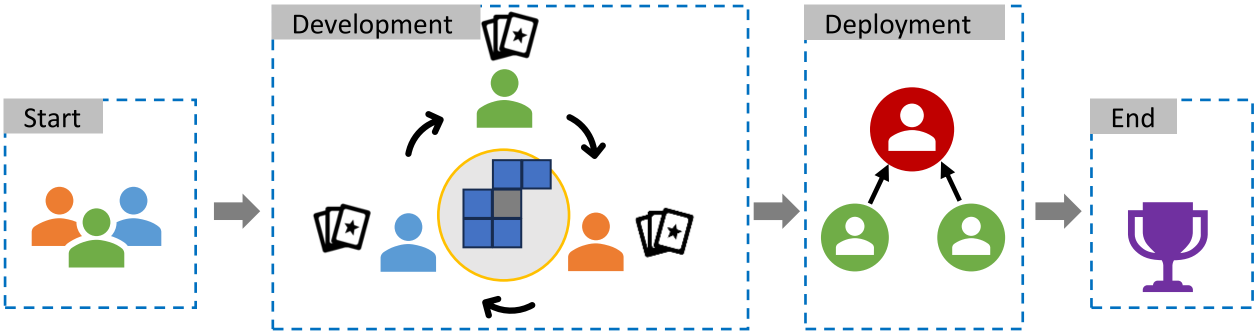


Figure 5. An illustration of a playthrough

3.3 Family Case Studies (the Beta version test)

A family case study was conducted to test this Beta version of AI Odyssey. Human subject research was approved before the study by the Institutional Review Board of the university where the first author was affiliated. The goal of this study is threefold: 1) to test how long it takes to play AI Odyssey, 2) to determine if there is any positive effect of using AI Odyssey to teach AI literacy, and 3) to solicit feedback on how to improve AI Odyssey. Figure 6 shows a family playing the game and the end of the game.

Figure 6. A screenshot of a family playing AI Odyssey

3.3.1 Participants

AI Odyssey was tested with three families, with a total of nine participants. Due to the challenges of recruiting families for research projects [48], we used a convenience sampling approach in which participating families were recruited through friends and family relationships. Parents were contacted via phone to solicit participation, and all three families agreed to participate upon contact. Each family had at least one child who was in either middle school or high school. Table 3 lists the participants' profiles (all names are pseudonyms). Family 1 described themselves as casual game players who play board games together occasionally. The children of Family 1 played games, including both video games and board games, with their friends more frequently than they played with family members. However, the children would not describe themselves as avid game players. While the child from Family 2 played some board games with friends a few times, they never played any games at home with family members. The father and children from Family 3 frequently played games not only with family members but also with their friends, and the games they played included a variety of game genres, ranging from board games to video games. Parents of the three families had little to no AI-related background, and all three families reported household incomes between $100,000 and $200,000.

Table 3. Participants' profile

Name	Parent/Child	Gender	Age	Ethnicity	Native English Speaker	Occupation
Family 1 (attended 1 game session)						
Mary	Parent	Female	48	Asian	No	Higher Education
John	Parent	Male	53	Caucasian	Yes	Tech Manager
Katie	Child	Female	14	Asian/Caucasian	Yes	High Schooler
Emma	Child	Female	12	Asian/Caucasian	Yes	Middle Schooler
Family 2 (attended 1 game session)						
Nancy	Parent	Female	46	Asian	No	Higher Education
Lily	Child	Female	13	Asian	Yes	Middle Schooler
Family 3 (attended 2 game sessions)						
Jack	Parent	Male	50	Caucasian	Yes	Multimedia Producer
Ethan	Child	Male	13	Caucasian	Yes	Middle Schooler
Mia	Child	Female	11	Caucasian	Yes	Middle Schooler

3.3.2 Data collection

All participants took pre-and post-tests of AI literacy and participated in follow-up interviews. In addition, the children took a survey measuring their interest, efficacy, and career choice in AI-related fields, as well as their perceived parental support of choosing a career in AI-related fields. Family 1 and 2 attended one game session separately (Family 1: 67 minutes; Family 2: 62 minutes), and Family 3 attended two game sessions (Session 1: 101 minutes; Session 2: 68 minutes). All game sessions and interviews were video recorded and transcribed.

The AI literacy pre- and post-tests were identical and consisted of 10 multiple-choice questions drawn from an AI literacy assessment developed by Ding and colleagues [49]. The ten questions corresponded to the ten AI competencies that AI Odyssey was designed to address. Each question was worth one point, making the test a total of 10 points maximum. The items used for the AI literacy test are provided in Appendix A. A survey consisting of 15 Likert-scaled items measuring self-efficacy (four items), interest (four items), perceived parental support (four items), and career choices (three items) was administered to the children twice, before and after attending the game sessions. Each item was rated from 1 (strongly disagree) to 5 (strongly agree). Items for self-efficacy were adapted from a subscale used to assess students' confidence in an AI class [50], and the rest of the three subscales were adapted from the scales used to measure middle school students' learning in an afterschool program for computational thinking [51]. The survey items are provided in Appendix B.

4. Data Analysis and Results

4.1 Test and survey results

Due to the limited number of participants, only descriptive statistics are reported here. The survey measuring interests, self-efficacy, and parental support of learning AI as well as career choices in AI-related fields was only administered to the children in the families, and the results show that overall, there was a slight increase in their averaged interests (by 0.25), self-efficacy (by 0.20), and career choice (by 0.35) but no change for parental support. Additionally, a slim increase in their AI literacy was also shown in their pre- and post-test scores (by 0.19).

Nevertheless, a further breakdown of descriptive statistics revealed an interesting pattern among the three families, as shown in Table 4. All three families had relatively high pre-test scores, with the lowest score of 6.0 from Family 2 and the highest of 7.75 from Family 1. Although the girl, Mia, did not display any changes in her AI literacy, her responses to all four subscales in the survey notably increased. Lily from Family 2 showed the highest increase in her efficacy in learning AI after playing AI Odyssey, and it is also interesting to see that Emma from Family 1 perceived a decreased parental support of learning in AI. It was observed that Family 3 exhibited the highest learning gain from playing AI Odyssey, as well as an overall increase in children's aspiration for AI, compared to the other families. Specifically, the boy Ethan and the dad Jack demonstrated the most significant learning gains among all participants, with both of their post-tests showing a 2-point increase from their pre-tests. The results are not surprising given that Family 1 and 2 only played AI Odyssey once, whereas Family 3 played the game twice.

Table 4. Breakdown of the overall learning effects

Family		Differences between pre and post				
		AI Literacy	Interests	Career Choice	Efficacy	Parental Support
1	Mary	-1.00	NA	NA	NA	NA
	John	0	NA	NA	NA	NA
	Katie	0	0.25	0.20	0.35	0
	Emma	0	0	0	0	-0.50
2	Nancy	0	NA	NA	NA	NA
	Lily	-1.00	0.5	0.33	1	0
3	Jack	2	NA	NA	NA	NA
	Ethan	2	0	0	0.25	0
	Mia	0	0.50	0.67	0.25	0.50

Since 10 multiple-choice questions measured distinct competencies of AI literacy, we further investigated each question to evaluate the effect of AI Odyssey on these competencies, as shown in Table 5. Overall, our participants demonstrated a good understanding of concepts such as the variability in AI creation methods (item 7), the reliance of AIs on algorithms to function (item 6), and the necessity for accurate data interpretation (item 3). Nearly all participants answered these questions correctly on both their pre- and post-tests.

Table 5. Pre- and Post-Test Scores for AI Literacy Assessment Items by Participant

Item	Mary	John	Katie	Emma	Nancy	Lily	Jack	Ethan	Mia
1	1/0	1/1	1/1	1/1	1/1	0/0	1/1	0/1	1/1
2	1/1	0/0	1/1	0/1	0/0	0/0	1/1	1/1	1/1
3	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
4	1/1	1/1	0/1	0/0	1/1	0/0	1/1	1/1	1/0
5	1/1	0/1	1/1	1/1	1/1	1/1	0/1	1/1	1/1
6	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
7	1/1	1/1	1/1	1/1	1/1	0/0	1/1	1/1	1/1

8	1/1	1/1	0/0	1/0	1/1	0/0	1/1	1/1	1/1
9	1/1	0/0	1/1	0/1	0/0	1/1	0/0	0/1	0/0
10	0/0	1/0	1/0	1/0	0/0	1/0	0/1	0/0	0/1

Note. Pre-test and post-test scores are displayed as pre/post, where "1" indicates a correct response and "0" indicates an incorrect response.

Some areas showed modest gains. Understanding the human role in AI (item 9) and recognizing that AI relies on sensors (item 5) showed the greatest improvement, with two participants correcting their responses in the post-test. Participants also demonstrated a slightly better understanding of the concept that AI learns from data (item 2), as one participant answered correctly after initially responding incorrectly. For the machine learning steps (item 1) and messy data (item 4), one participant improved, whereas one other participant regressed on both items.

Other concepts remained challenging. Ethical issues (item 10) were particularly difficult: while four participants answered correctly in the pre-test, only two did so in the post-test. Similarly, the strengths and weaknesses question (item 8) showed no overall improvement, with three participants maintaining incorrect responses and one shifting from correct to incorrect.

4.2 Video recording results

In analyzing the video recordings of parent-child gameplays, we used techniques from interaction analysis [52]. We particularly focused on the interactions of discourse around game rules and how to play AI Odyssey. In addition, to find out the influence of AI Odyssey on participants' AI literacy learning, attentions were paid to occasions where the participants expressed affective behaviors or utterances. We mainly looked at the three videos of the first play to investigate the design of the game and used the video of Family 3's second play to investigate the influence of AI Odyssey on participants' engagement. While we took a top-down approach, additional discoveries were also made, which were suggested as common practice by Derry and colleagues [53]. We analyzed the data in several passes, where two researchers first reviewed the recordings separately and took detailed notes on the occasions that were relevant to our inquiries. Table 6 shows the final coding book that the two researchers used to analyze the videos. The two researchers then used their notes to review the videos again and generated themes to capture their understanding of the dynamics of the interactions between the parents and the children during the gameplay. Finally, the two researchers met to discuss their findings and to reach an agreement by rewatching the video clips when there were any discrepancies.

Table 6. Coding book of the play videos

Code	Description of the code	Examples
Round	Records the turns taken during gameplay	NA
Positive Expression	Players express positive emotions	e.g., Haha; Yes; Oh, perfect!
Negative Expression	Players express negative emotions	e.g., Sigh; oh, no!
Strategy	Players discuss how to use the rules to maximize the effectiveness of a move	e.g., I can't do it, I will lose my algorithm if I lose the data.; I better move to the pool, so I can level up.
Encouragement	Players encourage each other during gameplay	e.g., You can do it; we have to cover each other's backs.

Rule Watch	Players point out or correct another player's rule-related actions	e.g., You can't move, that is a data set; No, you will need to draw card first.
Rule Check	Players ask the researchers to clarify game rules	e.g., [Asking the researchers] Do we need to roll dice here?
Negotiation	Players negotiate the correctness or consequences of a move	e.g., Players discuss back and forth if the move is correct.

4.2.1 The complexity of the game

All three families encountered a significant learning curve during their initial play session. Each of their first sessions ranged from one hour to one hour and 40 minutes. AI Odyssey consists of many game mechanics that encourage randomness, such as dice rolling and card drawing, and this may have also contributed to the great time range of the play. For instance, Family 3 almost went through the entire event deck and the main deck, whereas Family 2 had almost one-third of the main deck left. The primary challenge stemmed from the multitude of components that needed to be remembered and managed for each turn. Each turn involved drawing a card from the main deck, the room cards, and potentially drawing an event card if indicated by the room card, and required players to effectively manage their algorithm levels, data sets, and data storage. This might have created a great deal of cognitive load on the players and required many turns for them to understand how to play the game. For instance, at around 31 minutes into the game, John remained uncertain about whether he could draw a room card:

[John was trying to draw a room card]
Mary: You can't move, that is a data set (not an action card that can counter the event John had) because you need to counter that event before you can do anything else.
Emma: Daddy, cause you'll have events still need to finish.
John: Okay, I have to wait then. So, what do I do after I draw this messy card? Do I need to draw another room card?

Even during the second play, occasionally, Family 3 would turn to the researchers to confirm the rules, such as whether a room card could be drawn when their token was surrounded by room cards and had to move to another room to have an adjacent door to be connected to a new room.

The complexity of the game is not only reflected in requiring a long time to learn the rules, but also in the language used in the event cards. Particularly, younger participants and non-native speakers expressed some challenges in reading the cards. The events cards contained a considerable number of scenarios where ethical issues could occur during the development and application of AI. For example, in an event card where the scenario was about the security issues of AI, the phrase "*adversarial attacks*" was used. Mia (11 years old) had a hard time reading the text and turned to her dad to read it out loud for her. This also happened to Mia when the word "*opaque*" was used in one of the event cards. "*Explainability*" seemed to be challenging for Mary and Nancy to pronounce since English was not their native language.

The extensive learning curve may deter certain players from fully engaging with AI Odyssey and may prevent learning. After several turns of playing and learning the game, but still confused about the game rules, John turned his head away from the game table and was distracted by the television. Later, when John's team won the game, he commented, "*Oh, I won? I'm the most oblivious winner.*" Players found themselves primarily occupied with grasping the game mechanics, consequently impeding their learning from the text on the cards, as Katie expressed, "*For me. I'd have to understand how to play the game better. So, I can then* *focus on the learning.*" In a similar vein, Jack commented, "*I think when you're not worried about learning how to play, then you'll start appreciating the like, the text more.*"

An interesting pattern showed across the three families was that the children picked up the game much quicker than the parents, especially for Family 1 and Family 2, who considered themselves not avid game players. It usually took 3-4 turns for children in the families to be able to mostly play without guidance from the researchers and start to teach their parents what the rules were; however, it took at least 3 more turns for parents to catch up with the children.

4.2.2 The excitement and the boredom

Overall, when reflecting on their experiences with AI Odyssey, the majority of participants from the three families described it as enjoyable once they learned how to play. The participants appeared to especially enjoy rolling the dice, countering an event, leveling up, and competing against each other in the deployment phase. In Figure 7, Emma (left) was excited and standing up to check on her mom's levels, and Mia (right) was celebrating finally countering an event by drawing the card that she needed.

Figure 7. Children showed excitement from playing AI Odyssey

Compared to the development phase of AI Odyssey, we observed more excitement during the deployment phase. Not only did the children enjoy the attacking aspect of the game, but the parents also showed more enjoyment in this phase. The two excerpts from Family 2 and Family 3 below demonstrate how parents and children both enjoyed the deployment phase.

[Family 2: Nancy initiated the deployment and started to attack Lily's AI. After rolling the dice, Nancy was four points ahead of Lily.]
Lily: I'm going to use my cyber defense!
Nancy: OK.
Lily: Oh, I, I don't have it anymore.
Nancy: Haha, oh, oh, sorry, Lily. You can't cyber defend me. I'm unstoppable!
[Family 3: Jack's role was the rogue AI and the children (Ethan and Mia) needed to take down the rogue AI of Jack's.]
Jack: Are you gonna attack me?
Ethan: Yeah, I'm gonna attack you.
Jack: Go ahead.
Ethan: So I still have six (data sets), right?
Jack: That's five.
Ethan: Oh, yeah. (rolling dice and a two was rolled) Dude, I have the worst roll.
Jack: Muahaha. (rolling dice and a five was rolled)
Mia: One, one, one. Argh… (after seeing Jack rolled five) I will beat you, Dad!

While all three families were fond of certain game mechanics of AI Odyssey, there were several game mechanics that appeared to produce minimal enjoyment. The first mechanic was the instruction. Since the primary goal of AI Odyssey is to teach AI literacy, we have numerous scenarios and examples on the event cards, algorithm cards, and data set cards that teach AI-related concepts. To ensure players were cognizant of the information, the game rules required them to read out loud those texts on the cards when one was drawn. Reading the text substantially slowed down the game due to the presence of technical terms, as discussed in the previous section. Moreover, the act of reading appeared to disrupt the flow of gameplay, potentially impeding players from fully engaging in the game.

Despite most of the members from the families enjoying the counter events, several of them became frustrated when they were stuck in the events for too long. Because only certain action cards can be used to counter a particular event, the odds of having the action card to counter the event or drawing the needed action cards were relatively low. This happened to John, Ethan, and Mia during their separate plays. John had to stop for 4 turns due to being stuck on an event, and this might have contributed to his disengagement later in the game. Ethan and Mia were both stuck on one event for a couple of turns and started showing frustration; however, Jack offered to trade cards to help them out. In this initial version of AI Odyssey, we did not fully explore the trading mechanic, only incorporating two room cards that enabled players to exchange their cards and test this feature. Nevertheless, the trading room was discovered by Jack, and following the card exchange, Ethan and Mia noticeably regained their interest in the game. Below is the conversation Jack and Ethan had about their trading.

[Ethan was stuck on an event that needed a monitor card to counter]
Jack: Ethan is up.
Ethan: I can't roll, I can't move. I'm done. (expressed frustration)
Jack: Wasn't there a room here that you could trade in a card? Yeah, right there, the cafeteria. I'll trade you monitor for one of your data sets.
Ethan: Okay.
Jack: So how do I get to that room again?
Ethan: You gotta roll and you gotta move yours (token).
Jack: Okay, there's a long way to go, but I can do it, I'll do it.

4.2.3 The change from the first and second play

We investigated the two videos from the first and second play from Family 3 to assess the influence of AI Odyssey on players' engagement. Attention was paid to players' number of affective behaviors, including laughter and utterances of excitement (e.g., expressions such as Yay! Yes! Cool! etc.), strategic play, and rule checks. Strategic play is a way to show players how to cognitively engage with the game [54].

Strategic play includes those instances when players negotiated the rules when they had discrepancies in their understanding of the rules and discussed them to reach a consensus to keep the game going. For example, Mia's token was once surrounded by existing rooms, preventing her from revealing a new room to move her token unless she relocated it to a room that could be connected to a new one. During her turn, the three family members discussed whether she should roll the dice to move to a room that could be linked to other rooms or if she could still reveal a room card and place it at the nearest outlet card. Strategic play also included those moments when players expressed their strategies to achieve their goals. For example, when faced with the choices of revealing a new room card or moving to a certain room, the players would make a strategic decision to favor their play toward a win. Jack once needed to upgrade his AI to prepare for the deployment phase, and there was a room where he could upgrade his AI's algorithm, so that, in lieu of drawing a new room card, he chose to roll the dice to move to the already-revealed room. Rule checks are those occasions when players ask each other questions or the researchers to confirm certain game rules or to ask what the rule is about certain moves.

Table 7. Descriptive statistics of gameplay sessions

Play Session	Total length	Total Turns	Affective Behaviors	Strategic Play	Rule Checks
First	1h 30 mins	28	27	20	51
Second	1h 2 mins	27	40	40	3

As shown in Table 7, Family 3's first and second plays differed substantially in terms of time, even though the number of turns was similar. The main difference can be attributable to the time the players spent checking the rules. In addition, the players showed a considerably greater number of strategic plays compared to their first time playing the game. This indicates that once the players became familiar with the game and were not interrupted by having to check rules, AI Odyssey encouraged them to engage in strategic play. Compared to the first play, Family 3 also enjoyed more of the game; this was reflected in the significantly greater number of affective behaviors in the second play.

5. Discussion

5.1 Discussion of Main Results

Overall, AI Odyssey demonstrates some potential in engaging players in learning AI literacy. This is evident not only in the follow-up interviews but also in the changes observed during Family 3's first and second plays. Additionally, AI Odyssey appears to effectively facilitate AI literacy learning to a certain level, as evidenced by Family 3 showing the highest learning gain from pre- to post-tests compared to the other two families. It is noteworthy that Family 3 was the only family that played the game twice, and only their second play was not substantially impacted by rule checks. That is, once players are familiarized with the game and its rules, the game will then facilitate the learning of AI literacy. There are several valuable lessons learned from this preliminary test run of AI Odyssey.

5.1.1 Endogenous game mechanics are better at facilitating learning

The results indicate that the three families showed some modest learning gains between the pre- and post-tests, particularly in understanding the human role in AI, the application of sensors in AI operations, and recognizing that AI learns from data. However, participants continued to face challenges with concepts related to ethical issues. A closer examination of AI Odyssey's design may help explain these patterns. Concepts such as the human role in AI are more embedded in the gameplay: players make decisions at multiple stages, including training AI models, developing algorithms, and deploying their AI to complete the game. In contrast, topics like ethical considerations are presented through exogenous elements (e.g., event cards) rather than being integrated into gameplay. Players need to read the cards to learn the ethical issues that AI can have on human society and the counter strategies, rather than actively interacting with other players to learn the concept.

It has been shown that endogenous game designs are more interesting and prone to better motivate people to learn compared to exogenous game designs [55]. This highlights the importance of embedding educational content within interactive gameplay rather than relying on passive reading tasks. However, given the small sample size and variability in responses, these findings should be interpreted cautiously. In a future iteration of AI Odyssey, we are considering incorporating specific endogenous game mechanics to address the concepts, such as the ethical issues of AI, that proved challenging for our participants to grasp, and to test the game with a larger sample size.

5.1.2 Balancing game complexity and engagement

While AI Odyssey provided a rich learning experience, its complexity also introduced challenges. The complexity of the game rules could have added an extraneous cognitive load on players. Extraneous cognitive load is caused by elements in the learning environment or instructional design that are not essential for learning the material. This type of cognitive load can lead to frustration and/or boredom and eventually to giving up on learning [56]. In our study, the father from the first family, John, certainly lost interest in the game after several turns of trying to learn the game. In the follow-up interviews, several family members also expressed similar comments that they would appreciate the instructional aspect of the game more if they did not need to worry about how to play the game. Comparing Family 3's first and second plays, the affective behaviors and strategic plays significantly increased, which is an indicator of promoted engagement once past the learning curve. When designing this first version of AI Odyssey, we faced the dilemma of teaching as many critical concepts as possible and making the game too complex. For example, data storage is a critical concept in AI literacy [57], and we implemented this concept in AI Odyssey as a rule that players need to collect enough data storage to play their data. Nevertheless, similar designs like this may have contributed to the complexity of the game.

The complexity of the game was not only reflected in the game rules but also in the terms used in the scenarios on the event cards. Certain words appeared to be too challenging for younger players or non-native English speakers; however, it is also imperative for players to learn appropriate terms in AI-related concepts. However, repeated gameplay led to increased strategic decision-making and a deeper understanding. Simplifying rule explanations and providing adaptive scaffolding (e.g., visual aids, explanations of technical terminology) could enhance accessibility without sacrificing depth. In a later modification of AI Odyssey, we will also consider developing a tiered difficulty mode to meet players' varied background knowledge.

5.1.3 Encouraging more Collaboration

While the three families all enjoyed the competition aspect of AI Odyssey more than the other aspects of the game, it has been shown that collaboration in educational games also offers numerous learning opportunities, such as positive social behaviors [58]. Collaboration allows players to execute altruistic behaviors and encourages players to learn through discourse with each other. AI Odyssey certainly provides ample opportunity to incorporate collaborative game mechanics that facilitate learning, especially during the Development phase, as our families have already been doing. For instance, when Ethan found himself stuck in an event for several turns, Jack stepped in and offered to move his token to a room with a trade icon, proposing an exchange of cards with Ethan. This trading scenario required Ethan to carefully read his card to select the necessary action card, presenting a valuable learning opportunity. Additionally, Jack required a data set card to upgrade his AI model, providing another opportunity for them to grasp the concept of AI's reliance on data to operate.

Another aspect where AI Odyssey could be improved by integrating more collaborative game mechanics, which was not directly reported in our results section, as it could not be classified into any larger themes, is the lack of clear motivation for players to launch the deployment phase. For instance, after Mia was selected as the Rogue AI and eventually lost the game, she commented, "*I did not choose to be the bad AI!*" This comment indicates the absence of a clear goal for players to start the deployment phase. In future modifications of AI Odyssey, some collaborative game mechanics could be implemented in the Development phase to create a shared goal among the players, encouraging them to deploy their AI to help identify the

Rogue AI. Additionally, mission-based goals will also be considered to improve the motivation for players to proceed to the second phase.

5.1.4 Parents' assistance in learning

Parents played a crucial role in supporting their children's learning of AI concepts when playing the game, particularly when encountering complex terminology, and were there for emotional support when facing frustration. For instance, in the third family, when Mia could not understand certain words, Jack was there to help. Although AI literacy differs from science learning, where parents typically guide their children, the relative novelty of AI in everyday life means that parents and children often start with similar levels of AI knowledge. However, their learning patterns still resemble those seen in science education. In science learning, parents, as the more knowledgeable members, guide their children's engagement [59]. Similarly, in AI literacy, even when parents and children share similar baseline knowledge, parents can still support their children by helping them understand key AI terminology and complex concepts.

Parental emotional support is one of the best predictors of students' engagement in learning [60]. This is also true in learning AI literacy together through AI Odyssey. Among the three families, the father in the third family was the most engaged, actively assisting Ethan and Mia when they encountered challenges. Ethan showed the highest AI literacy gains among the children, while Mia exhibited the greatest increases in interest, career aspirations, and perceived parental support in AI-related fields. In contrast, John, the father from the first family, was the least engaged due to the game's complexity, and his children showed the least impact from playing. Therefore, when played by younger players, it is critical for parents to be behaviorally and emotionally engaged with their children. This can also be a great time to increase bonding in the family.

5.1.5 Children as facilitators of playing

In most families, children adapted to the game mechanics more quickly than parents and subsequently took on instructional roles, guiding their parents on rules and strategies. This reciprocal teaching process not only reinforced children's own understanding but also helped parents engage with the game more effectively. Results from video analysis showed that children in all three families demonstrated increasing autonomy in rule comprehension after a few rounds of play, often providing corrective feedback when parents misunderstood a rule, such as the children correcting the father's play from Family 1. This type of democratic education embraces the idea of joint participation in learning activities, where parents and students co-construct knowledge rather than adhering to traditional hierarchical roles. Particularly, children being more knowledgeable in gameplay, while parents were more knowledgeable in supporting learning, may facilitate an equilibrium power dynamic in learning AI literacy at home, which may make learning more enjoyable for both groups.

These findings suggest that AI Odyssey has the potential to foster intergenerational learning, where children serve as knowledge brokers for their parents. Future iterations of the game could intentionally incorporate mechanics that encourage peer and intergenerational teaching, further amplifying the benefits of this co-play-learn model for parents and children learning AI literacy at home through board games.

5.2 Limitations and Future Directions

It should be emphasized that this is a design study featuring the design and development of a board game teaching AI literacy and a case study of a small sample of families. Although the parent–child pairs were diverse in terms of gender, prior game experience, and ethnicity, the results may still be limited in their generalizability to family dynamics alone. First, no systematic assessment of broader technical literacy was collected. While this aligns with our goal of designing a game accessible to non-experts, future research should include more systematic measures of participants' technical proficiency to account for potential confounding factors. Secondly, future studies should utilize the findings of this study to adapt AI Odyssey and test it with a larger sample size. This expanded research should not only include families at home but also encompass environments such as library game events, afterschool programs, community center activities, and include individuals across a wider age range and different group dynamics. Third, given the fact that families with low socioeconomic status may benefit most from this low-tech board game learning activity for learning AI literacy, future work should explore how AI Odyssey can be adapted for those groups.

Additionally, our study is also limited by a brief 10-item AI literacy assessment designed to capture a range of competencies. Future studies should employ a more comprehensive approach to formally test participants' understanding of AI literacy concepts and conduct inferential statistical analyses to test the learning gains. Finally, we did not systematically examine which AI literacy concepts were most effectively conveyed through gameplay. Future research should explore how specific game mechanics align with different AI concepts to better understand which elements support learning which AI concept.

6. Conclusions

In this paper, we described the design and an evaluation of AI Odyssey, a non-digital serious game aimed at supporting AI literacy through family co-play. Using in-depth case studies of parents' and children's play with the game, we uncovered patterns of collaborative reasoning, explanation, and role-switching that facilitated interaction with fundamental AI ideas. The results confirm the potential of tabletop games to be utilized as accessible and socially meaningful tools for promoting public awareness of artificial intelligence in nonformal educational contexts.

The findings of this study indicate that for game designers, the utilization of open-ended scenarios, dialogue prompts, and cooperative mechanics can enhance user engagement and facilitate a richer learning dialogue. For educators and outreach professionals, AI Odyssey provides a valuable tool to stimulate family-level discussions regarding emerging technology. Follow-up research will extend these results to further iterate on game mechanics and assess educational impact in more varied familial contexts and cultural settings.

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Conflicts of interest

There are no possible conflicts of interest.

References

[1] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and M. S. Qiao, "Conceptualizing AI literacy: An exploratory review," *Computers and Education: Artificial Intelligence*, vol. 2, Jan. 2021, doi: 10.1016/j.caeai.2021.100041.

[2] A. Bewersdorff, X. Zhai, J. Roberts, and C. Nerdel, “Myths, mis- and preconceptions of artificial intelligence: A review of the literature,” *Computers and Education: Artificial Intelligence*, vol. 4, p. 100143, 2023, doi: 10.1016/j.caeai.2023.100143.

[3] L. Ding, T. Li, S. Jiang, and A. Gapud, “Students’ perceptions of using ChatGPT in a physics class as a virtual tutor,” *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, Dec. 2023, doi: 10.1186/s41239-023-00434-1.

[4] D. Long and B. Magerko, “What is AI literacy? Competencies and design considerations,” in *Conference on Human Factors in Computing Systems - Proceedings*, Association for Computing Machinery, Apr. 2020. doi: 10.1145/3313831.3376727.

[5] M. C. Laupichler, A. Aster, N. Haverkamp, and T. Raupach, “Development of the “Scale for the assessment of non-experts’ AI literacy” – An exploratory factor analysis,” *Computers in Human Behavior Reports*, vol. 12, Dec. 2023, doi: 10.1016/j.chbr.2023.100338.

[6] P. Mertala, J. Fagerlund, and O. Calderon, “Finnish 5th and 6th grade students’ pre-instructional conceptions of artificial intelligence (AI) and their implications for AI literacy education,” *Computers and Education: Artificial Intelligence*, vol. 3, Jan. 2022, doi: 10.1016/j.caeai.2022.100095.

[7] P. Antonenko and B. Abramowitz, “In-service teachers’ (mis)conceptions of artificial intelligence in K-12 science education,” *Journal of Research on Technology in Education*, vol. 55, no. 1, pp. 64–78, 2023, doi: 10.1080/15391523.2022.2119450.

[8] L. Casal-Otero, A. Catala, C. Fernández-Morante, M. Taboada, B. Cebreiro, and S. Barro, “AI literacy in K-12: a systematic literature review,” Dec. 01, 2023, *Springer Science and Business Media Deutschland GmbH*. doi: 10.1186/s40594-023-00418-7.

[9] D. Touretzky, C. Gardner-Mccune, F. Martin, and D. Seehorn, “Envisioning AI for K-12: What should every child know about AI?,” in *The 33rd AAAI Conference on Artificial Intelligence*, 2019, pp. 9795–9799. [Online]. Available: https://playground.tensorflow.org

[10] Museum of Science and Industry, “Robot Revolution,” 2018, *https://www.msichicago.org/explore/whats-here/exhibits/robot-revolution/, Chicago*.

[11] D. Long, T. Blunt, and B. Magerko, “Co-designing AI literacy exhibits for informal learning spaces,” *Proc ACM Hum Comput Interact*, vol. 5, no. CSCW2, Oct. 2021, doi: 10.1145/3476034.

[12] D. Long, A. Teachey, and B. Magerko, “Family learning talk in AI literacy learning activities,” in *Conference on Human Factors in Computing Systems - Proceedings*, Association for Computing Machinery, Apr. 2022. doi: 10.1145/3491102.3502091.

[13] J. Su, D. T. K. Ng, and S. K. W. Chu, “Artificial intelligence (AI) literacy in early childhood education: the challenges and opportunities,” *Computers and Education: Artificial Intelligence*, vol. 4, Jan. 2023, doi: 10.1016/j.caeai.2023.100124.

[14] I. Celik, “Exploring the determinants of artificial intelligence (AI) literacy: Digital divide, computational thinking, cognitive absorption,” *Telematics and Informatics*, vol. 83, Sep. 2023, doi: 10.1016/j.tele.2023.102026.

[15] M.-T. Tai, “The impact of artificial intelligence on human society and bioethics,” *Tzu Chi Med J*, vol. 32, no. 4, p. 339, 2020, doi: 10.4103/tcmj.tcmj_71_20.

[16] A. Kaplan and M. Haenlein, “Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence,” Jan. 01, 2019, *Elsevier Ltd*. doi: 10.1016/j.bushor.2018.08.004.

[17] I. H. Sarker, “AI-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems,” *SN Comput Sci*, vol. 3, no. 2, p. 158, Mar. 2022, doi: 10.1007/s42979-022-01043-x.

[18] C. McBride, *Children’s literacy development*. Routledge, 2015. doi: 10.4324/9781315849409.

[19] S.-C. Kong, W. Man-Yin Cheung, and G. Zhang, “Evaluating an artificial intelligence literacy programme for developing university students’ conceptual understanding, literacy, empowerment and ethical awareness,” *Educational Technology & Society*, vol. 26, no. 1, pp. 16–30, 2023, doi: 10.2307/48707964.

[20] V. Olari, K. Tenório, and R. Romeike, “Introducing artificial intelligence literacy in schools: a review of competence areas, pedagogical approaches, contexts and formats,” in *IFIP advances in*

information and communication technology, Switzerland: Springer Nature, 2023. doi: 10.1007/978-3-031-43393-1_21.

[21] L. Ding, T. Li, and A. Turkson, "(Mis)conceptions and perceptions of artificial intelligence: A scoping review," *EdArXiv*, 2023, doi: https://doi.org/10.35542/osf.io/y627r.

[22] M. Hornberger, A. Bewersdorff, and C. Nerdel, "What do university students know about Artificial Intelligence? Development and validation of an AI literacy test," *Computers and Education: Artificial Intelligence*, vol. 5, Jan. 2023, doi: 10.1016/j.caeai.2023.100165.

[23] I. Lee, S. Ali, H. Zhang, D. Dipaola, and C. Breazeal, "Developing middle school students' AI literacy," in *SIGCSE 2021 - Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*, Association for Computing Machinery, Inc, Mar. 2021, pp. 191–197. doi: 10.1145/3408877.3432513.

[24] A. van Wynsberghe, "Sustainable AI: AI for sustainability and the sustainability of AI," *AI and Ethics*, vol. 1, no. 3, pp. 213–218, Aug. 2021, doi: 10.1007/s43681-021-00043-6.

[25] H. Lei, M. M. Chiu, D. Wang, C. Wang, and T. Xie, "Effects of game-based learning on students' achievement in science: A meta-analysis," *Journal of Educational Computing Research*, vol. 60, no. 6, pp. 1373–1398, Oct. 2022, doi: 10.1177/07356331211064543.

[26] L. H. Wang, B. Chen, G. J. Hwang, J. Q. Guan, and Y. Q. Wang, "Effects of digital game-based STEM education on students' learning achievement: a meta-analysis," Dec. 01, 2022, *Springer Science and Business Media Deutschland GmbH*. doi: 10.1186/s40594-022-00344-0.

[27] F. Ke, "A case study of computer gaming for math: Engaged learning from gameplay?," *Comput Educ*, vol. 51, no. 4, pp. 1609–1620, Dec. 2008, doi: 10.1016/j.compedu.2008.03.003.

[28] M. Akbar *et al.*, "Sol y Agua: A game-based learning platform to engage middle-school students in STEM," in *2018 IEEE Frontiers in Education Conference (FIE)*, 2018, pp. 1–11. doi: doi:10.1109/FIE.2018.8659071.

[29] M. B. Pierce, W. J. Shelstad, E. Rickel, and B. S. Chaparro, "Thinking 'out-of-the-box' with board games," in *Proceedings of the Human Factors and Ergonomics Society*, Human Factors and Ergonomics Society Inc., 2018, pp. 1321–1325. doi: 10.1177/1541931218621302.

[30] R. Y. Bayeck, "Examining board gameplay and learning: A multidisciplinary review of recent research," *Simul Gaming*, vol. 51, no. 4, pp. 411–431, Aug. 2020, doi: 10.1177/1046878119901286.

[31] V. R. Lee, F. Poole, J. Clarke-Midura, M. Recker, and M. Rasmussen, "Introducing coding through tabletop board games and their digital instantiations across elementary classrooms and school libraries," in *SIGCSE 2020 - Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, Feb. 2020, pp. 787–793. doi: 10.1145/3328778.3366917.

[32] G. Musick, G. Freeman, and N. J. McNeese, "Gaming as family time: Digital game co-play in modern parent-child relationships," in *Proceedings of the ACM on Human-Computer Interaction*, Association for Computing Machinery, Sep. 2021. doi: 10.1145/3474678.

[33] S. Siyahhan, S. A. Barab, and M. P. Downton, "Using activity theory to understand intergenerational play: The case of Family Quest," *Int J Comput Support Collab Learn*, vol. 5, no. 4, pp. 415–432, Dec. 2010, doi: 10.1007/s11412-010-9097-1.

[34] B. Wang, L. Taylor, and Q. Sun, "Families that play together stay together: Investigating family bonding through video games," *New Media Soc*, vol. 20, no. 11, pp. 4074–4094, Nov. 2018, doi: 10.1177/1461444818767667.

[35] J. Goodall and C. Montgomery, "Parental involvement to parental engagement: a continuum," *Educ Rev (Birm)*, vol. 66, no. 4, pp. 399–410, Oct. 2014, doi: 10.1080/00131911.2013.781576.

[36] E. K. Malm, S. M. Hufsteler, S. L. Dietz, M. V. Malikina, and C. C. Henrich, "Associations of parent and staff factors with parent engagement in after-school programs," *J Community Psychol*, vol. 45, no. 4, pp. 473–485, May 2017, doi: 10.1002/jcop.21859.

[37] E. F. Dubow, P. Boxer, and L. R. Huesmann, "Long-term effects of parents' education on children's educational and occupational success: Mediation by family interactions, child aggression, and teenage aspirations," *Merrill Palmer Q*, vol. 55, no. 3, pp. 224–249, 2009, doi: 10.1353/mpq.0.0030.

[38] A. Bandura, *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice Hall, 1986.

[39] M. Sénéchal and L. Young, “The effect of family literacy interventions on children’s acquisition of reading from kindergarten to grade 3: A meta-analytic review,” *Rev Educ Res*, vol. 78, no. 4, p. 880, 2008, doi: doi.org/10.3102/0034654308320319.

[40] A. Joy *et al.*, “Understanding parents’ roles in children’s learning and engagement in informal science learning sites,” *Front Psychol*, vol. 12, Mar. 2021, doi: 10.3389/fpsyg.2021.635839.

[41] S. Druga, R. Williams, H. W. Park, and C. Breazeal, “How smart are the smart toys? Children and parents’ agent interaction and intelligence attribution,” in *IDC 2018 - Proceedings of the 2018 ACM Conference on Interaction Design and Children*, Association for Computing Machinery, Inc, Jun. 2018, pp. 231–240. doi: 10.1145/3202185.3202741.

[42] S. D. Simpkins, C. D. Price, and K. Garcia, “Parental support and high school students’ motivation in biology, chemistry, and physics: Understanding differences among latino and caucasian boys and girls,” *J Res Sci Teach*, vol. 52, no. 10, pp. 1386–1407, Dec. 2015, doi: 10.1002/tea.21246.

[43] S. L. D. Restubog, A. R. Florentino, and P. R. J. M. Garcia, “The mediating roles of career self-efficacy and career decidedness in the relationship between contextual support and persistence,” *J Vocat Behav*, vol. 77, no. 2, pp. 186–195, Oct. 2010, doi: 10.1016/j.jvb.2010.06.005.

[44] A. Hirumi and C. Stapleton, “Applying pedagogy during game development to enhance game-based learning,” in *Games: Purpose and Potential in Education*, Springer US, 2009, pp. 127–162. doi: 10.1007/978-0-387-09775-6_6.

[45] S. Grover, R. Pea, and S. Cooper, “Remedying misperceptions of computer science among middle school students,” in *SIGCSE 2014 - Proceedings of the 45th ACM Technical Symposium on Computer Science Education*, Association for Computing Machinery, 2014, pp. 343–348. doi: 10.1145/2538862.2538934.

[46] S. Heintz and E. L. C. Law, “The game genre map: A revised game classification,” in *CHI PLAY 2015 - Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play*, Association for Computing Machinery, Inc, Oct. 2015, pp. 175–184. doi: 10.1145/2793107.2793123.

[47] M. P. J. Habgood, “Endogenous fantasy and learning in digital games,” *Simul Gaming*, vol. 36, no. 4, pp. 483–498, Dec. 2005, doi: doi.org/10.1177/1046878105282276.

[48] R. G. Mirick, “Challenges in recruiting parents to participate in child welfare research: implications for study design and research practice,” *Child Fam Soc Work*, vol. 21, no. 4, pp. 484–491, Nov. 2016, doi: 10.1111/cfs.12165.

[49] L. Ding, S. Kim, and R. A. Allday, “Development of an AI literacy assessment for non-technical individuals: What do teachers know?,” *Contemp Educ Technol*, vol. 16, no. 3, p. ep512, Jul. 2024, doi: 10.30935/cedtech/14619.

[50] C. Sing Chai, P.-Y. Lin, M. Siu-Yung Jong, Y. Dai, T. K. F Chiu, and J. Qin, “Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students,” *Educational Technology & Society*, vol. 24, no. 3, pp. 89–101, 2021, doi: 10.2307/27032858.

[51] J. Clarke-Midura, C. Sun, K. Pantic, F. Poole, and V. Allan, “Using informed design in informal computer science programs to increase youths’ interest, self-efficacy, and perceptions of parental support,” *ACM Transactions on Computing Education*, vol. 19, no. 4, Oct. 2019, doi: 10.1145/3319445.

[52] B. Jordan and A. Henderson, “Interaction analysis: Foundations and practice,” *The Journal of the Learning Sciences*, vol. 4, no. 1, pp. 39–103, 1995, doi: doi.org/10.1207/s15327809jls0401_2.

[53] S. J. Derry *et al.*, “Conducting video research in the learning sciences: Guidance on selection, analysis, technology, and ethics,” *Journal of the Learning Sciences*, vol. 19, no. 1, pp. 3–53, Jan. 2010, doi: 10.1080/10508400903452884.

[54] F. Ke, K. Xie, and Y. Xie, “Game-based learning engagement: A theory- and data-driven exploration,” *British Journal of Educational Technology*, vol. 47, no. 6, pp. 1183–1201, Nov. 2016, doi: 10.1111/bjet.12314.

[55] M. P. J. Habgood, S. E. Ainsworth, and S. Benford, “Endogenous fantasy and learning in digital games,” *Simul Gaming*, vol. 36, no. 4, pp. 483–498, Dec. 2005, doi: 10.1177/1046878105282276.

[56] S. D’Mello and A. C. Graesser, “Dynamics of affective states during complex learning,” *Learn Instr*, vol. 22, no. 2, pp. 145–157, 2012, doi: 10.1016/j.learninstruc.2011.10.001.

[57] P. Mertala and J. Fagerlund, "Finnish 5th and 6th graders' misconceptions about Artificial Intelligence," 2023, doi: https://doi.org/10.35542/osf.io/hw9fr.

[58] A. R. Finlinson, A. M. Berghout Austin, and R. Pfister, "Cooperative games and children's positive behaviors," *Early Child Dev Care*, vol. 164, no. 1, pp. 29–40, 2000, doi: 10.1080/0300443001640103.

[59] C. Eberbach and K. Crowley, "From seeing to observing: How parents and children learn to see science in a botanical garden," *The Journal of the Learning Sciences*, vol. 26, no. 4, pp. 608–642, 2017, doi: 10.2307/48541103.

[60] A. Harris and J. Goodall, "Do parents know they matter? Engaging all parents in learning," *Educational Research*, vol. 50, no. 3, pp. 277–289, Sep. 2008, doi: 10.1080/00131880802309424.

Appendix A. Mapping of AI literacy assessment items to competencies

Item	Assessment Item	Competency
1	Drag and drop and put the following Machine Learning steps in order. ((a) Collect data, (b) train the model, (c) deploy the model.)	ML Steps
2	Machine learning is a kind of statistical inference. (True/False)	AI Learns from Data
3	Data can be error-prone and requires interpretation. (True/False)	Data Literacy
4	AI algorithms can figure out all your messy data. (True/False)	Data Can Be Messy
5	AIs "see" and "hear" the world through the process of extracting information from sensory signals. (True/False)	AI Relies on Sensors
6	AIs rely on algorithms to make decisions. (True/False)	AI Relies on Algorithms
7	All AIs are created the same way. (True/False)	AI Can Be in Various Forms
8	Walking down a street as well as a 5-year-old can be very difficult for an AI robot. (True/False)	Strengths & Weaknesses
9	AI is not entirely automated and always requires human decision-making. (True/False)	Human Is Essential
10	Which one of the ethical issues is the least likely caused by AI if it's used inappropriately. ((a) discrimination, (b) lack of accountability, (c) lack of privacy, & (d) lack of compassion)	Ethical Issues

Appendix B. Survey items

Self-Efficacy (4 items)
- If I took a class on AI, I could do well.
- If I want to, I could be an AI expert in the future.
- I think I could do more challenging AI-related work.
- I can learn to do AI-related work.

Interest (4 items)
- I enjoy learning about AI.
- I am interested in learning more about AI.
- I think learning AI is interesting.
- I think learning AI is boring. (Reverse-coded)

Perceived Parental Support (4 items)
- My parents have encouraged me to learn AI.
- My parents have shown no interest in whether I learn AI. (Reverse-coded)
- My parents think I could be a good AI developer.
- My parents think I'll need to learn AI for the future.

Career Choices (3 items)
- I can't imagine myself working in an AI-related career. (Reverse-coded)
- I would like to get a degree in AI-related field.
- I am interested in working in a job that involves AI.