Agent: Increasing Children's Literacy on Cognitive Systems Using Behaviour Tree Based Gameplay

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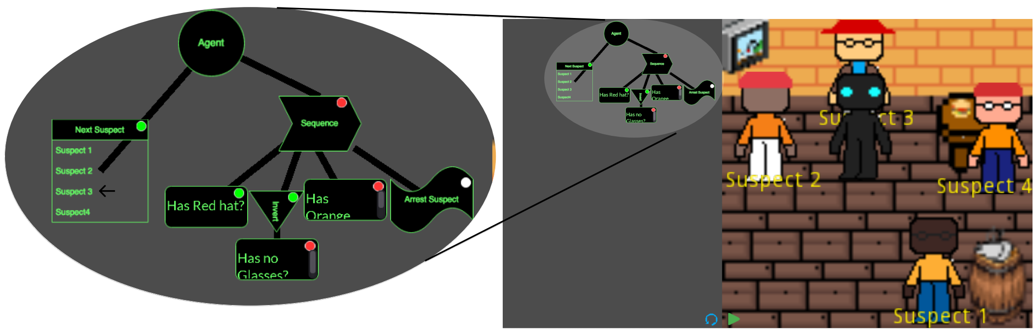

Fig. 1. Screenshot of Agent showing a behaviour tree and its evaluation for suspect number 3

As artificial intelligence (AI) becomes ubiquitous in everyday technologies, there is a stronger need to develop AI literacy especially in early stages of development. While researchers have explored AI literacy tools for children, these technologies have largely focused on communicating machine learning principles such as data literacy and how a system can learn from data. However, establishing AI literacy also requires addressing the ability to understand cognitive systems, or systems which mimic the human mind. In this work, we present Agent, an educational game designed for children to learn cognitive system concepts. By incorporating behaviour trees as a gameplay system Agent gives players an inside look into how AI systems represent knowledge and how they make decisions. To evaluate the efficacy of our system we conduct a qualitative user study, with 4 adults from ages 20-27, to gauge their understanding of cognitive systems. Agent pushes AI literacy work by incorporating game based learning to the underdeveloped field of cognitive science in order to promote true AI literacy among children.

CCS Concepts: • **Human-centered computing** *User studies*; • **Applied computing** **Interactive learning environments**.

Additional Key Words and Phrases: game based learning, AI literacy, cognitive systems, behaviour trees

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1 INTRODUCTION

The permeation of AI technology into tools used everyday has created a need to generate techniques and tools to better facilitate the education of AI concepts. There is ongoing research into how to better enable the education of children on AI concepts and other emerging technologies [1, 4, 5, 11]. Additionally, researchers are making steps into working out how students should be made AI literate [3, 5, 7, 11].

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Simultaneously in the world of education over the last decade research has seen a rise in interest in game based learning where games are employed to teach students specific content. Researcher are using game based learning to effectively teach computer science concepts and more specifically machine learning [8, 9].

However, there is a lack of research into the efficacy of game based learning approaches towards improving AI literacy in children. Previous works involve designing guidelines for teaching AI literacy [4, 11], activity based learning [3, 5], or interactive systems [7]. The usefulness of game based learning in other fields shows promise as a strategy for improving AI literacy. Current AI literacy tools revolve around machine learning as the main entry point for students, but there are other undeveloped fields. According to Long et al., AI can be subdivided into three fields: cognitive systems, machine learning, and robotics [4].

Current interactive systems for teaching children AI concepts are heavily focused on machine learning techniques. This is done largely due the presence of machine learning in many of the everyday AI technologies a child might interact with; but if we want to promote true AI literacy we must engage with all areas of AI not just the most common.

So why cognitive systems? Cognitive systems involve many important AI competencies such as how agents represent knowledge and make decisions. These skills are valuable and carry over into the other areas of AI, machine learning and robotics [4]. *How might we effectively leverage video games to educate kids on high level cognitive systems concepts?*

In order to build off of current tools and expand AI education into untapped concepts we present Agent, a video game based learning tool. Agent leverages the effective teaching potential of video games to educate children on cognitive systems. Agent uses a common AI tool, behaviour trees, as a game play mechanic. Behaviour trees are a visual way for AI designers to control the behaviour of non-playable characters in video games.

In game kids will control the actions of a character by building out their behaviour tree to complete various tasks. Behaviour trees offer a unique way of visualizing exactly how an AI agent is making it decisions. This project presents two core contributions for AI literacy education:

- An interactive game that allows children to manipulate a behavior tree and alter actions of an agent in a game.
- An evaluation of Agent as a tool for increasing AI literacy in children

We evaluated this system using an informal qualitative study involving 4 adults and had them play the game. We conducted a pre/post-survey and an interview in order to analyze their understanding of cognitive systems concepts and determine the efficacy of Agent and game based learning at increasing AI literacy in users.

In the next section we will discuss some of the previous and ongoing research in AI literacy, children-AI interactions, and game based learning systems. Then we will discuss the formative process of building the game and what we took away from it. After that we will discuss the technical details of Agents implementation. Finally, we will give the details of our user study and discuss the results.

By applying game based learning to AI literacy we can build upon the current research and expand game based learning to a underutilized field. By focusing on the under-explored area of cognitive systems Agent can help promote true AI literacy among children.

2 RELATED WORK

2.1 AI Literacy

A burgeoning field of research revolves around increasing AI literacy. AI literacy as defined by Long et al. seeks to increase the understanding about how AI systems work and how to use them [4]. They defined AI literacy and also create a set of competencies that are required to be truly literate as well as subdividing AI into three areas: cognitive systems, machine learning, and robotics. Current research seeks to create systems that promote literacy through interactive toys such as PlushPals which uses a plush toy and web tool to teach kids machine learning competencies [7]. Long. et al. also expanded their work by creating interactive exhibits that promote different areas of AI literacy [5]. Lee et al. developed a curriculum that they applied at a summer program for middle school kids using Long et al.' competencies [3]. Agent builds upon this work by incorporating the AI literacy competencies into a game based learning system. Unlike previous efforts to improve AI literacy, Agent focuses on cognitive systems rather than machine learning.

2.2 AI Education

A large portion of current research is focused on educating children on AI's impact on society. Zhou et al. focused on creating a design framework for creating learning experiences for K12 students to understand the societal impact of AI [11]. Meanwhile Tamashiro focused on supporting K9 children's understanding of emerging technologies including machine learning [1]. Williams et al. created interactive lessons to measure the impact of AI education on children's perception of robots [10]. All of these systems focused on educating children about the role of AI in our world outside of the perspective of AI literacy. Our system separates itself from previous this research by focusing on obtaining AI literacy in children so they both understand how common AI tools work, but also how they can use said tools.

2.3 Game Based Learning Systems

Video game based learning is a wide field with application in many domains. Jihae introduces an adventure game that teaches students chemistry and also has guidelines that can be used for creating games in other domains [2]. Gogonis et al. applies games to the field of microbiology and finds some success in using to teach student those concepts though they found more success using traditional methods [6]. Turchi et al. are able to apply video games to increase computational thinking skills [8]. Voulgari et al. show promise in using a video game to teach kids machine learning concepts while keeping students more engaged than traditional methods [9]. Our system differentiates itself from previous works by focusing on AI literacy in the field of cognitive systems, while previous works that focused on AI focused on machine learning, or completely different domains.

3 FORMATIVE STUDY

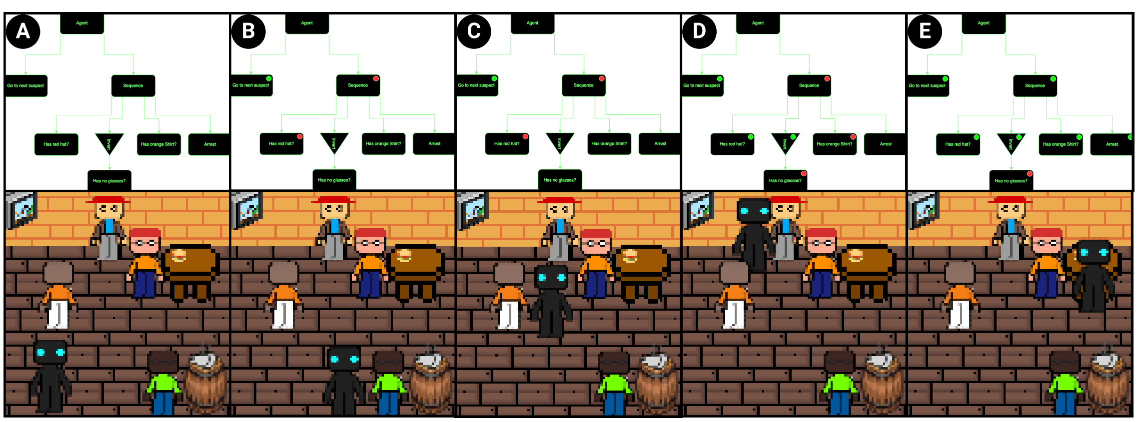

Fig. 2. Storyboard

To begin the development process for Agent we create a storyboard for the proposed introductory level of the game. The main design goal behind the development of the level was to ensure that the game displayed some of the core competencies of cognitive system literacy namely: knowledge representation and decision making. Knowledge representation is the act of putting information in such as way that the computer understands it. Decision making denotes the process by which the AI makes decision

Game Mechanics. For the game we decided to use the setup of a secret agent looking for a suspect in a restaurant. The player is given a description of the suspect, in this case the suspect is wearing a red hat, an orange top, and glasses. The full storyboard is depicted in Fig. 2. The player is tasked with building a behaviour tree that will allow the agent to complete the task.

In the storyboard along the top is the completed behaviour tree that leads to successful solution. The agent moves from suspect to suspect and evaluates each one to see if they match the description. The order in which the agent evaluates the nodes in the tree is dependent on how players choose to connect the nodes. Additionally, in each frame the tree updates showing which tests have failed and which ones have succeeded. For example, in Fig. 2B, the agent approaches a suspect dressed in a green shirt, with glasses and no hat. Based of the order of the tree the agent first checks to see if the suspect is wearing a red hat. This test returns false and the tree is updated to display that, where the red hat check is there is now a red dot indicating that the test failed. Inversely if the test had succeeded the dot would be green.

Behaviour Trees. The tree involves a couple of common nodes present in behaviour trees. First the leaf node which depicts actions for the AI to take in its environment. The game has a few sub classes of these leaf nodes. The first of these are: checking for a red hat, checking for an orange shirt, and checking if the suspect is not wearing glasses. Another leaf node is the Go to next suspect node which allows the agent to seek out a new target. The final leaf node is the arrest node this node represents the overall goal of the level, to arrest a suspect. Second we have the sequence node, this is akin to a while loop in traditional computer programming. The node continues to evaluate its next child until one of the child nodes evaluates false at which point the sequence node evaluates false. There is also the inverse node which inverts the evaluation of its child. For example, if the has red hat node was a child of inverse and evaluated to true the inverse node would change that evaluation to a false.

Reflecting on the Design Process. After developing the initial storyboard we asked are selves a couple of questions: Does the game adequately cover the competencies that laid out (knowledge representation, decision making)? And does the game give enough information for players to adequately distinguish the tree nodes from each other. Upon personal reflection we determined the fact that the player creates the order of the tree was enough to establish that the game incorporates decision making. Unlike decision making knowledge representation is purely visualized via the true false visualisation on the nodes in the game.

Finding 1: Visualizing Knowledge Representation. Since we want to add in an element of knowledge representation it would make sense to allow players to individually add the suspects to a list that is fed into find next suspect node to get a sense of how that data might be stored in the system. But, this would introduce its own set of problems. Allowing users to insert the suspects into a list themselves can allow them to circumvent actually solving the puzzle. For example, they could visually inspect the environment and only put the correct suspect in the list and then have the AI immediately arrest the suspect. This would defeat the purpose of having the player build out the tree and hinder there ability to see the agents decision making process in action. It was decided that a good halfway point would be to represent the list as part of the node but make it non-editable so the player will still be forced to fill out the tree correctly. This representation can be seen in Fig. 3 in the next suspect node.

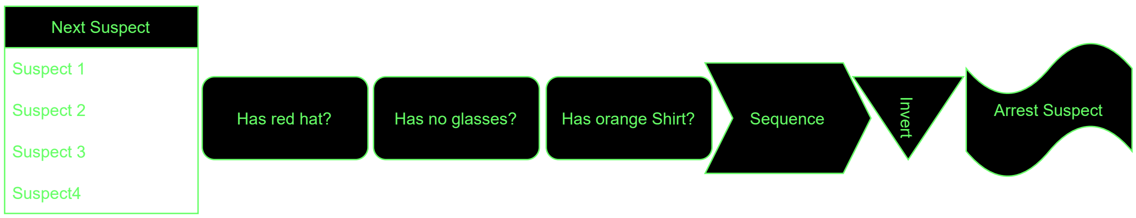

Fig. 3. Revised Nodes

Finding 2: Creating a Visual Language. Additionally, while the nodes all have names which can give the user an idea of what they do, we should categorize the nodes and give each categorization a separate shape. This would be beneficial for users since for future nodes the player would have some expectation of the nodes intended use based off its shape. To this end we introduce a new set of node shapes shown in Fig 3. The next suspect node now is a list. The query node retain their rectangular shape and the invert node is a triangle. The sequence node is now shaped like an arrow. Even though the goal node and the query nodes are all leaf nodes in the traditional behaviour tree structure, since the goal node serves a special purpose within the gameplay system we decided to give it a flag shape to separate if from the other leaf nodes.

4 AGENT

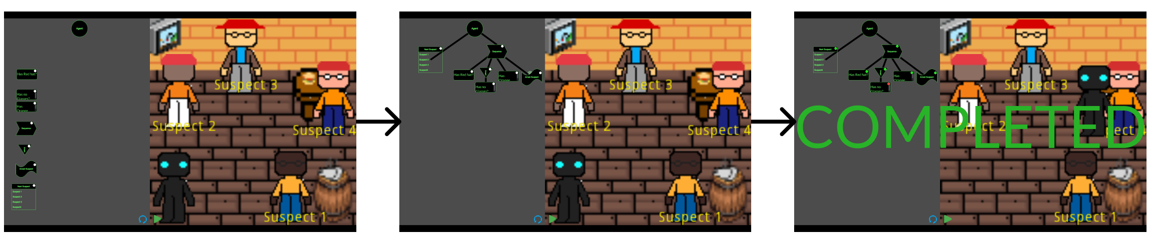

Fig. 4. Walkthrough of Game

The game begins with all the nodes disassembled at the side of the board this can be seen in Fig. 4. Then users build out the tree in whichever way they want by moving the nodes and connecting them to each other. If users incorrectly make a connection they can simply hit the reset button, but this reset all of their connections. When users are finished building their tree they can test it by hitting the play button. A single click of the run button will only run through one iteration of the tree allowing users to see which nodes in the evaluate to true or false. In a complete run The user will have to click the run button a total of four times before getting the complete screen.

4.1 implementation

In order to create the game, a few core components are needed on the software end. Firstly, we need a game engine. A game engine is a software framework that supports the backend for a video game. All the basic graphics, music, and gameplay software you need to make your own game are included. For Agent we chose Godot since it is opensource and supports its own proprietary python-esque scripting language which should help make implementation easier. The second thing we need is an implementation of a behaviour tree.

The implementation features a couple of key features required for it to work first we have the node functions which encompass the behaviour of each node in the tree. Then the tree constructor which allows the program to build a data representation of the behaviour tree from the visual representation built by the player. Extending from that we also have the tree visualizer which handles connection between nodes i.e., ensuring they are viable connections. Finally we have the evaluation loop which at the player behest begins the process of evaluating their tree.

4.1.1 Node Functions. In order to properly implement our evaluation function we require each node in the system to have its own function that can be called in place of its self. Among these nodes only the sequence and inverse function are not level specific. The rest of the nodes are leaf nodes which must be changed from level to level as they implement the behaviour that we want the agent to perform. The only common feature of these function is they must return true or false.

Sequence and Invert. The sequence and invert nodes, as they possibly have children, function as recursive calls to the evaluation function. The sequence simply returns the evaluation function of its children. And the inverse node does the same but returns the logical not of its child.

Leaf Function. Leaf functions include any node that does not have children. They can be implemented in a variety of ways depending on their purpose. The only thing they have in common is they make the AI do something, such as: move to the next suspect, check a suspects description, or arrest a suspect.

4.1.2 The Behaviour Tree. The behaviour tree given to the player has a limited number of nodes that they can choose from and they are only given enough of these nodes to solve the given problem. Another important note to keep in mind for the nodes is that they are not all capable of having child nodes. The leaf nodes (list, arrest, and query nodes) cannot have children unlike the sequence, root, and invert nodes.

Tree Visualization. In order to facilitate the gameplay system and to encode the data for backend a couple of requirements must be met. First for every node we must define a number of child connection points and parent connection points. Parent connections are always on the top of the node and child connections are on the bottom. Each node can have a single parent connection, but have no or multiple child connections. This is important so that when any connection between two nodes is made we can save the hierarchy between them (i.e. parent to child) which will come in handy when we need to construct the data representation of the tree for evaluation purposes. Additionally, when the connection is made we must check to ensure that the connection is allowed so that no child to child or parent to parent connections are made. We must also keep track of which nodes are connected in order to draw lines between them.

Tree Constructor. Once the player is ready to evaluate their tree we need to have a way of converting the visualized tree into a data format for the program to read. Like mentioned previously the parents to child relationships are stored when a connection is made. We simple create a a 2D array where each sub array represents a node that is able to have children, and stores the children of that node in their sub-array when a connection is made.

4.1.3 Evaluation Function. The final necessary item is the evaluation function. This function is responsible for taking the constructed tree and calling all the necessary nodes in the right order. The function acts recursively, first its called on the root nodes children evaluating them from left to right. Like stated earlier the sequence and invert nodes call the evaluation function on their own children arrays. This ensures that every node is evaluated in depth first order meaning the tree evaluates nodes starting by going down and left as much as possible as it goes back up it evaluates the child nodes to the right.

5 USER STUDY

5.1 Methodology

To test Agents efficacy we conducted a user study with Agent. Due to limitations in recruiting child participants, Agent was evaluated with adults without background knowledge of cognitive systems. The study was designed in such a way that our current methodology should be able to be carried over for future studies that do involve children. Since we are working with the college age demographic, we took special care to ensure that none of our participants had a background with AI systems, since the overall goal is to reach out to children with little background knowledge on AI. All the studies were conducted one on one in private.

We had four participants for this study. Participant 1 was a 27 year old male with a computer science background. Participant 2 was a 20 year old male with some web development experience. Participant 3 was a 21 year old male with a computer science background. Participant 4 was a 22 year old female with no computer science background of any kind.

In order to evaluate the users we employed a pre and post study survey. All survey questions were gauged with a 5-point Likert statement. The survey questions are meant to gauge how much and how interested in AI the users are and how their experience playing the game affects them. Self-report surveys have been used in prior research as a tool to gauge the efficacy of child AI literacy activities [5]. We have a specific interest in seeing how user interaction with Agent affects perceptions and interest in AI after the study.

The questions included on the pre and post survey are:

- I understand how AI represent knowledge
- I understand how AI agents make decisions
- I am interested in learning more about AI

Additionally, some questions were reserved purely for the post survey as they were meant to indicate user engagement:

- I found the games instructions easy to follow
- I found the activity to be enjoyable

After taking the pre-survey participants were instructed on how to use UI in the game, allowed a minute to play with the controls and ask question, and then play the game to completion. After completing the game participants were administered the post-survey and then were given the opportunity to expand upon their answers in a post-survey discussion.

5.2 Survey Results

Pre-Survey Results. As can be seen in Fig. 5, users self reported a median score of 2.5 for understanding knowledge representation. Users reported more understanding about decision making with a median score of 3 though the minimum score was a 1. This is to be expected since none of the participants have any experience with AI systems. For reported interest in learning about AI systems users reported fairly high with a median score of 4.5 and a minimum of 3.

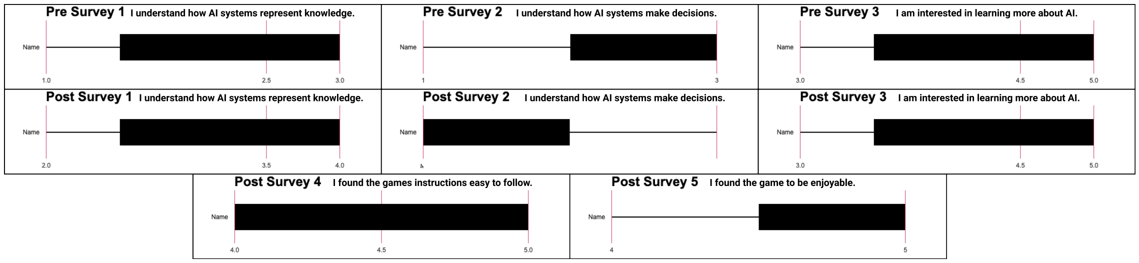

Fig. 5. Box plots showing results for all 8 questions from survey.

Pre/Post-Survey Questions	MeanΔ in Participant Score
I understand how AI represent knowledge	+1.0
I understand how AI make decisions	+1.75
I am interested in learning more about AI	0.0

Table 1. Mean Δ in Pre/Post Survey Results

Post-Survey Shared Questions Results. Additionally, in Fig.5, we can see the results for the same question after the users played the game. The users median self-reported understanding of both knowledge representation and decision making are 3.5 and 4 respectively. Showing that Agent has some ability to raise people perceptions on cognitive systems concepts. The reported interest scores remain the same in all cases, this could mean that agent is not adept at increasing interest in learning about cognitive systems, but the scores we already on the high end with a minimum rating of 3 for the Pre-Survey. In table 1 we can see the reported gains this includes a +1.0 increase for participants understanding of knowledge representation and a +1.75 point gain for decision making. Of course these results are dependent on the participant understanding of the question.

Post-Survey Questions	Mean Participant Score
I found the games instructions easy to follow	4.5
I found the activity to be enjoyable	4.75

Table 2. Mean Post Survey Results

Post-Survey Specific Questions. In table 2 we can see the results for the post-survey specific questions. The first question ask users whether or not they understand the instruction for the game. User reported high understanding of the game with a mean score of 4.5. Additionally, from Fig. 5 we can see the box plot for this question and see the results were consistent as the minimum score was a 4. The same can be said for the second question regarding user enjoyment of the game. Users averagely gave a 4.5 for this question with a median score of 5. These results would suggest that the game is easy to understand and has high engagement as users enjoyed playing it.

5.3 Post-Survey Discussion

Knowledge Representation. After the survey users were asked to expand upon their answers to whatever extent they wished. We gleamed some important findings from these results. Firstly, when asked about how their perception of knowledge representation changed after playing the game all users discussed an answer that sounded more like decision making and matched there general description of decision making. With many user bringing up the structured process that the agent goes through. Participant 1 even noted that the first question was a bit confusing to them. This would suggest that the users did not actually understand what question one meant and calls into question the efficacy of Agent in producing literacy gains for knowledge representation. That being said participants 2 and 4 also remarked about the way the AI in Agent represents the description of the suspects as Boolean variables that are then visualised to the player. This in conjunction with the overall confusion about the first question could suggest that users may have had knowledge gains in knowledge representation, but the question as it was worded in the survey was to ambiguous for general users to understand and accurately gauge their perceived gains.

UI Issues. Users did not have much to add when relating to whether they understood the instructions or not. Most users did indicate that they believed that the controls and the behaviour tree worked took a while to get use this. This would indicate a learning curve, but since this is a video game this is not necessarily a bad thing. At this point users were also asked if they faced any issues while playing the game. Participants 1, 2, and 3 all noted ambiguity as to where nodes were connected. In the game the nodes are connected from center to center. This caused issues with users not understanding whether a child node was the first or second node and not being able to discern the evaluation order of the nodes. Additionally, users 1 and 3 noted that finding the connection points was overly difficult as you had to hover over the point, and wished that the point was clearly marked instead.

6 DISCUSSION

6.1 Behavior trees

As the results of the post-survey show participants came out their experience with agent with a well founded feeling of understanding of AI decision making processes. Participant response's generally matched a high level description of decision making. This was accredited by participants to the tree structure and being able to visually see the agents process play out. In that regard the usage of behaviour trees was justified. That being said none of the participants were able to clearly define knowledge representation. Many of their responses were redundant and matched their description of decision making. As stated in the previous section participants 2 and 4 did note an understanding of these visual clues but did not recognize it as a facet of representing knowledge in the system, so it could be an issue with the question. Overall we can conclude that behaviour trees are highly adept at showing off decision making, but needs some added features to become a good way of learning about knowledge representation.

6.2 Gameplay

As discussed in section 5, participants had difficulty fully understanding some of the UI elements. Specifically, for nodes with more than one child. Users felt that it was ambiguous which child was the first, second, third, etc. and this caused many users not understand the exact execution order of nodes. This is due to the fact that node connections are made from the center of the nodes. This could be changed to have the connection be made to the actual connection points rather than the node which would stem that issue by visualising the order of a nodes children. Also, many participants found it cumbersome to search for the connection points on a node. As it stands connection points reveal themselves when the mouse hovers over them. This was something that all participants were observed to be struggling with during gameplay. Though once again this could be easily fixed by adding a visual marker for connection points. If adults all struggled with these things than a child user would as well and could even be more confused, so these changes would need to be implemented before any children could play Agent.

6.3 Future Work

Future work on Agent should first focus on fixing UI issues brought up by participants. Following this the user study should be expanded to include child participants to ensure the results can carry over into the target demographic. Additionally, we would want to develop more levels of Agent to see if continued playing of Agent with more complex behaviour trees leads to higher long term increases in AI literacy. A point of contention during the evaluation was the lack of appropriate responses to knowledge representation. We pointed out that the issue could been the question itself, or the lack of representation of the concept within the gameplay features. Future work on Agent should include a reworking of the evaluation method to include hard skill test like a worksheet of some kind to investigate whether the issue is the former. If using worksheets does not reveal an increased understanding of knowledge representation, then the issue would likely be the latter and we should investigate new gameplay mechanics that we can add to introduce knowledge representation.

Through Agent we have shown that game based learning can be applied to AI literacy as effective way of teaching conceptual information. In the future this should be applied to other underdeveloped fields of AI like robotics. Also, behaviour trees are only a single model that cognitive systems use to visualize the control flow of an AI. Other models could show better efficacy in increasing AI literacy when implemented as gameplay mechanics and should be tested.

6.4 Limitations

While Agent has shown some early success there are a few limitations to these results. The usage of adult participants means the specific gains we saw in self-reported knowledge are not completely reliable since the target demographic are children. Adults could have a higher capacity to understand these topics meaning children may not see as large of, or even any gains in understanding knowledge representation or decision making. Additionally, some of the participants had computer science knowledge while neither had any AI experience the two participants with a computer science background had the shortest game times. Through our observations of their play sessions we attribute this to their understanding of depth first search which is how the behaviour tree evaluates nodes. Other users had some trouble understanding this concept as such it may be necessary to include additional content such as slides or info-graphics that explain depth first search for child users.

7 CONCLUSION

In conclusion, through Agent we have shown how game based learning can be an effective way of increasing AI literacy as long we choose the correct gameplay mechanics to express our concepts. Through a careful selection of behavior trees as a gameplay mechanic we were able to run a user study that successfully had participants gain a high level understanding of decision making processes, but more work needs to be done before we can determine Agents efficacy with knowledge representation. Additionally, there are plenty of avenues that we could take to improve Agents shortcomings. And there are also a variety of ways that other researchers could build off of this work to increase AI literacy.

REFERENCES

[1] Mariana Aki Tamashiro. 2021. How Do We Teach Emerging Technologies in K-9 Education? Using Design Fiction and Constructionist Approaches to Support the Understanding of Emerging Technologies' Societal Implications in Formal K-9 Education. In *Interaction Design and Children* (Athens, Greece) *(IDC '21)*. Association for Computing Machinery, New York, NY, USA, 637–640. https://doi.org/10.1145/3459990.3463402

[2] Jihae Han. 2021. *ChemCraft: A Ludic Approach to Educational Game Design.* Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411763.3451854

[3] Irene Lee, Safinah Ali, Helen Zhang, Daniella DiPaola, and Cynthia Breazeal. 2021. Developing Middle School Students' AI Literacy. In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education* (Virtual Event, USA) *(SIGCSE '21)*. Association for Computing Machinery, New York, NY, USA, 191–197. https://doi.org/10.1145/3408877.3432513

[4] Duri Long and Brian Magerko. 2020. What is AI Literacy? Competencies and Design Considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–16. https://doi.org/10.1145/3313831.3376727

[5] Duri Long, Aadarsh Padiyath, Anthony Teachey, and Brian Magerko. 2021. The Role of Collaboration, Creativity, and Embodiment in AI Learning Experiences. In *Creativity and Cognition* (Virtual Event, Italy) *(C&C '21)*. Association for Computing Machinery, New York, NY, USA, Article 28, 10 pages. https://doi.org/10.1145/3450741.3465264

[6] Angelos R. Gogonis and Rabindra Ratan. 2021. Using Video Games to Help Visualize and Teach Microbiological Concepts: A Study Analyzing the Learning Implications of a Video Game in Comparison to a Traditional Method. In *ACM International Conference on Interactive Media Experiences* (Virtual Event, USA) *(IMX '21)*. Association for Computing Machinery, New York, NY, USA, 264–266. https://doi.org/10.1145/3452918.3468027

[7] Tiffany Tseng, Yumiko Murai, Natalie Freed, Deanna Gelosi, Tung D. Ta, and Yoshihiro Kawahara. 2021. PlushPal: Storytelling with Interactive Plush Toys and Machine Learning. In *Interaction Design and Children* (Athens, Greece) *(IDC '21)*. Association for Computing Machinery, New York, NY, USA, 236–245. https://doi.org/10.1145/3459990.3460694

[8] Tommaso Turchi, Daniela Fogli, and Alessio Malizia. 2019. Fostering computational thinking through collaborative game-based learning. *Multimedia Tools and Applications* 78, 10 (Feb 2019), 13649–13673. https://doi.org/10.1007/s11042-019-7229-9

[9] Iro Voulgari, Marvin Zammit, Elias Stouraitis, Antonios Liapis, and Georgios Yannakakis. 2021. Learn to Machine Learn: Designing a Game Based Approach for Teaching Machine Learning to Primary and Secondary Education Students. In *Interaction Design and Children* (Athens, Greece) *(IDC '21)*. Association for Computing Machinery, New York, NY, USA, 593–598. https://doi.org/10.1145/3459990.3465176

[10] Randi Williams, Hae Won Park, and Cynthia Breazeal. 2019. *A is for Artificial Intelligence: The Impact of Artificial Intelligence Activities on Young Children's Perceptions of Robots*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3290605.3300677

[11] Xiaofei Zhou, Jessica Van Brummelen, and Phoebe Lin. 2020. Designing AI Learning Experiences for K-12: Emerging Works, Future Opportunities and a Design Framework. arXiv:2009.10228 [cs.CY]