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AN INTELLIGENT APPROACH TO GENERATE PERSONALIZED HINTS IN A SERIOUS GAME

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A thesis submitted to the Nanyang Technological University in partial fulfilment of the requirement for the degree of Master of Engineering (M.Eng)

2022

Statements of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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12 Jan 2022

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Date | Prof. Miao Chunyan

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This thesis does not contain any materials from papers published in peer-reviewed journals or from papers accepted at conferences in which I am listed as an author.

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Date   Lin Zichun

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Abstract

With the development of Internet Technology and Artificially Intelligence, online learning is gaining popularity. Students may encounter resources like video lectures, reading content, quizzes, discussion forums, and games in online learning. As one of the most efficient and engaging methods of online learning, games naturally get more attention than other methods, especially among children.

This thesis proposes an intelligent approach for generating personalized hints in a serious educational game. A serious educational game is intended primarily for educational reasons, specialized content is interwoven within complex game scenes, and students can learn the relevant information or knowledge while playing. With the past successful experience of the Virtual Singapura game, some classic learning scenarios were extracted and recreated into a lightweight mini game to facilitate learning of the plant transport system. There are virtual experiments, reading contents, and multiple-choice questions in the game. For the virtual experiment, players need to conduct the assigned experiments; if the task is completed, the player will receive virtual coins as a reward in the game. A Reinforcement Learning model could be built to generate next-step hints to assist students in playing the game. However, the generated raw hints will not be displayed to the player directly, which need to be processed again. Each player's Felder-Silverman learning style is calculated based on a pre-designed questionnaire. A hint library was created in order to personalize hints based on the player's learning style, which may inspire their curiosity. The final hint is chosen from the library.

To make learning more enjoyable and to provide learning companionship, the TmallGenie Smart Speaker is used to communicate with players. In addition to displaying text hints in the game, hints may be played by the speaker using its pleasant voice. It can also read aloud the introduction contents and respond to simple questions from the player.

According to results, the majority of students agreed that the game with personalized hints improves their knowledge comprehension and makes them feel better. Combining the

game with TmallGenie also provides them a lot of excitement and novelty. However, the result has some limitations. Due to insufficient students participated in the experiment, the experiment's outcome may not be particularly compelling. And because the learning content is not complicated, the quizzes didn't distinguish the learning outcome with good precision. In conclusion, by playing the educational game, students can learn the knowledge in a more personalized way, achieving both personalized learning and education through entertainment.

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Acronyms

RL	Reinforcement Learning
DRL	Deep Reinforcement Learning
MOOC	Massive Opening Online Course
R	Reward
S	State
A	Action
MDP	Markov Decision Process
DQN	Deep Q-Network
NN	Neural Network
ILS	Index of Learning Style
MCQ	Multiple-choice Question
NLG	Normalized Learning Gain
NLP	Natural Language Processing

Chapter 1

Introduction

1.1 Background

With the advancement of technology and the passage of time, the concept of traditional education has changed significantly over the past two decades. Online education has also played an important role, particularly during the COVID-19 period, when many students are required to engage in online learning. In 2016, 43 percent of students were enrolled in one or more online undergraduate courses, according to a report [1]; the percentage of students enrolled in online study during the 2020 COVID-19 period has increased rapidly. Online education is a convenient learning activity for children and teenagers. Learners can access numerous educational resources, such as video lectures, reading content, discussion forums, online quizzes, and serious educational games, from a computer, tablet, or smartphone connected to the internet at any time and place. This thesis will concentrate on the serious educational game.

Collins's dictionary defines a game as an activity in which participants utilize their skill and knowledge to defeat competitors or solve a puzzle [2], winning the game can give players a sense of accomplishment. The classic book *Game People Play*: *The Psychology of Human Relationships* was published by psychiatrist Eric Berne in 1964, and its definition of game is "A GAME is an ongoing series of complementary ulterior transactions progressing to a well-defined, predictable outcome. Descriptively it is a recurring set of transactions, often repetitious, superficially plausible, with a concealed motivation; or, more colloquially, a series of moves with a snare." [3]. "Game" is an activity that has been passed down through human culture for a very long time; it is part of everyone's everyday existence, including life games, sports games, mind games, etc.

With the growth of electrical technology, computer games or video games were created. A video game requires a player's interaction with the user interface or input devices to generate the corresponding visual feedback on the video display. "Computer Space" released in 1971 was the first commercially available and well-known video game; it requires players to use a joystick to control a rocket and fire missiles to battle with the computer-controlled flying saucers. If the rocket missile strikes a saucer, the player will be rewarded one point; if the saucer's missile hits the player's rocket, the player will lose one life. The objective of this game is to obtain a higher score while using less lives, which is very similar to the objective of contemporary shooting video games.

There are several ways to categorize video games. Eric Solomon categorized video games simply into simulation games, abstract games, and sports games in 1984 [4]. In 1997, Wright categorized video games as educational games, strategy games, sports games, sensorimotor games, and other vehicular simulator games [5]. In the contemporary, almost all young people have played video games on their computers or smartphones. Video games have become an integral component of the global economy and people's daily life. According to the NewZoo 2021 Global Games Market Report [6], the global games market might generate 175.8 billion US dollars in 2021, driven by over 3 billion players worldwide. STEAM (see Figure 1.1) is one of the largest game platforms in the world, and it contains six major game genres: Action, Role-Playing, Strategy, Adventure & Casual, Simulation, and Sports & Racing.

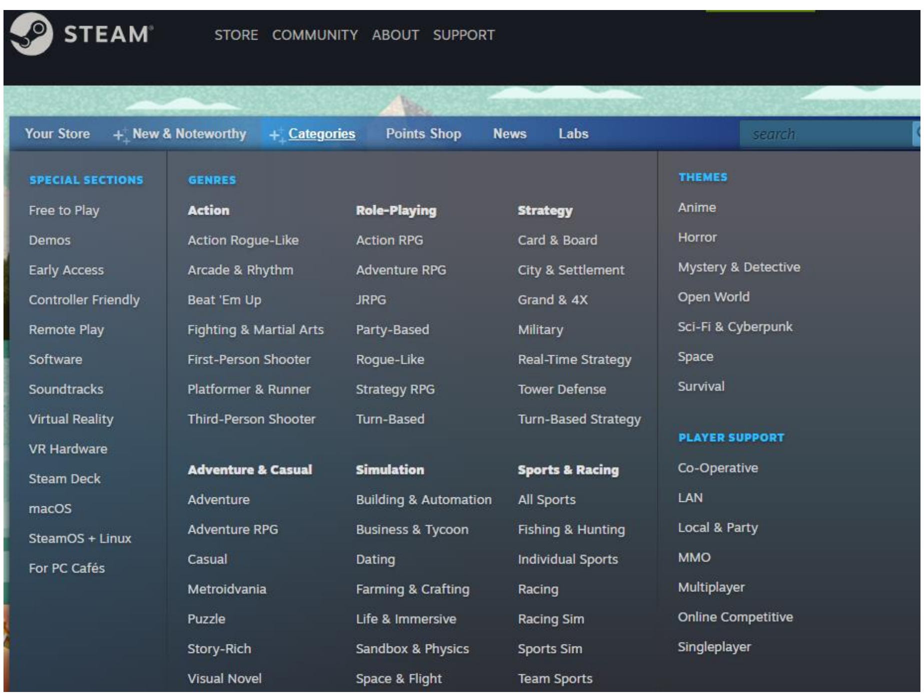


Figure 1.1: Game categories in STEAM game platform

The majority of people play video games for entertainment or relaxation, and video games can provide players with a pleasant and stress-free virtual world. This feature is useful for facilitating enhanced learning in a relaxing game environment. A serious educational video game is a game developed for a purpose other than sheer pleasure [7]; the primary objective of the serious game is to provide players with learning or training. Typically, serious educational games include both storytelling and simulation. Learners can study the designated knowledge through storytelling and apply them in simulation. A serious game is one of the most effective and enjoyable methods in online education, which naturally attracts more attention and engages students more than other methods, particularly for children and adolescents. The emphasis of the thesis is on the serious educational game.

Many children today begin playing video games on smartphones, tablets, and laptops at a young age. Games can facilitate children’s development in some way, allowing them to develop the ability on linguistic, social, and cultural. If learning content is integrated into games, which the majority of children like, the game can contribute to children's learning motivation. The serious educational game is becoming increasingly prevalent in educational activities.

Popularity of serious educational games is on the rise. As a learning environment, serious educational games offer the following benefits: Firstly, the paradigm shifts from teacher-centred learning to student-centred learning, where the student takes the lead and learns proactively; the student is the protagonist, deciding when and how to explore the game to learn, which inspire student’s motivation and creativity. Secondly, it enables the practice of situated learning, in which the student can learn by positioning themselves in situations where the knowledge is applicable. Thirdly, to practice experimental and constructionist learning, students can play the game at home or school at a time that is convenient for them.

1.2 Objectives

In traditional education, a single teacher instructs numerous students in a single class. Due to the large class size and limited teaching time, the teacher is unable to provide personalized or individualized instruction to each student. Figure 1.2 depicts a simulated closed feedback loop of the tutoring process. If teachers want to tutor a student contrapuntally, they must collect student data, such as performance of class participation, homework, and quizzes, then analyse all the performance and make a customized tutoring plan for the student based on their teaching experience. Finally, teachers must refine or optimize the teaching plan based on student feedback after each round of instruction. Thus, it can be observed that special tutoring in traditional education demands a great deal of teachers' time and attention; also, the importance of teachers' teaching experience in traditional education makes it impractical to provide special tutoring to all students.

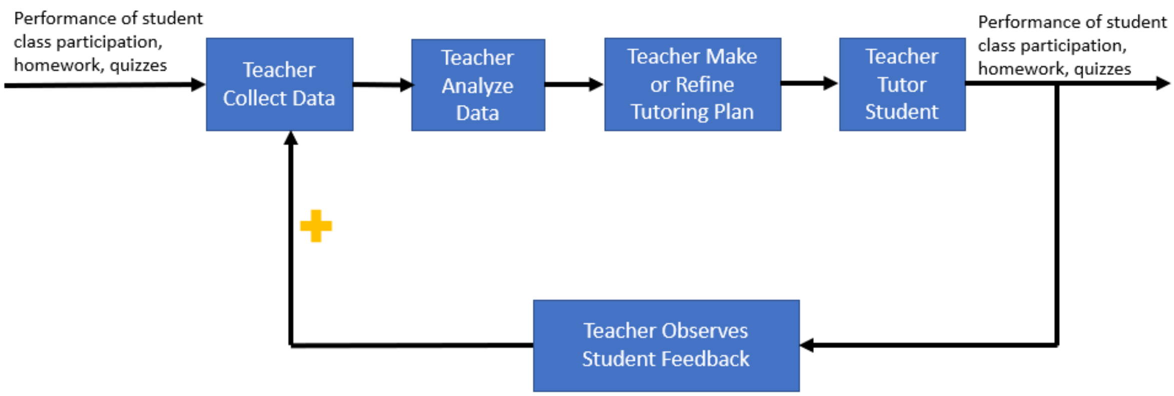


Figure 1.2: Feedback loop of traditional tutoring process

In online education, students may have greater opportunities to obtain special individualized instruction or tutoring. For example, there are an increasing number of serious educational games in the classrooms and homework assignments of primary and secondary students, particularly in some scientific classes. Video games can be used as a teaching and diagnostic tool by educators. For those experiments in science class, they can appear as a virtual experiment simulation in the game, the corresponding knowledge points and quizzes could be added after the virtual experiment. Students can use the game as a learning tool at any time and place. All the data collected while playing the game could be submitted to the game server for future analysis to enhance learning and teaching. The teacher's monitoring panel allows teachers to view the game progress and quiz scores for each student.

In addition, video games foster a range of virtual learning companions, which provide a social learning environment and permit the application of numerous peer-learning theories. Curiosity is a type of human natural motivation related with human exploration and learning, and it is especially crucial for the development of children. A curious learning companion, for instance, engages in curiosity-driven learning, since educational theories have demonstrated that a curious peer can arouse the curiosity of a student, hence enhancing the depth and quality of learning. Due to its extensive use of fancy gaming aspects to make studying entertaining, the learner may become engrossed in the game environment and lose focus on the learning path. In such situations, persuasive learning companions can employ intelligent strategies to redirect the learner back onto the path of learning.

Providing a personalized learning experience in serious educational games is not an easy task; it involves psychology, pedagogy, and information technology. The purpose of this thesis is to explore a method for providing a personalized learning experience to improve learning performance for students in serious educational games.

1.3 Contributions

Major contributions of this thesis include:

- **The Uncharted Island game**: A lightweight educational game titled "The Uncharted Island" was developed for research purposes. It is compatible with web browsers and mini game platforms, such as WeChat and Alipay Mini-program platform, making it accessible on smartphones, tablets, and desktops. Virtual Singapura is a serious educational game created to assist primary and secondary school students in Singapore learn about the plant transportation system a few years ago. Some classic scenes from the game Virtual Singapura, such as inside the tree and virtual labs, have been extracted and recreated in the new game The Uncharted Island. They contain comparable amount of scientific knowledge.

Figure 1.3: Login page of The Uncharted Island

- **The integration of the game and TmallGenie Smart Speaker**: To make learning more enjoyable and provide companionship for them, the TmallGenie Smart speaker was integrated with the game to communicate with players. The speaker can read aloud the introduction contents, answer player's simple questions related to the learning contents, and play the hints by its pleasant voice.
- **Raw hints generation using Reinforcement Learning (RL)**: RL is the core technology for personalized learning in the Uncharted Island game. RL is a common machine learning paradigm for real-world tasks like as game playing, robotics control, and go, and it performs particularly well on sequential decision-making tasks [8]. The capability of sequential decision making has the potential to be used in the interactive system in order to facilitate decision making. RL is ideally suited for game agent development and recommendation systems, as well as serious educational games. In the Uncharted Island, a RL model was built to generate next-step hints to assist students in playing the game.
- **Hints strategies with different learning style:** The raw hints generated by the RL model will not be displayed to the player directly, which need to be processed again. Each player's Felder-Silverman learning style is determined based on a pre-designed questionnaire. A hint library was created in order to customize hints

based on learning style, which may inspire the player’s curiosity. The final hint is chosen from the library.

In short, students can acquire science-related knowledge by playing the Uncharted Island game. Students can receive personalized hints generated by the RL process and hints library if they are having trouble performing virtual experiments or are stuck in a game. The hints are generated by the system based on the student's learning style, game status, and other factors, so different students will typically receive their own customized hints. The TmallGenie Smart Speaker can play text hints with a pleasant voice, and students can ask the TmallGenie simple questions about the learning content. The process of generating hints resembles a procedure for making recommendations. By providing hints throughout the game, students will not become stuck, the game process will be more fluid, and students' learning experience and performance will be enhanced.

1.4 Organization of the thesis

The structure of the thesis is as follows: In Chapter One, we introduce the background, objectives, and contributions. In Chapter Two, a literature review on personalized learning, Reinforcement Learning, and serious educational games is presented. In Chapter Three, the Index of Learning Style, the Uncharted Island, and implementation details are introduced. In Chapter Four, we present the results and discuss the limitations and future research. In Chapter Five, we draw a conclusion of the thesis.

Chapter 2

Literature Review

2.1 Introduction

The goal of personalized learning is to personalize the learning experience according to each student's personality, interests, needs, abilities, and so on. In the 1950s, Skinner's Teaching Machine was used by students to answer questions and receive feedback at their own pace, as a result of educators' extensive efforts and trials to give students with individualized instruction. Massive Opening Online Course was created in the 2000s to facilitate online education.

In the late 1980s and 1990s, a proliferation of serious educational games occurred. Numerous of these games are simulation games, high-fidelity simulators that strive for realism. Currently, educational video games have a history of almost 40 years. There are an increasing number of high-quality games, and nearly all subjects have the corresponding educational games, including science, music, history, mathematics, language, etc.

In traditional education, personalized learning is not a novel concept. There was a lot of exploration on it. With the rapid advancement of personal computers and machine learning, online education and educational video games have made significant strides toward personalized learning. Reinforcement Learning is the most important machine learning paradigm for use in games and personalized learning.

2.2 Personalized Learning

Personalized learning is an educational approach that tailors learning according to the personality, interests, and abilities of each student. The goal is for every student to maximize their learning potential through a better learning experience. In a traditional classroom, it is impractical to allow teachers to always stop the class to help a student who has not grasped the content. However, it is possible to provide individualized instruction to the student after class; the teacher must first assess the student's understanding, and then provide tutoring based on the student's knowledge level and ability. Therefore, there are limitations for personalized learning in traditional education, as it is not viable to provide personalized teaching to each student in a class, as this would need an enormous amount of time.

If a teacher wants to be responsible for all of the kids in the classroom, he or she will likely gear the class toward students of average ability. Slower learners may be left behind, while faster learners may become bored and disinterested. At some schools, teachers split the class into "quick" and "slow" learning groups based on students' academic performance; two groups will receive different instructional strategies. Some parents may not wish for their children to be placed in a "slow" group, despite the fact that this method can facilitate personalized group learning.

The advancement of technology provides an opportunity to overcome the shortcomings of limited instructional resources. With the use of technology, more personalized learning approaches have been developed, allowing students to get individualized study plans.

Intelligent Tutoring System (ITS) is a computer system that provides learners with real-time, individualized teaching and feedback in the absence of teachers. There are many instances of ITS in the world of education. Skinner's Teaching Machine is the earliest mechanical ITS device. In 1993, the DENISE system was created as an ITS to assist students in learning economics via learning-by-teaching methods. This system enabled students to build relaxing relations through question-and-answer dialogue sequences in which they play the major role in teaching computer. Modern ITS still seek to replace the role of the teacher in order to provide a personalized learning experience; they may generate problems and feedback automatically, creating a proper learning sequence for each student. In 1998, the Andes ITS system was developed to provide learners with hints and feedback when they are stuck on certain problems. However, Andes required a better analysis of learners' dialogue, as it was not possible to improve it automatically at the time. Current ITS incorporates numerous advanced techniques, such as machine learning, reinforcement learning, natural language processing, emotion recognition, multi-agent systems, etc.

2.2.1 Skinner’s Teaching Machine

In the 1950s, American psychologist Burrhus Frederic Skinner devised a teaching machine that allowed pupils to answer questions and receive feedback at their own pace [9]. A response can produce consequences like as the correct spelling of a word or the solution of a math problem, according to his theory of learning. When a specific Stimulus-Response pattern is reinforced, an individual is conditioned to respond. Based on this theory, he conducted experiments with the teaching machine to teach subjects such as math and spelling. He believed that pupils in the traditional classroom were obliged to progress at the same rate, regardless of their ability and comprehension, and that reinforcement was also delayed due to the large class size and lack of individual attention.

Skinner's Teaching Machine consisted of a fill-in-the-blank method on a workbook or a computer. If students properly answer the question, they will receive positive reinforcement and move on to the next question. If a student does not correctly answer the question, he or she must study the correct answer to raise the likelihood of being reinforced the next time, hence enhancing the student's mastery of the knowledge point.

Figure 2.1: Skinner’s teaching machine

Skinner’s Teaching Machine was mostly based on the response and reward mechanism. It required that students fully comprehend each idea before going on to the next. In addition, he advised that the learning process be broken into numerous little parts, with reinforcement occurring following the completion of each step. Therefore, the Skinner's

Teaching Machine can achieve fundamental personalized learning by allowing students to study at their own pace and enhancing their information comprehension in areas where they struggle.

The theory underlying the Skinner's Teaching Machine is comparable to the modern Reinforcement Learning procedure. Skinner's Teaching Machines were not accessible on the market at the time since technology was insufficiently evolved and handy, but this is still an excellent exploration. He proposed that teaching should be programmed so that each student can study at his or her own speed. We can see that the existing eLearning system can deliver immediate and precise feedback, which is a crucial component of learning. Skinner also established the theory of radical behaviouralism; he stated that all types of human action can be considered behaviour, and all behaviours can be strengthened or adjusted through reinforcement strategies. The teaching machine and the Stimulus-Response behaviour theory on which it is based contribute to the modern notions of Adaptive Learning System, which are widely utilized in contemporary e-learning systems.

2.2.2 Flipped Classroom

With the popularity of personal computers and the support of information technology, the flipped classroom became a new trend in the early 2000s. "Flipped" refers to the inversion of the normal learning process: instead of attending group lectures at school and completing homework at home, students can watch recorded lecture videos at home and participate in normal classroom activities at school. Two benefits are associated with the flipped classroom: Firstly, students can watch lecture videos at their own pace, pausing or rewinding the video if they fall behind, and interacting with classmates and lecturers on the online platform. Secondly, after watching video lectures, returning to classroom activities is more efficient for both the teacher and the students. Because students already have a foundational understanding of the topic, they are able to ask prepared questions that they do not comprehend, and the teacher is able to convey more in-depth information. Teachers can also monitor students' video-viewing progress; the website could collect students' video-viewing behaviour data, such as where they frequently pause or replay, so that the teacher can provide extra context for this section.

After flipping the classroom, the failure rate for freshmen in English reduced to 19 percent from 50 percent, while the failure rate for freshmen in mathematics went from 44 percent to 13 percent [10]. The flipped classroom model provides students with a light, personalized learning environment. This strategy relies on students self-preparing for classes in advance; some students may be too indolent to watch video lectures before classroom activities, in which case the student will perform worse than with the traditional method. Long video lectures are not ideal for the eye health of elementary school kids due to their youth. During the COVID-19 period, this type of flipped class has been used at numerous colleges and corporate training programs.

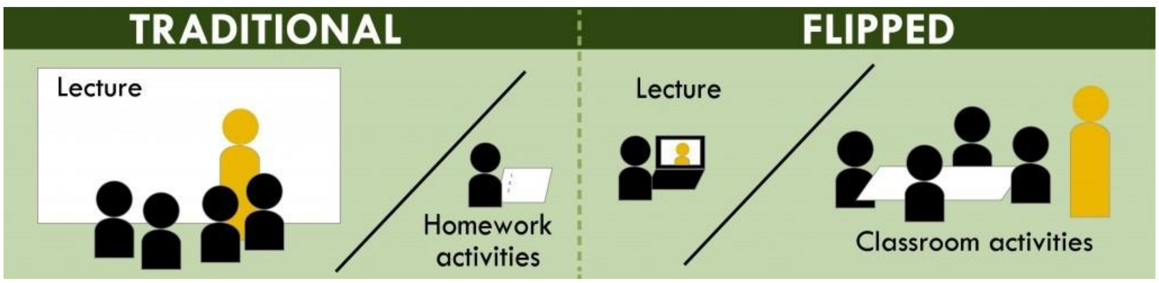


Figure 2.2: Illustration of traditional and flipper class
Source: adapt from [11]

2.2.3 Massive Opening Online Course (MOOC)

MOOC is an online course that provides education to a huge number of students worldwide over the internet. The first mention of MOOCs occurs in 2008. With the increase of internet speed and video technology, MOOCs grew fast between 2008 and 2012, when several US colleges began offering free online courses on their websites. Some firms, such as Coursera, Udacity, and edX, collaborated with numerous prestigious colleges around the globe to offer an abundance of high-quality courses.

In MOOCs, thousands of students from diverse backgrounds (nationality, personality, age, etc.) are enrolled in a single course [12]; hence, personalized learning should enhance learning efficiency. However, several MOOC courses prioritized standardization over customization. The diversity of learners necessitates that MOOCs personalize the learning content and delivery method. Students can generate a large amount of learning behaviour data during the learning process by interacting with learning content [13], such as where they pause a lecture video and for how long, or their performance on quizzes or multiple-choice questions. MOOC platforms are attempting to improve the learning experience by employing Artificial Intelligence (AI) approaches with the vast amounts of data available.

Current MOOCs utilize course recommendations extensively. Xia developed an effective course recommendation system in 2017; it is a content-aware algorithm based on students' interests, access behaviour, and demographic profile [14], and their personal information may be used to tailor the course to the individual. Goal Net is a goal-oriented model proposed by Yu Han [15]; it can adjust the learning sequence and create a personalized learning path for each student. In conclusion, course recommendation is the most widely utilized AI technique in MOOCs, and many research organizations and companies are working hard to provide learners with a more personalized learning experience.

2.3 Reinforcement Learning (RL)

2.3.1 Introduction

RL is a semi-supervised learning paradigm in machine learning. It allows an agent to perform actions and interact with an environment in order to maximize task rewards and achieve optimal control, thus the agent learns an optimal or nearly optimal policy for taking actions. Simply said, RL agents can optimize their performance by gaining knowledge through experience.

RL is a rapidly evolving technique in recent years. Currently, RL agents can perform better than humans in a lot of video games. The OpenAI Five system defeated the professional Dota 2 world champion team in April 2019 [16]. Dota 2 is a multiplayer online battle arena video game, and it is one of the most complex strategy video games. Deep Reinforcement Learning is the technology behind the OpenAI Five system (DRL).

RL is typically employed for continuous-type control and playing games. Figure 2.3 depicts the RL flow diagram in which an agent learns through interactions with the environment and then makes optimal decisions to control the agent's action to the environment by receiving state and reward [17]. The environment is the "world" with which the agent interacts, state (S) is the current state of the agent, reward (R) is the environment's feedback, and action (A) is the agent's actions.

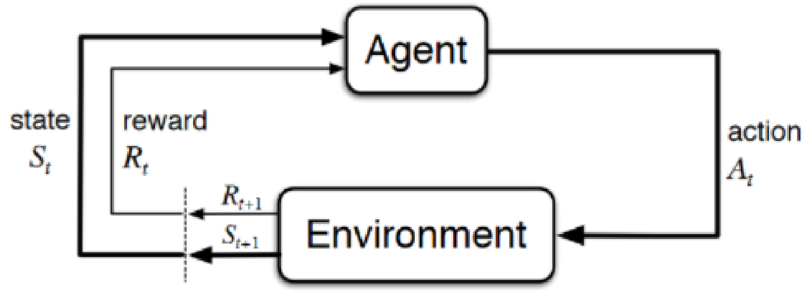


Figure 2.3: Flow diagram of Markov Decision Process

Source: adapt from [18]

As we all known, a model in machine learning is a mathematical representation of certain types of patterns hidden in the data of the history. Two types of RL exist: model-based and model-free. In recent years, model-free RL, which uses the trial-and-error method to learn, has found great success, particularly Deep learning-based RL. To learn, model-free RL requires a massive amount of historical data. Model-based RL use models of the environment for problem-solving and planning, requiring fewer data and reducing sample complexity. In general, model-free RL methods are the most prevalent in real-world applications, as they are simpler to construct without an environment model and can react consistently to new and unknown states. Model-free RL relies largely on stored state-action pairs over numerous learning trials.

Ideally, all environment variables are completely observable in Markov Decision Process (MDP), it can be used to build a model to deal with sequential decision-making tasks. Some variables of real environment are not observable for many cases, it can be generalized to Partially Observable MDP, however this type of partially observable problem can also be transferred to the MDP problem. MDP is a framework for modelling the environment in RL; the agent is the one that takes actions. Figure 2.3 shows a basic interaction in MDP, which consists of:

- A set of environment and agent states S.
- A set of agent actions A.
- Probability of transition that map a state-action pair at time t to t+1 under action a, $P_a(s, s') = P_r(s_{t+1} = s' \mid s_t = s, a_t = a)$.
- An immediate reward function after transition from s to s′, $R_a(s, s')$.

Time steps are set to t = 0, 1, …, T. The agent receives the state s_t from the environment at each time step t, then generates action a_t according to the policy π. At the next step t+1, the agent takes the action and receives the new state s_{t+1} and a reward R_t or $R_a(s, s_{t+1})$ from the environment. This process is called state transition. There is a policy π that maps from states to a probability distribution over action a:

$$\pi : S \rightarrow A \quad \text{or} \quad \pi(a \mid s) = P(a_t = a \mid s_t = s) \qquad (2.1)$$

The above Formula 2.1 is referred to as the policy function. A policy is a strategy that defines what action an agent should take in the next step under a certain state. The current state only affects the next state, therefore any decision taken at s_t solely relies on s_{t-1} and not the previous historical state. The ultimate objective of RL is to find the optimal policy π^* that yields the maximum reward from all states:

$$\pi^* = \underset{\pi}{\operatorname{argmax}}\ \mathbb{E}[R|\pi] \qquad (2.2)$$

There are both on-policy and off-policy learning methods in RL. On-policy RL leverages the experience that is being collected by the most recent learning policy to improve the policy. This implies that the policy used for updating (behaviour policy) and the policy used for acting (target policy) are same, and the agent needs to interact live with the environment in order to learn. Off-policy RL can use the experience that being collected by the historical policy to improve the policy. Behaviour policy and target policy could be different in this condition, this improves the flexibility and efficiency of data collection. So off-policy RL has the ability to transform vast historical datasets into highly effective recommendation engines.

2.3.2 Q-Learning

Q-Learning is an off-policy RL that finds the optimal course of action given the current state. ‘Q’ is the action-utility function; it represents the quality of an action's ability to generate a future return. The temporal difference is used to estimate the value of Q*(s, a) in Q-learning, Q*(s, a) is the expected value of doing action *a* in state *s*. A Q-table Q [S, A] is maintained by the agent, it can be used to calculate expected future rewards for each state-action pair. Q-table can tell us how to select the best action for each state, hence the primary task of Q-learning is to learn all values of Q-table.

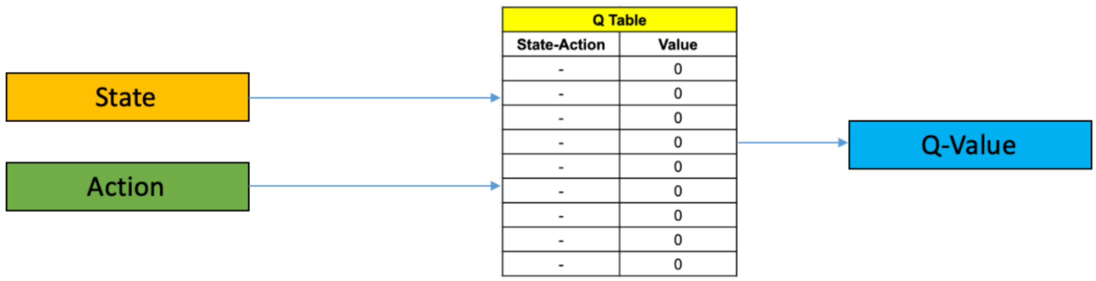


Figure 2.4: Illustration of Q-learning

Source: adapt from [19]

Q-function calculates the value of the state-action pair under policy π. The Q-function utilizes the Bellman equation and takes state s and action a as inputs. It's a very important function in RL. According to Bellman equations, the optimal value of the current state could be easily calculated if the optimal value of the consecutive state is known.

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha(R_{t+1} + \gamma \max_a Q_t(s_{t+1}, \mathrm{a}) - Q_t(s_t, a_t)) \qquad (2.3)$$

In the above Formula 2.3, α is the learning rate that determines how much the learning process accepts the new value to override the old value. The learning rate is manually set between 0 and 1. A value of 0 indicates that Q-value is never updated, and nothing is learned. Higher α value indicates quicker learning, however higher is not always preferable. γ is the discount factor that strikes a balance between immediate and future rewards. The discount factor is also manually set between 0 and 1. The Formula 2.3 is used to update the Q value for the state at t+1 with the state-action pair s_t and a_t, the agent will select the best action to take based on the value of Q.

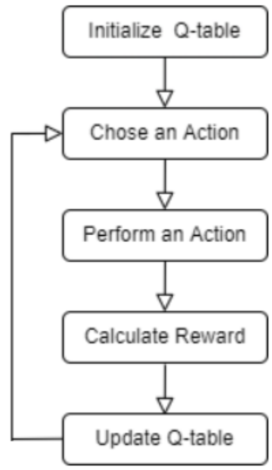


Figure 2.5: Flow chart of Q-learning process

The process of Q-learning is depicted in the image above; the process is repeated a number of iterations until learning is terminated; the Q-table is then updated; and the value function Q is maximized. If the environment has a small number of state-action pairs, the Q-table will be built up easily and the RL process will be highly effective. In the most RL jobs, the state space is continuous, there will be an infinite number of states, and the very large Q-table will be difficult to maintain in computer memory.

2.3.3 Deep Q-Network (DQN)

In order to tackle the problem of limitless states in the standard Q-learning RL, a table could not be utilized to hold Q values. Value Function Approximation can utilize a function to approximate the action-value function, requiring far less memory space than the Q-table method. In formula (4), Q (s, a; θ) can represent the estimation of optimal action-value function Q* (s, a), there is a neural network as approximator with parameter θ in Q (s, a; θ).

$$\mathrm{Q}(s,a;\theta) \approx Q^{*}(s,a) \text{ or } Q^{\pi}(s,a) \qquad (2.4)$$

DeepMind developed the DQN in 2015, which was derived from the Q-Learning RL algorithm. In DQN, a Neural Network (NN) could be used as a value function approximation to approximate the Q values, and a technique called experience replay is employed to make greater use of experience to learn. DeepMind utilized DQN to play a series of Atari games and outperform a human expert [20]. The actions can be taken in

Atari 2600 games is not sophisticated. For instance, there are only left move and right move in the game Breakout.

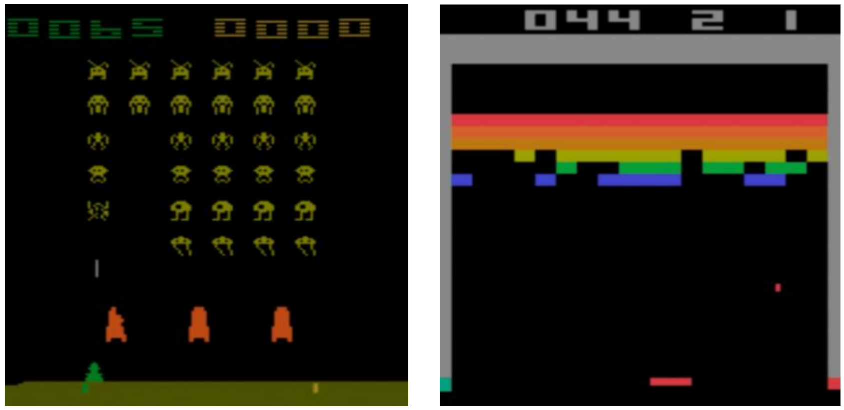


Figure 2.6: Screen shots of two Atari 2600 games: Space Invaders, Breakout

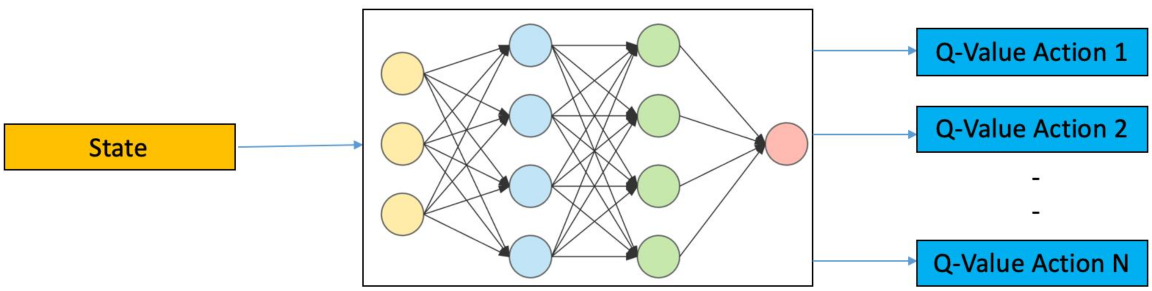


Figure 2.7: Illustration of Deep Q-Network with NN

Source: adapt from [19]

The above figure illustrates a fundamental structure of Deep Q-Network with NN. The given state is the input, and the Q-value of possible actions is output; the agent will then take the action with the highest Q value. In Formula 2.5, Q* represents the target Q value and is equal to the sum of the immediate reward of current action and the maximized future reward.

$$Q^*(s,a) = \mathrm{r} + \gamma \max_{a'} Q^*(s',a') \qquad (2.5)$$

The estimation error of Q (s, a; θ) needs to be minimized in the DQN task by optimizing the loss function to obtain the final optimal policy π. The loss function is DQN, which can be calculated as the squared error between the target Q value and the predication Q value. The target Q value can be calculated using Formula 2.5, and loss function L(θ) can be easily produced using the following Formula 2.6. Here, NN is the approximation function, and NN is trained to obtain the optimal weights θ by optimizing the loss function. The weights of NN will be kept in the computer memory, similar to how Q-table weights are stored in classic Q-Learning.

$$L(\theta) = ((r + \gamma \max_{a'} Q(s', a', \theta^{target})) - Q(s, a, \theta^{predict}))^2 \quad (2.6)$$

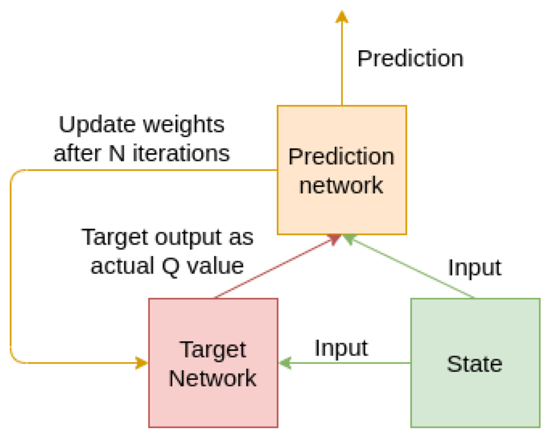


Figure 2.8: Illustration of DQN architecture

Source: adapt from [21]

Unlike the traditional NN, DQN has both target and predication networks, as depicted in the figure above. A separate target network with frozen weights is used to estimate the target output; the architecture of the target and predication network are identical. The output of the target network serves as the ground truth of the predication network. Every fixed N iteration, the weights in the target network are replaced with weights from the predication network, and the weight of the predication network is updated with each iteration. Consequently, the target network function with temporally frozen weights can result in a more stable NN training.

To make network updates more stable in DQN, a key mechanism called Experience Replay is introduced. The data produced in the training is correlated in some way. It's inefficient to use all the recent data one by one, so the transition {state, action, reward, next state} is added to the replay buffer at each step. During training, a batch of transitions sampled randomly from the replay buffer is used to calculate the loss of the gradient. The random sampling batch can lower the correlation between the samples, which can provide better data efficiency and better stability. DQN is the first RL to use a deep learning model, and due to the adaptability of DQN, it is widely utilized in a variety of games.

2.4 Serious Educational Game

There are currently numerous websites and applications that deliver serious educational games. PBS Kids and Turtle Diary website offer a wide variety of educational games for children and young adolescents, including math, language, geography, and scientific activities. NASA Science introduces a serious game website that allows students to explore earth and space through gaming. Students may utilize these games as homework or for knowledge review.

For instance, "Changes in States of Matter" in Figure 2.9 is an educational game to teach students about states of matter, which is taught in science subject in primary 5 or 6 schools, students need to select the correct process to complete the game task, such as selecting "heat" and "melting" to melt the hard chocolate, students can understand "states of matter" concepts better by simulating the melting experiment in the game, and the game "experiment" is easier to understand than the actual physical experiment. "Mixed Fraction Maze" in Figure 2.10 is a stimulating maze game designed for primary students to understand how to convert mixed fractions into improper fractions. Students control the scorpion's movement to eat bugs in the maze by answering questions about mixed fractions; the scorpion will eat bugs faster and the student will win if the correct answer is chosen more quickly. The game is relatively simple, but it makes arithmetic learning more engaging, and youngsters like to study in this type of game environment as a supplement to traditional instruction.

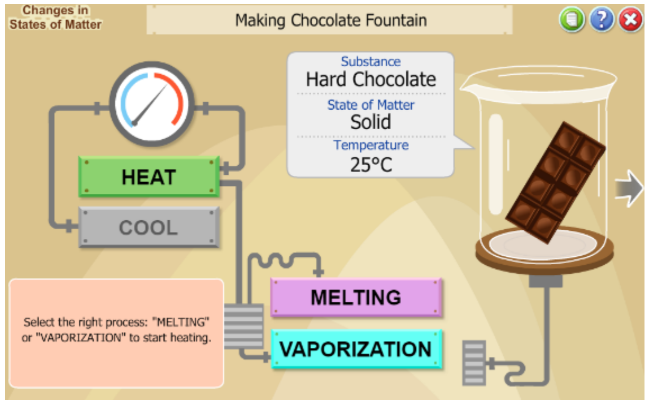


Figure 2.9: Game "Changes in States of Matter"

Source: adapt from [22]

Figure 2.10: Game "Mixed Fraction Maze"

Source: adapt from [23]

Both of the above games are uncomplicated, and the playing environment is simple and uniform for all pupils. There are numerous educational games like this, however they do not offer a very personalized learning experience.

2.4.1 Virtual Singapura

Virtual Singapura is one of the most successful educational games created by Nanyang Technological University [24]; it has been piloted in 16 future schools of Singapore, which are prestigious secondary schools selected by the Singaporean government to test innovative teaching technologies. Virtual Singapura is a 3D educational game that runs on a computer platform; through playing the game, students can learn some secondary school science knowledge. In the game Virtual Singapura, students can manipulate an avatar to shrink to ant size and reach the root of a tree through ant holes in order to learn about the knowledge on nutrition transportation. The student can witness from the root how water and minerals are transferred to the leaf for photosynthesis. In the game environment, it is simple to construct virtual labs for conducting experiments on osmosis and diffusion, the scientific principles underlying the transport system of plants. Additionally, there are multiple-choice questions to assess the student's comprehension of the content.

Figure 2.11: Knowledge introduction in Virtual Singapura

Figure 2.12: Plant root scene in Virtual Singapura

Virtual Singapura is a type of Virtual Learning Environment (VLE) in which students gain knowledge via the use of a virtual environment or game. By incorporating the educational practice of peer-to-peer learning into the game, a virtual learning companion was created to assist students in the learning process; this learning companion could be considered a learning trigger for students. They can "assist" each other and develop a bi-directional peer relationship; this can be an excellent motivation for active learning, and students tend to spend more time on the learning content.

In addition, a curious function is added to the learning companion. Curiosity is a natural human motivation that drives individuals to explore the unknown. Numerous studies have demonstrated that curiosity makes the human brain more receptive to learning; people will learn and memorize more effectively if their curiosity is sparked by the appropriate questions. If a student struggles in math, the teacher can create personalized math questions that reflect the kid's individual interests rather than generic math questions to assist the student learn how to answer math problems more effectively. Curiosity can also make subsequent learning more rewarding and enjoyable. Plan-based knowledge representation was utilized to create the curiosity model in Virtual Singapura. According to the results of the experiment, a curious learning companion can improve the learning in multiple ways, including learning outcome and efficiency.

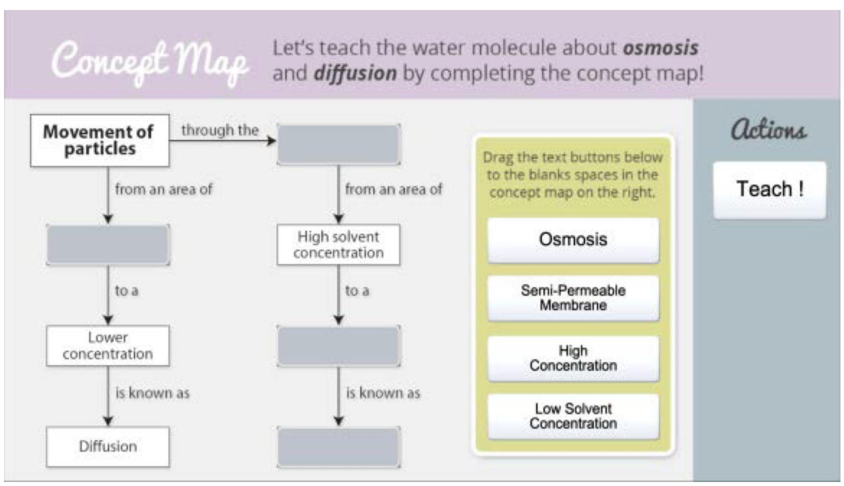


Figure 2.13: one of scenarios on teachable agent in Virtual Singapura

In Virtual Singapore, there was a teachable agent. Teachable agent (see Figure 2.13) is used to motivate students to teach the agent. Based on the theory of learning by teaching, students can improve their own learning outcomes by teaching others. It can also assist students develop responsibility and motivation. Teachable agent in Virtual Singapura is a virtual agent with artificial intelligence that is capable of interacting with players, learning, thinking, and reasoning. Appropriate activities are provided for the agent to conduct in order to influence the players' decision to teach the agent.

2.4.2 Crystal Island

Crystal Island is a 3D computer-based interactive narrative-centered educational game for secondary school science and literacy [25]. On Crystal Island, students should control the avatar of a medical detective in order to investigate an infectious disease. The game requires students to use their learning and literacy skills to comprehend the symptoms of the infection in order to stop its spread. To stop the spread of disease in the game, students should read and understand all the material from complex literature about microbiology. Trophies will be awarded to students who complete reading-related challenges.

Figure 2.14: Screen shot of infirmary investigation in Crystal Island

Figure 2.15: Screen shot of interactive narrative environment in Crystal Island

Both Crystal Island and Virtual Singapura are virtual learning environments or game-based learning environments. Students can interact with virtual lab equipment, read relevant content, and utilize textbook knowledge to solve in-game problems.

The game contains intelligence, such as an intelligent tutoring system, dialogue breakdown prediction, and interactive narrative personalization. There are numerous interactions and conversations between player and non-player characters (see Figure 2.15). Good interactions can improve the story experience for students and increase their motivation to learn. In Crystal Island, the RL model was employed to construct personalized interactive narratives based on player interaction logs. As discussed in section 2.3, the RL technique has proven to be highly effective in sequential decision-making tasks with delayed rewards. The actions of human players in a game are usually difficult to foresee and comprehend. True rewards are constantly delayed in the interactive narrative generation system, and the player can only judge the quality of the generated narrative after a few episodes. These factors all contribute to the uncertainty of the interactive narrative generation model.

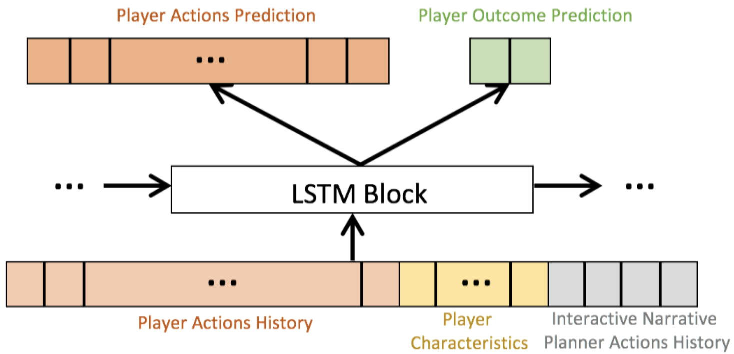


Figure 2.16: Implementation of a player simulation for interactive narrative planning

Source: Adapt from [26]

Clearly, training a deep reinforcement learning (RL) model of interactive narrative generation requires a massive amount of interaction history data. To address the data requirement, they generated training data using a simulated user approach based on a bipartite player simulation model. Normalized learning gain was utilized to quantify the difference between a student's pre-test score and post-test score in order to determine how useful the personalized interactive narrative is for learning. The game recorded the player's action, interactive narrative, and subsequent response with a timestamp. Students were requested to complete a questionnaire to determine their characteristics, personality, level of knowledge, and level of engagement.

The player simulation model is constructed using a long short-term memory (LSTM) recurrent neural network, which is used to predict the player's next action. Figure 2.16 demonstrates that this LSTM model takes as input a 21-feature representation including player action history, player characteristics from the questionnaire, and interactive narrative planner action history [26]. The action prediction problem is transformed into a classification problem.

Crystal Island use Q-network to build the interactive narrative planner; Q-network is a neural-network structure based on Q-learning. DQN is an RL algorithm that optimizes the planning policy for interactive narratives, selecting the optimal interactive events for the player. The interaction state is the input of the Q-network, and the Q values of a few interactive narrative planning actions are the output.

Chapter 3

The Uncharted Island Game

3.1 Introduction

A serious educational game "The Uncharted Island" was built to research personalized learning. The objective of this game is to teach pupils some secondary school science knowledge, such as diffusion, osmosis, and active transport of plant transport system. By conducting virtual laboratory experiments, quizzes, and simulations within the game, students gain knowledge. Some personalized hints could be provided to students via text or audio while they play the game, so enhancing their learning and igniting their curiosity. The thesis's primary focus is on how to generate personalized hints.

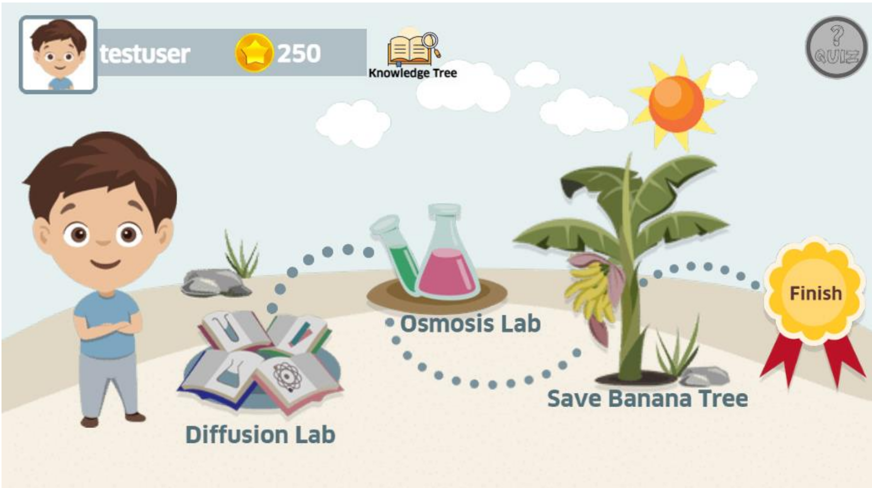


Figure 3.1: Screen shot of main page in the Uncharted Island

Prior to playing the game, students must complete an online pre-survey on the website, as shown in Figure 3.2 below. Some personal information (such as gender and age) must be gathered, and there is a questionnaire with 22 two-choice questions on the Index of Learning Styles to complete. The questionnaire is used to determine the student's learning style, which can then be incorporated into the personalization procedure.

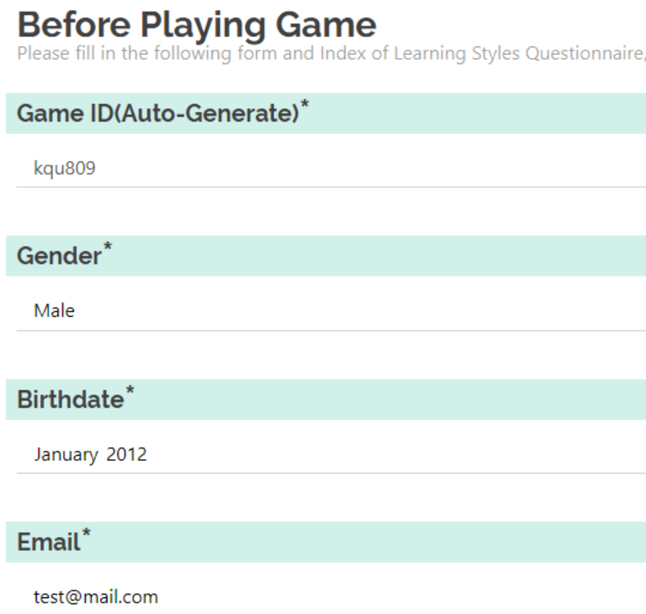
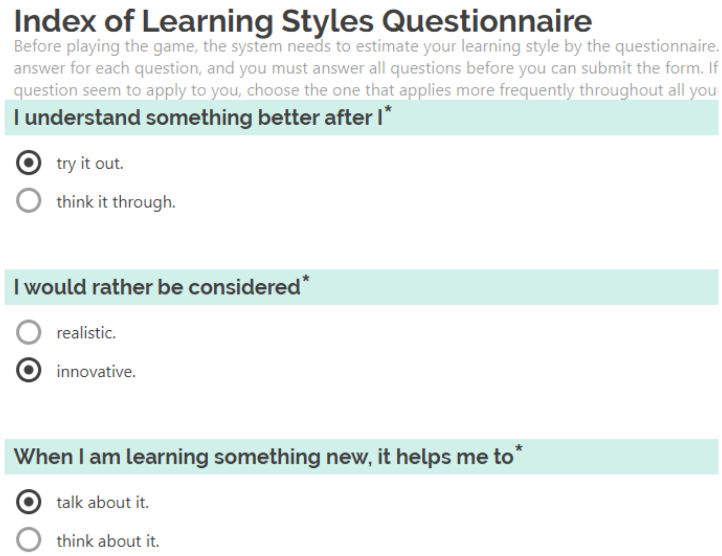


Figure 3.2: Personal information page in survey website

To make learning more enjoyable and to provide learners with learning companionship, the TmallGenie smart speaker is used to communicate with learners; it can read aloud the learning materials, play the hints using a pleasant voice, ask some questions, and listen to and understand the learners' responses. The TmallGenie smart speaker contains an open-platform intelligent voice assistant system that runs in the cloud and has superior Automatic Speech Recognition (ASR), Natural Language Processing (NLP), and Text-to-Speech (TTS) capabilities. With these capabilities, a nice learning companion TmallGenie may be created to interact with and accompany young students.

3.2 Index of Learning Style (ILS)

Richard M. Felder and Barbara A. Soloman created the Index of Learning Style, which is one of the most widely used tools for determining the learning style of an individual. The questionnaire's outcome reveals the learner's preferences on four dimensions of a learning style model.



Index of Learning Styles Questionnaire

Before playing the game, the system needs to estimate your learning style by the questionnaire.
answer for each question, and you must answer all questions before you can submit the form. If
question seem to apply to you, choose the one that applies more frequently throughout all you

I understand something better after I*

try it out.

think it through.

I would rather be considered*

realistic.

innovative.

When I am learning something new, it helps me to*

talk about it.

think about it.

Figure 3.3: Questionnaire page in the survey website

Richard M. Felder and Linda K. Silverman introduced the learning style model in 1988; it is also known as the Felder-Silverman model [27]; it was originally intended for use by college teachers and students in engineering and science study or teaching. The ILS was created with the Felder-Silverman model. Students typically absorb knowledge in several ways, such as by sight or hearing, reflection and action, logical and intuitive reasoning, analysis and visualization. Different styles of students may demand varying pedagogical approaches.

The model consists of four dimensions: active or reflective, visual or verbal, sensing or intuitive, sequential or global. As can be seen, each of the four dimensions has two preferences that are diametrically opposed. Typically, students favour one option over the other. When the student's learning style and the teacher's teaching style are too dissimilar, the student's learning may be less effective.

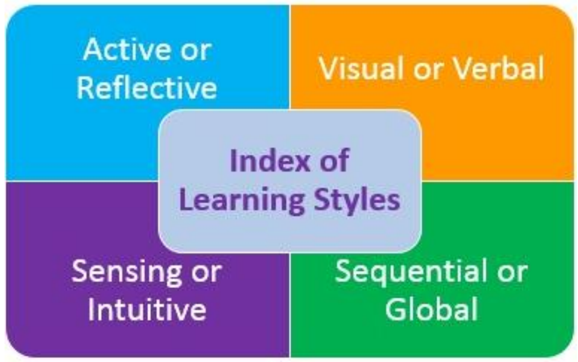


Figure 3.4: Four dimensions of learning style model

Source: Adapt from [28]

For example, the active or reflective dimension. It reveals the learner's preference on how to process information. Active learners prefer to discuss, apply, and explain the information to others. Reflective learners prefer to work alone and understand the problem before acting. In traditional classes, teachers can organize a study group for "active learner" students and have them engage in problem-solving activities and discussion. Students who are "reflective learners" should attempt to write summaries of readings or class notes in their own words, as this will aid their comprehension.

In the sensing or intuitive dimension, it indicates how learners like to take in information. Sensing learners tend to take in knowledge that is concrete and factual; they are extremely patient to the smallest of details and excel at laboratory work. Intuitive learners have a tendency to take in information that is theory and concept-based material; they can understand the big picture of the knowledge content and like discovering the connections between knowledge points. Teachers should provide 'sensing learner' pupils with examples of concepts and procedures, allowing them to comprehend how concepts relate in the real world. Students who are 'intuitive learners' should be more patient with details and attempt to relate concepts to real-world experiences.

ILS originally consists of 44 multiple-choice questions, with 11 questions determining the preference on each dimension. The answers to each question are either 'active' or 'reflective,' making it simple to assess the learning style through the questionnaire. To facilitate the application of the ILS to the game, only 22 two-dimensional questions (active or reflective, sensing and intuitive) are adapted for use in the game pre-survey.

Question	Choice a	Choice b
I prefer the idea of	certainty	theory
I understand something better after I	try it out	think it through
I am more likely to be considered	outgoing	reserved
When I am reading for enjoyment, I like writers to	clearly say what they mean	say things in creative, interesting ways

Table 3.1: Some example question of ILS

3.3 Game Design

The Uncharted Island is a lightweight 2D mini game developed using the Cocos Creator game engine that can be converted to any webpage platform, WeChat Mini Program, Alipay Mini Program, etc. Some classic scenarios, such as the virtual diffusion and osmosis lab and saving the banana tree, have been redesigned and recreated for the new game, which is based on the Virtual Singapura game. By playing the game, students can gain relevant knowledge about science and plant transportation systems.

As shown in Figure 3.5, each player is given a certain number of coins at the beginning of the game to incentivize students or players and measure the experiment's outcome. During virtual experiments, players must spend virtual coins to purchase and utilize the necessary equipment. When a player successfully completes an experiment, he or she will receive a large number of coins. If the player does not have a thorough understanding of the knowledge or experiment, he or she may purchase or use the incorrect equipment, resulting in the expenditure of coins. If the player does not have enough coins to continue the experiment, he or she will be required to complete a knowledge quiz in order to earn extra coins. The quiz also aids the player in gaining additional relevant knowledge.

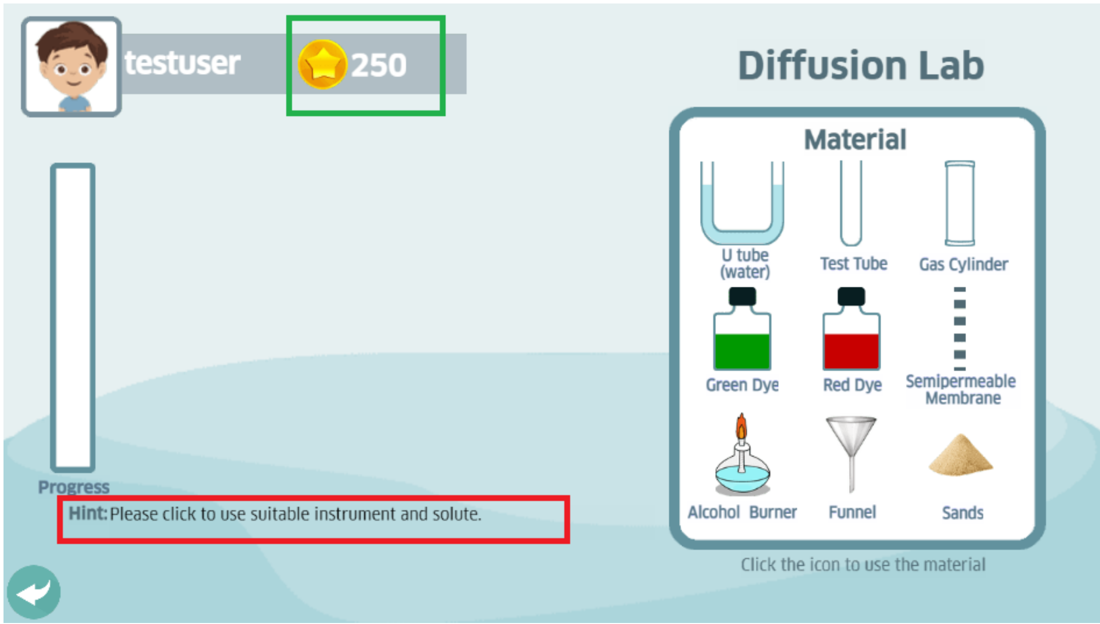


Figure 3.5: Initial page of diffusion lab

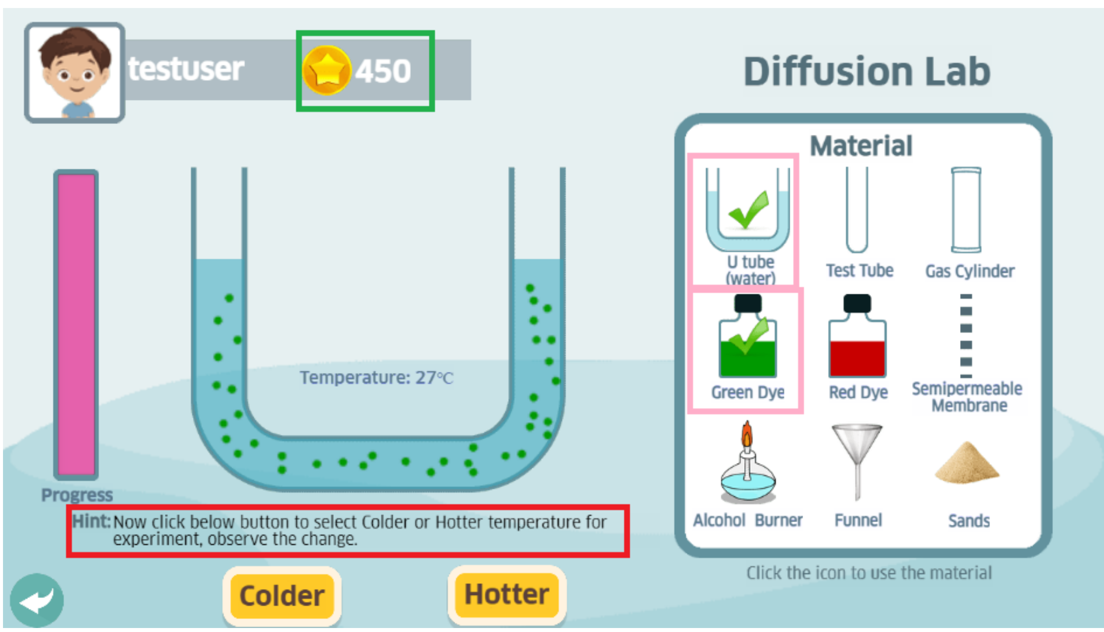


Figure 3.6: End page in diffusion lab

The beginning page of the diffusion lab is depicted in Figure 3.5. Players must conduct a diffusion experiment by purchasing and utilizing the required materials from the right-side material box with an initial 250 coins. To properly complete the experiment, the player must understand the concept and methodology of diffusion. In order to avoid players from being stuck in the game if they purchase and use the incorrect materials, hints will be displayed. Following the completion of the basic diffusion experiment, the player will receive 300 coins.

Figure 3.6 is the final page of the diffusion lab. The pink box contains the essential materials, and the experiment is relatively simple to do if players are familiar with the experiment in the textbook. The player can continue to click "Colder" or "Hotter" to observe the transformation of "green dye" in a U-shaped tube, demonstrating the relationship between diffusion rate and temperature. Performing the diffusion experiment is relatively simple if the student is familiar with the experiment's setup from the textbook.

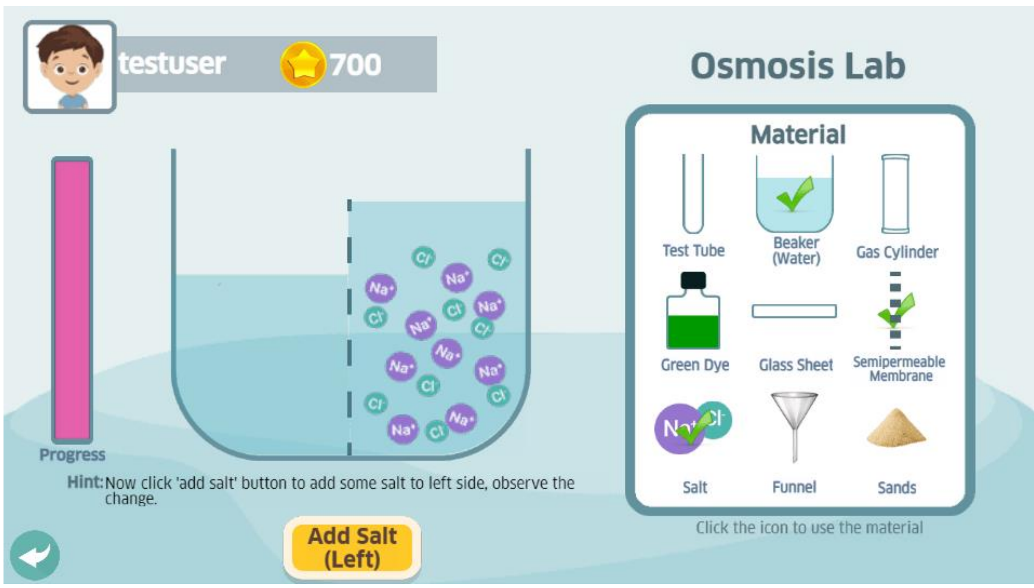


Figure 3.7: End page in osmosis lab

The final page of the osmosis lab is depicted in Figure 3.7; the process is similar to diffusion. For the osmosis experiment, three materials are need. The player can understand the relationship between osmosis performance and concentration difference by clicking "Add Salt (Left)" after completing the basic experiment. A semipermeable membrane is a crucial component of the experiment, and students frequently make mistakes here.

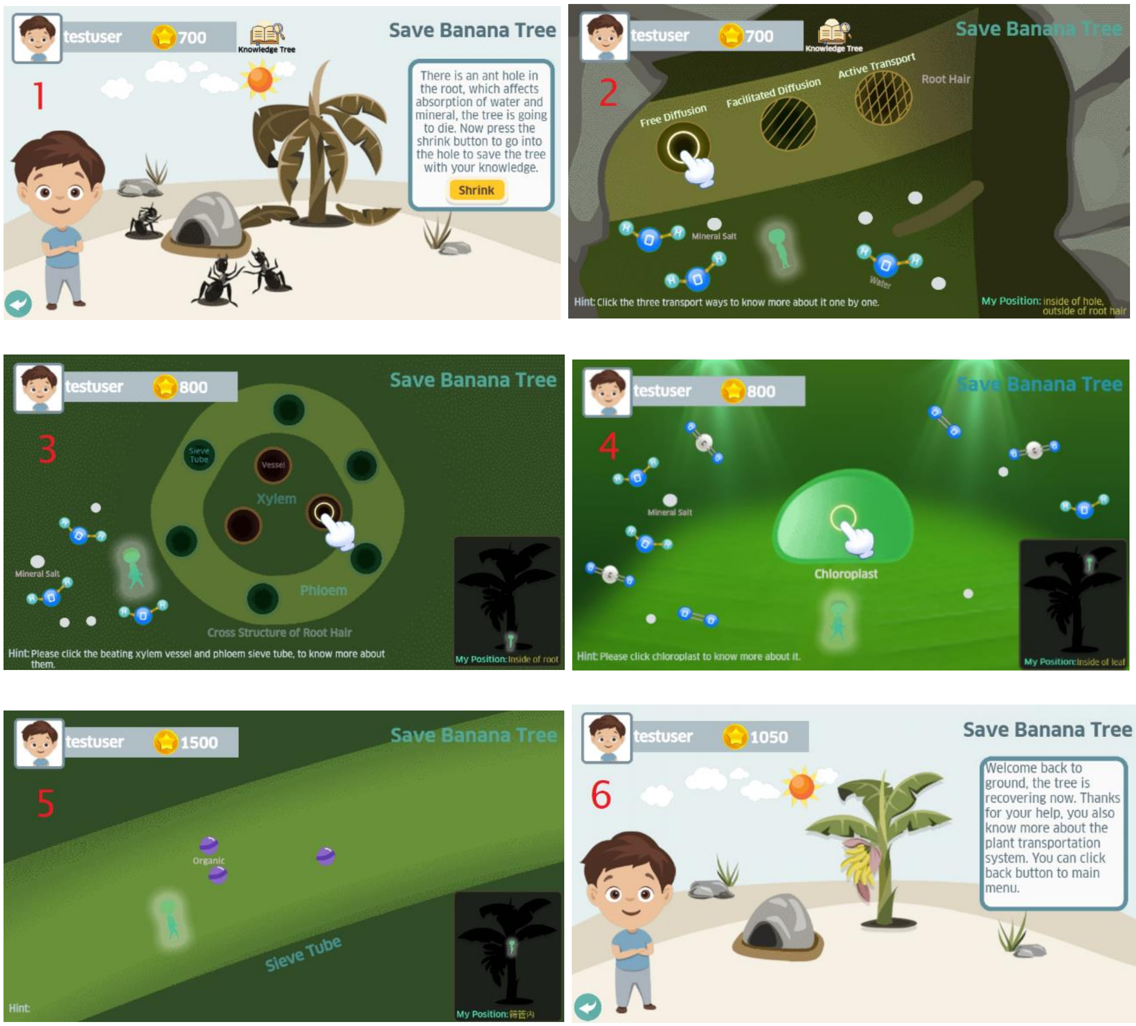


Figure 3.8: Process of ‘Save Banana Tree’

Figure 3.8 shows the "Save Banana Tree" process. This section is more like a role-playing game. The player controls the avatar's size reduction in order to enter the ant hole and save the banana tree. Throughout this process, there are game contents pertaining to diffusion, osmosis, plant structure, plant transportation system, photosynthesis, etc. Each page contains a few multiple-choice questions or a game-like selection. The banana tree will recover well if the player properly applies the acquired knowledge to its preservation.

When the player begins a new virtual experiment, such as the diffusion lab, TmallGenie will play the introduction of diffusion by voice. The player can also ask TmallGenie,

"TmallGenie, what is the definition of diffusion?" and TmallGenie will read the answer to the learner. There are a few frequently asked questions related to the learning content that we have prepared within the TmallGenie mini-program. TmallGenie can also play the personalized hints, which makes learning more enjoyable.

"Smurf Story Machine" is the name of a special TmallGenie smart speaker device for children. The objective of TmallGenie smart speakers designed for children is to provide companionship and early education. Other TmallGenie products, such as X1 and Sugar Cube, have a significant number of child users. TmallGenie smart speakers can aid in establishing emotional bonds and companionship with the children learners in the game. TmallGenie enables more natural interactions between students and the game agent, hence enhancing the learning experience and making it more entertaining.

Figure 3.9: TmallGenie Smart Speaker CCL

Many families have adopted the widespread use of smart speakers. Some parents have purchased smart speakers for their children; smart speakers can answer their children's homework questions. Parents can use it as a teaching tool to answer questions they are unsure of, and it can be used to teach youngsters new vocabulary and information about a given topic. Serious educational games, particularly voice educational games, are great learning tools. In recent years, voice games have become popular due to the rise of smart speakers; there are also puzzle games, escape room games, and other games that help develop general abilities. A smart speaker is an excellent learning partner for youngsters; therefore, we wish to utilize smart speakers to make the Uncharted Island more engaging.

3.4 System Architecture

The whole game's system architecture is visualized in Fig 3.9. The game's user interface was created with the Cocos Creator Game Engine and the Javascript programming language. In the game, there are several interactions and communications with servers. Socket.IO is a framework for establishing bidirectional real-time communication between a game's client and server. NodeJS server is the backend server that will function as a data transit hub. WebSocket is utilized to construct communications between the NodeJS Server and the TmallGenie Mini Program. All data is kept on the MySQL server. The RL process server is used to produce personalized hints. All of the above servers are built using the cloud server provided by Amazon Web Services.

Once a new player begins playing, a unique socket.io thread will be established between the game client and backend NodeJS server. This thread will remain active until the player exits the game, and it can handle several concurrent players. In addition, a websocket thread will be established to facilitate communication between the NodeJS server and the TmallGenie mini-program. At the outset, players must register an account with a game ID and create a character profile (i.e., nickname, gender, avatar). This information will be stored in the database immediately for future use.

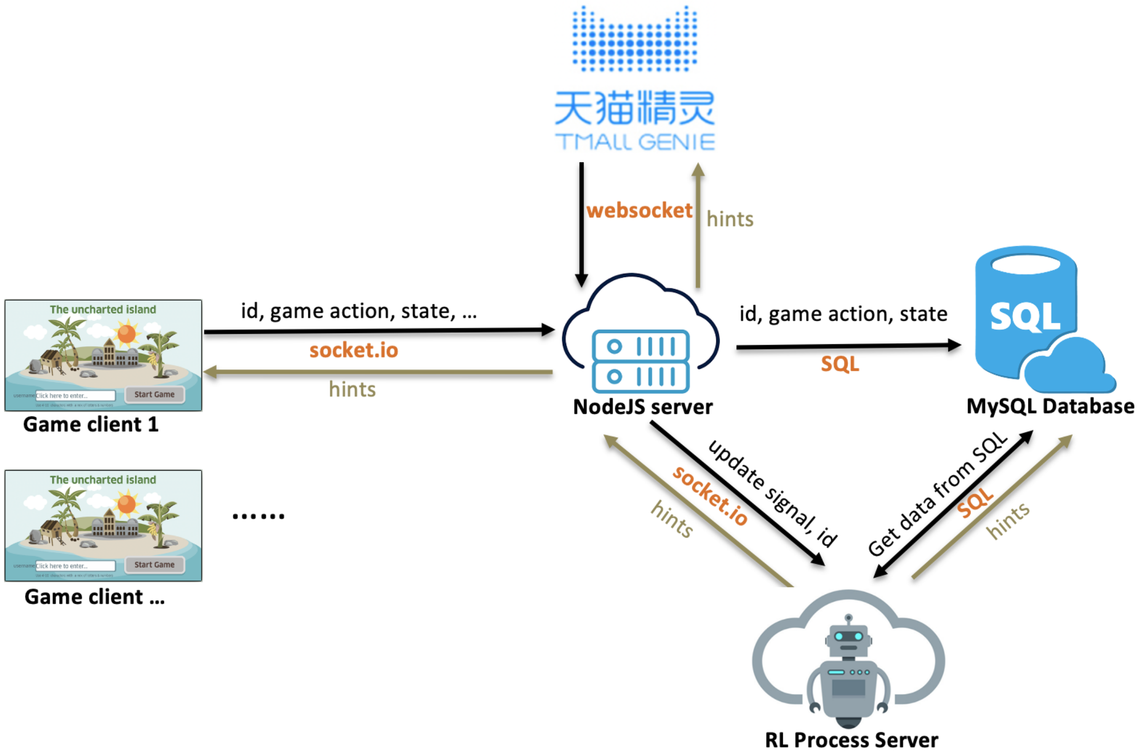


Figure 3.10: System architecture

During game play, a log of all user actions and game states with a timestamp will be transmitted to the NodeJS server and then transferred to the database. Once the RL process server receives an update signal from the NodeJS server, it will extract log data from the database and perform processing to generate a next-step hint. The hint will then be forwarded to the game client and TmallGenie mini-program by the NodeJS server so that it can be displayed on the game page or played by the TmallGenie speaker. The NodeJS server is the communication hub in this system, while the RL process server is the true brain. The RL Process server is written in Python and supported with libraries for data analysis and machine learning.

3.5 Game Data

The game's database has four tables: 'survey,' 'user_information,' 'activity,' and 'training_data.' The system assigns the gameID (username) when players begin the survey; players use the same gameID when playing the game. The 'style' column in the 'survey' table represents the learning style determined by the ILS questionnaire.

'user_information' includes gameID (username), nickname, gender, time of registration, number of coins possessed, etc.

gameID	gender	birthdate	email	style1A	style1B	style2A	style2B	style	updatetime
pup416	M	1992-05	@gmail.com	4	7	3	8	R7_I8	2020-07-19 22:52:13
dch835	M	1995-06	gmail.com	6	5	2	9	A6_I9	2020-07-20 09:05:20
oli339	M	1992-09	gmail.com	3	8	4	7	R8_I7	2020-07-20 10:04:26
gbm292	M	1996-06	outlook.com	2	9	2	9	R9_I9	2020-08-05 16:17:22
xgd833	M	2003-06	@gmail.com	2	9	3	8	R9_I8	2020-08-07 11:16:28
yez692	F	2003-09	gmail.com	1	10	1	10	R10_I10	2020-08-07 13:53:52
cpl517	M	1993-05	@outlook.com	3	8	6	5	R8_S6	2020-10-08 14:09:04

Figure 3.11: Samples in table of 'survey'

username	nickname	sex	timeofbirth	coins	whichavatar	updatetime	lastLoginTime
pup416	hello12	girl	2020-07-19 22:52:50	420	1	2020-07-19 22:55:13	2020-07-19 22:52:50
test12	gfdgd2	girl	2020-07-19 23:01:15	30	1	2020-07-19 23:02:24	2020-07-27 09:53:51
test26	gfd23	boy	2020-07-19 23:06:26	590	0	2020-07-19 23:07:39	2020-07-19 23:06:26
oli339	helop1	girl	2020-07-20 10:04:41	590	0	2020-07-20 10:08:18	2020-07-20 10:04:41
test2	test2	boy	2020-07-27 09:54:04	670	0	2020-07-27 09:56:06	2020-07-27 09:55:46
gbm292	hellome	girl	2020-08-05 16:17:43	650	1	2020-08-05 16:19:22	2020-08-05 16:17:43
yez692	hello	girl	2020-08-07 13:57:09	1150	1	2020-08-07 14:06:25	2020-08-07 13:57:09

Figure 3.12: Samples in table of 'user_information'

username	sequenceID	time	stage	actionType	operatedItem	rewardType	rewardQty	totalCoins	itemsState
pup416	0	2020-07-19 22:52:59	diffusion	init	na	na	0	200	001001001001001001001001001
pup416	1	2020-07-19 22:53:07	diffusion	read	introduction	na	0	200	001001001001001001001001001
pup416	2	2020-07-19 22:53:10	diffusion	buy	U-Tube	penalty	50	150	010001001001001001001001001
pup416	3	2020-07-19 22:53:13	diffusion	use	U-Tube	penalty	10	140	100001001001001001001001001
pup416	4	2020-07-19 22:53:16	diffusion	buy	Funnel	penalty	50	90	100001001001001001001010001
pup416	5	2020-07-19 22:53:20	diffusion	refuseusing	Funnel	na	0	90	100001001001001001001010001
pup416	6	2020-07-19 22:53:30	diffusion	buy	Semipermeable M	penalty	50	40	100001001001001010001010001
pup416	7	2020-07-19 22:53:33	diffusion	wronguse	Semipermeable M	penalty	10	30	100001001001001010001010001
pup416	8	2020-07-19 22:53:42	diffusion	bankrupt	na	na	0	30	100001001001001010001010001

Figure 3.13: Samples in table of 'activity'

The 'activity' table is comprised of all game actions and game status. As depicted in Figure 3.12, once a single action has been taken, a single log will be saved. Under the same username 'pup416', 'sequenceID' rises sequentially from 0 in accordance with action time order, beginning with 0. The term 'stage' refers to the current game level. 'actionType' represents the type of action taken in the game, such as buying and using the lab material ('operatedItem'). 'rewardType' contains three values: 'na' for not available or no change, 'reward' for acquiring some coins, and 'penalty' for losing some coins. 'itemsState' is the status of nine experiment materials in the diffusion and osmosis lab; each item's status is represented by three digits 0 or 1 using One-Hot Encoding; '001' means the item is in original status (not bought or used); '010' means the item was bought; and '100' means the items were used; therefore, 'itemsState' contains a total of 27 digits. The format of 'itemsState' also makes it more acceptable for usage as an input for the NN state in the RL processing.

3.6 Setting Up for RL

In the diffusion and osmosis experiment, RL is utilized to generate hints, which are the proper next-step game actions. Here, the gaming environment may be considered an MDP environment, given the game status is completely observable. Let's specify the game's RL conditions:

- Environment: diffusion and osmosis experiment in The Uncharted Island game.
- States (S): the combination of all item/material usage status (original, bought, used).
- Actions (A): buy, use or put back the item/material.
- Rewards (R): reward points if experiment is done, lose some points if act wrongly or experiment failure.
- Game finished: the virtual experiment is done successfully.
- Game failed: Without enough coins to buy material to do the experiment.

Completing the experiment successfully signifies the end of the game. Failure to complete the experiment due to inadequate coins signifies the failure of the game. The objective of this game is to complete the experiment with more coins. We define correct actions in the game as buying or using the correct material required for the experiment, and incorrect actions as buying or using material that is not required.

Player's action	**Cost (coins)**	**Note**
Buy U tube	50	Correct action
Use U tube	10	Correct action
Put back U tube	0	Wrong action
Buy sands	50	Wrong action
Use sands	10	Wrong action
Put back sands	0	Correct action
Buy green dye	50	Correct action
Use green dye	10	Correct action
Put back green dye	NA	Once green dye used, experiment done.

Table 3.2: Some examples of Player's actions in diffusion lab

Formally, when a player takes an action a_t at time step t, action a_t is from a discrete action set A = {a^1, a^2, ..., a^m}, and the current state $s_t \in S = (o^1, o^2, ..., o^n)$, in which o^n is the usage status of the nth material. o^n is represented by three digits 0 or 1 using One-Hot Encoding. Training the RL model gradually adjusts the policy π to the optimal:

$$\pi : S \rightarrow A \qquad (3.1)$$

The policy π is adjusted to maximize discounted cumulative return:

$$R_t = \sum_{\tau=t}^{\infty} \gamma^{\tau-t} r_\tau \qquad (3.2)$$

The discount factor, γ, is a real value $\in [0, 1]$.

Outcome of Reinforcement Learning training process is indeed the optimal policy π*, which directs an appropriate action in state s, which is obtained when the training converges with the optimal value Q*(s, a).

$$\pi^*(s) = argmax_a Q^*(s, a) \qquad (3.3)$$

Here, a DQN model serves as the RL engine, while a standard NN serves as the approximation function. The employed model is not complicated. Python's Keras Deep Learning package is utilized to build the DQN model. The neural network comprises 27 nodes to represent game states in the input and output layers, and the recommended action can be simply determined by comparing game states in the output layer with those in the input layer. It indicates that the recommendation problem is phrased as a classification problem with 27 classes. In the NN, there are two hidden layers, each with 32 neurons, and an adaptive moment estimation optimizer is used.

To train a good RL model, sufficient data is required. Manually playing the game to collect game data is one of the approaches, however it is inefficient and impractical for actual training. Due of the simplicity of the game, a simulated game data generator was created to generate logical game data. The data was stored in the database for the training process.

The importance of reward strategy in RL training cannot be overstated. Correct actions result in positive rewards and incorrect actions result in negative rewards, with a greater positive reward if the experiment is completed successfully and a greater negative reward if the experiment cannot continue due to a lack of coins. According to the reward strategy, any correct actions can earn the agent 10 reward points, while any incorrect actions can result in 10 deducted reward points. Completing the game can earn the agent 30 reward points, but a failed experiment can result in 20 deducted reward points.

As stated in section 2.3, the epsilon-greedy policy is utilized in DQN to encourage agents to conduct extensive exploration and exploit the experience learned. The epsilon value is initially set to 1 and decreases with a rate of 0.99 every action. If the value of epsilon is greater than a randomly generated number between 0 and 1, a random action will be generated and carried out.

3.7 Hints Personalization

The trained model was saved for use in future predictions. Because the game's complexity is not high and the state-action space is not vast, the prediction accuracy is nearly 100%. The final output is a combination of item and item action type keywords, such as "purchase" and "U-shaped tube." However, the system will not display the output hints directly, as it would be too easy for players and make the game too monotonous; instead, personalization will be added to the hints. We intend to add more curiosity effect to the hints. The idea of curiosity is succinctly described by William James, renowned philosopher and psychologist, summed up the concept of curiosity succinctly by defining it as the urge to understand what you know you do not know.

Modern research has attempted to find out what motivates human curiosity. One popular current viewpoint asserts that curiosity is a "cognitive induced deprivation that arises from the perception of a gap in knowledge and understanding" [29]. It is believed to have similar functions to other human drive states, such as hunger, which motivates eating. As such, it appears that the major function of curiosity is to facilitate learning. In a condition of information deprivation, according to Loewenstein's information gap theory, a small bit of information acts as a priming dose, which significantly raises curiosity. This implies that when knowledge and understanding are insufficient, the "consumption of information is rewarding, but eventually, when sufficient information is consumed, satiation occurs, and information serves to reduce further curiosity" [30].

Considering that research indicates that curiosity enhances learning [31], it is a crucial concept to keep in mind when designing educational games. In accordance with the information gap theory, different hint strategies are subsequently incorporated to serve as curious functions.

Students who are stuck in a game will receive helpful hints, but not the complete solution. In each experiment, it is possible to determine a player's lack of understanding when he selects the incorrect equipment for that experiment. When this knowledge gap emerges, we continue to provide students with pertinent information and allow them to play an active role in using the information. The provision of suggestions can afterwards stimulate curiosity, hence enhancing learning. In order to prevent satiation and accommodate for information overload, each experiment employs distinct hinting strategies for each type of information gap. This allows players who have used the incorrect equipment several times to engage with other forms of information, thereby maintaining their curiosity to access the correct content. Based on the learning style calculated from the ILS, the hint strategy is determined.

Learning style	Hint content type	Hint presentation
active	concrete	questions/conversational
reflective	abstract	statement/suggestions
sensing	concrete	statement/suggestions
intuitive	abstract	questions/conversational

Table 3.3: Hints strategies with different learning style

Depending on the player's learning style, different hint generation strategies are utilized. As an illustration, an active learner will receive concrete questions as a hint, whereas a reflective learner will receive abstract statements. A hints library is created to generate personalized hints from RL predication output keywords. Currently, the specific hints in the hints library are composed by knowledgeable individuals using the strategies outlined in Table 3.2.

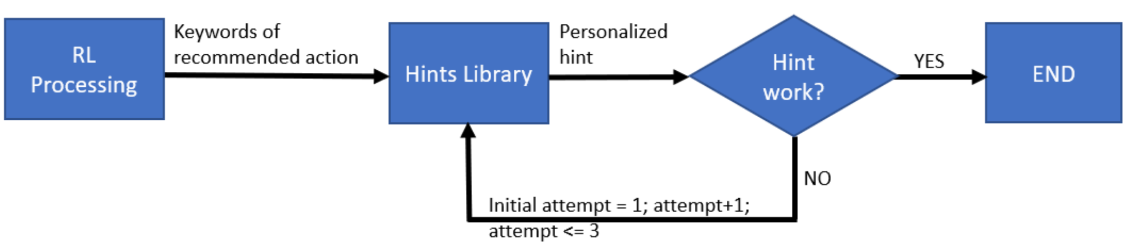


Figure 3.14: Flowchart of hints library working flow

On occasion, if a player fails a virtual experiment, they can receive up to three hints. In the context of the hints library, the more recent hint is more specific than the older one. If, after getting the initial hint, the player is still unable to do the proper action, a second hint will be generated. And the third suggestion provides a nearly clear answer as to how to proceed with the next step.

Define a demonstration condition for the hint library. Assuming that a player with a sensing or intuitive learning style is doing the diffusion experiment in the game, and that the U-shaped tube has been properly employed, the next step should be to add colour dye to the water in the tube. If the player chooses the incorrect next-step action, a hint will be generated as shown in Table 3.4. According to the hint strategy, concrete statements are used as hints for sensing learners, whereas abstract questions are used for intuitive learners.

Learning style	First hint	Second hint	Third hint
Sensing	Think about the relations to how water turn into tea.	In tea, diffusion occurs when tea leaves are added to water to turn into tea.	Color dye should be added into water.
Intuitive	How can there be a higher concentration of water molecule?	What can be added in water to create a concentration difference?	Color dye should be added into water.

Table 3.4: Example hints generated by hint library

Chapter 4

Results and Discussion

The Uncharted Island is a serious educational game designed for secondary school students. It is important to devise a method for measuring the educational value of the game. Some secondary school kids were selected to participate in the game's testing.

For the experiment setup: before playing the game, the student participants need to complete a ten multiple-choice questions (MCQ) quiz to determine their knowledge level on the learning content, including five questions about diffusion and five questions about osmosis. In addition, they need to conduct a questionnaire of learning style to determine the learning style before game. Participants then start playing the game. They played the osmosis experiment of the game without helpful hints, followed by the diffusion experiment of the game with personalized hints. During game play, TmallGenie smart speaker was used to play the introduction and hints, answer the question. After playing the game, the participants redid the 10-question quiz to determine the learning outcome. At last, a post-game survey was conducted after completion of the game, and we also spoke with them to get additional feedback.

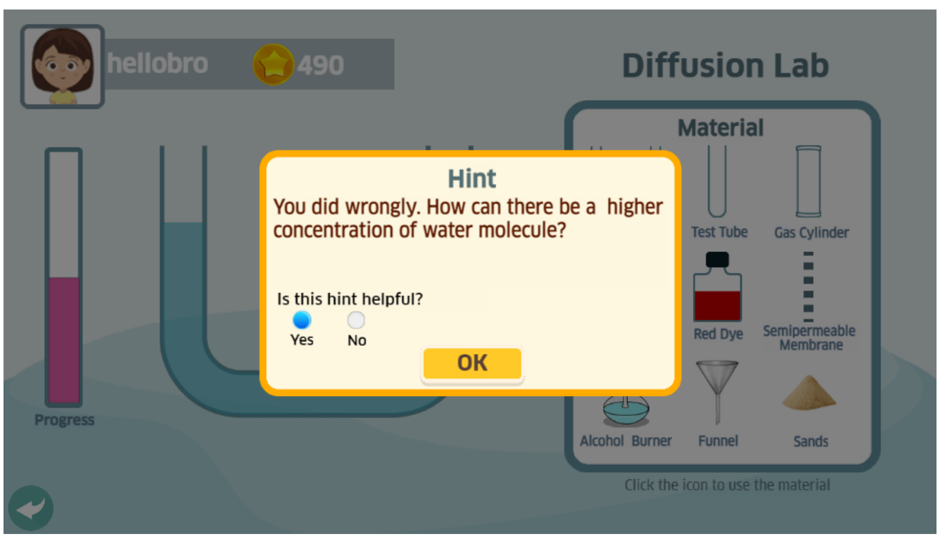


Figure 4.1: Diffusion experiment with personalized hints

Questions of post-game survey:

1. I prefer the game (The Uncharted Island) with personalized hints.

   A: agree B: disagree C: not sure
2. The game can help me understand the knowledge better.

   A: agree B: disagree C: not sure
3. The game is interesting enough.

   A: agree B: disagree C: not sure
4. Learning with playing such kind of games makes me feel better.

   A: agree B: disagree C: not sure

The purpose of the above post-game survey was to determine how beneficial the game was to learning. The more students who participated in the test, the more convincing the results will be. Testing involving human participants particularly requires a lot of time and resource. We have aggressively sought out participants, but there were not enough qualified candidates to invite in a limited time. Firstly, the knowledge of plant transport system is taught in the first year of secondary school science subject in Singapore, which limited our choice. The most suitable participants are those in their first year of secondary school, followed by students who are in Primary 6. Primary 4 students are not suitable participants, because the knowledge gap is substantial. Secondly, since the knowledge of diffusion and osmosis is not complicated, it's illogical to let senior students participate in the test. Lastly, it's not very convenient to arrange an on-site game experiment for young students in the COVID-19 period.

4.1 Result

Nine first year students of a secondary school participated in the game testing.

	agree	disagree	not sure
I prefer the game with personalization hints	7	0	2
The game can help me understand the knowledge better.	6	0	3
The game is interesting enough.	2	5	2
Learning with playing such kind of games makes me feel better.	6	1	2

Table 4.1: Survey result

The majority of students agreed that the game with personalized hints is beneficial to their knowledge comprehension and makes them feel better. Even if there is no personalization capability, a serious educational game should be an excellent teaching tool for young students. The personalization hints can give students better learning experience in the game. Nonetheless, it is evident that many students find that this game is not interesting enough. The learning content in the game is not substantial, hence the game's scenes is not sophisticated. We think this may diminish the enjoyment element in some way. According to the feedback we collected from students, the combination of the game and TmallGenie provides them a great deal of excitement and novelty, hence increasing their motivation to study within the game. According to the majority of students, they like the voice of TmallGenie, it sounds very much like a genuine person, which might provide learning companionship for young students.

In order to determine the learning outcome, the identical quiz was conducted prior and following the game, it consists of five osmosis and five diffusion questions. The participants performed the osmosis experiment without hints and the diffusion experiment with personalization hints within the game. By comparing quiz score, we aimed to determine whether the personalization hints facilitate learning in game. The Table 4.2 show the average score of quizzes.

Average score (total **5**)	Osmosis quiz (without hints)	Diffusion quiz (with hints)
Before game	1.67	1.78
After game	4.22	4.33
Score change	+2.55	+2.55
Normalized Learning Gain (NLG)	+0.766	+0.792

Table 4.2: Quiz score

After playing the game, the quiz score increases dramatically in both conditions, as shown in Table 4.2. There is no doubt that students can learn the knowledge while playing the game. The change in scores on the osmosis and diffusion quizzes are coincidentally identical. Using score change as a metric, we may conclude that the personalization hints in game did not improve the learning outcome. It would not be appropriate to utilize score change as a metric here, normalized learning gain (NLG) is widely used to measure the efficacy of alternative teaching methods in the education field.

The normalized gain was introduced by Hake in 1997, as a measure of change when same concept test is used to gauge student understanding at the beginning and again at the end of a course [32]. In our case, normalized learning gain is used to measure the change between a student's pre-quiz result and post-quiz result, which is illustrated in the following Equation 4.1.

$$NLG = \frac{Score_{post} - Score_{pre}}{Score_{max} - Score_{pre}} \qquad (4.1)$$

$Score_{max}$ is 5 in this case. Higher NLG indicates better efficacy. NLG for the method with hints is 0.792 in Table 4.2, which is slightly greater than the method without hints. Given the small NLG difference and the small sample size, we cannot conclude that the efficacy of personalization hints method is better.

While the outcome of NLG is neutral, the post-game survey yields good result. The survey questions focus primarily on student participants' overall feeling and ratings of the game, most students prefer the game with personalization hints. This positive feeling can also be contributed to the motivation of continue learning for students, which is a significant advantage.

4.2 Limitations of the result

There are some restrictions on the result. In particular, there were insufficient participants of this study. Given that hints are provided based on the characteristics of a single participant, it is essential to measure the participant's own feelings through a survey or interview. As we all know, a person's feelings or perceptions are not always 100 percent accurate; there can be occasional outliers. Insufficiency in participants may result in some result uncertainty.

Before and after the game, there are MCQ quizzes on the learning content. Due to the limited number of participants, we decided to have each participant test both the method without hints in osmosis and the method with hints in diffusion. Actually, the optimal method is to divide them into two testing groups, with one group playing the entire game without hints and the other group playing the entire game with personalized hints. If there are enough student participants, that will be a good setting.

And because the learning content is simple, the quizzes are unable to distinguish the learning outcome with precision. The majority of students may get a full or near-full score on the post-quiz with or without personalization hints, indicating that we were unable to fully utilize this indicator. It is difficult to overstate the importance of extensive learning content.

4.3 Limitations of Work and Future Work

The game design is straightforward. In the diffusion and osmosis virtual lab, not many actions are necessary, which minimizes the difficulty and enjoyment of the game. Consequently, the majority of students found the game to be uninteresting. There is insufficient learning content in these two scenes. If there is adequate learning content, game settings will be more adaptable.

The hints in the hint library were prepared by a knowledgeable individual or teacher. However, the quality of the hints is not guaranteed, and the individual must be familiar with the knowledge content and hint strategy. It will take a great deal of time if the game's learning content is excessive. For future work, an intelligent automatic mechanism for generating final hints should be devised. Natural Language Processing (NLP) appears to be a worthwhile field of study, as it is already commonly utilized to generate text. The task should not be easy too, as the NLP engine requires a deep understanding of the player's characteristics and game content.

The Uncharted Island has not utilized TmallGenie to its full capacity. TmallGenie supports a limited number of voice kinds; however, it would be easier to create rapport with learners if a voice could be intelligently selected or suggested to match the learner's personality, as people have varied preferences for voice types. If TmallGenie can ask the proper question to the learner at the right time, it can help students learn more effectively and increase their motivation and interest. It should also be explored how to select the question and when to ask it.

The only input for the RL process in the game is the game state. In the future, other features, such as player gender, learning style, learning ability, and knowledge level, can be added to input. This will increase the usefulness of generated hints and allow for a more personalized learning experience for learners.

Chapter 5

Conclusion

This thesis proposes an intelligent approach to generate personalized hints to help students' learning in a serious educational game. Combining games and the TmallGenie Smart Speaker can make learning more entertaining and construct companionship for children learners. With the reinforcement learning technique employed in the game, generating hints becomes easier and faster, and this framework is also applicable to other educational games based on experiments. The learning style was adapted to personalize hints in order to construct a hint library that can select the most appropriate hints for the learner in any given situation. Students can finally gain knowledge in a more personalized way by playing the educational game, which achieves education through entertainment.

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Appendix A

Questionnaire on Index of Learning Styles

Please fill in the following form and Index of Learning Styles Questionnaire, your response data and learning style profile are not stored or sent to anyone other than you.

Game ID (Auto Generate): _________________

Gender (F/M): ________________

Birthdate (YYYYMM): _____________

Email: ________________

Before playing the game, the system needs to estimate your learning style by the questionnaire. You may only choose one answer for each question, and you must answer all questions before you can submit the form. If both answers to a question seem to apply to you, choose the one that applies more frequently throughout all your courses.

1. I understand something better after I _____

    A: try it out.   B: think it through

2. I would rather be considered _____

    A: realistic.   B: innovative

3. When I am learning something new, it helps me to _____

    A: talk about it.   B: think about it.

4. If I were a teacher, I would rather teach a course ______

    A: that deals with facts and real life situations.

    B: that deals with ideas and theories.

5. In a study group working on difficult material, I am more likely to _____

    A: jump in and contribute ideas   B: sit back and listen

6. I find it easier ________

A: to learn facts. B: to learn concepts.

7. In classes I have taken ________

A: I have usually gotten to know many of the students.

B: I have rarely gotten to know many of the students.

8. In reading nonfiction, I prefer _________

A: something that teaches me new facts or tells me how to do something.

B: something that gives me new ideas to think about.

9. When I start a homework problem, I am more likely to _______

A: start working on the solution immediately.

B: try to fully understand the problem first.

10. I prefer the idea of ______

A: certainty. B: theory.

11. I prefer to study ______

A: in a study group. B: alone.

12. I am more likely to be considered _______

A: careful about the details of my work. B: creative about how to do my work.

13. I would rather first _______

A: try things out. B: think about how I'm going to do it.

14. When I am reading for enjoyment, I like writers to ________

A: clearly say what they mean. B: say things in creative, interesting ways.

15. I more easily remember __________

A: something I have done. B: something I have thought a lot about.

16. When I have to perform a task, I prefer to _________

A: master one way of doing it.   B: come up with new ways of doing it.

17. When I have to work on a group project, I first want to _______

A: have "group brainstorming" where everyone contributes ideas.

B: brainstorm individually and then come together as a group to compare ideas.

18. I consider it higher praise to call someone ________

A: sensible.   B: imaginative.

19. I am more likely to be considered __________

A: outgoing.   B: reserved.

20. I prefer courses that emphasize _________

A: concrete material (facts, data).   B: abstract material (concepts, theories).

21. The idea of doing homework in groups, with one grade for the entire group, _____

A: appeals to me.   B: does not appeal to me.

22. When I am doing long calculations, ________

A: I tend to repeat all my steps and check my work carefully.

B: I find checking my work tiresome and have to force myself to do it.

Thank you for completing the survey!

Appendix B

Some Scenes of Uncharted Island

Figure A.1: Scene of creating character

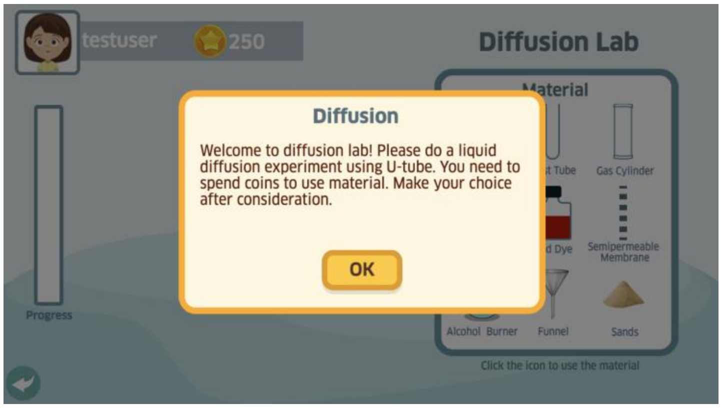

Figure A.2: Introduction dialogue in diffusion lab

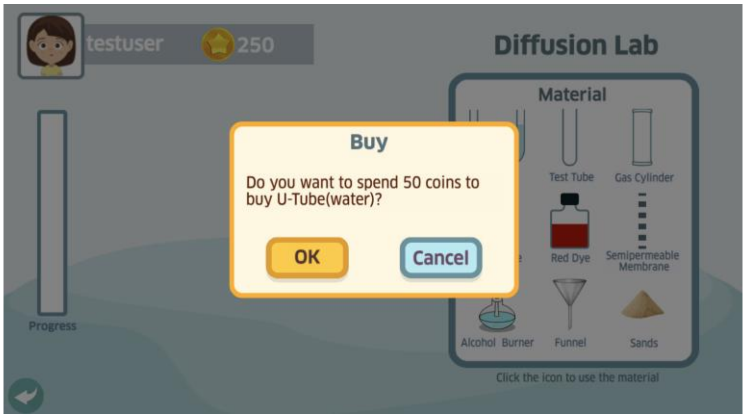

Figure A.3: Buying dialogue in diffusion lab

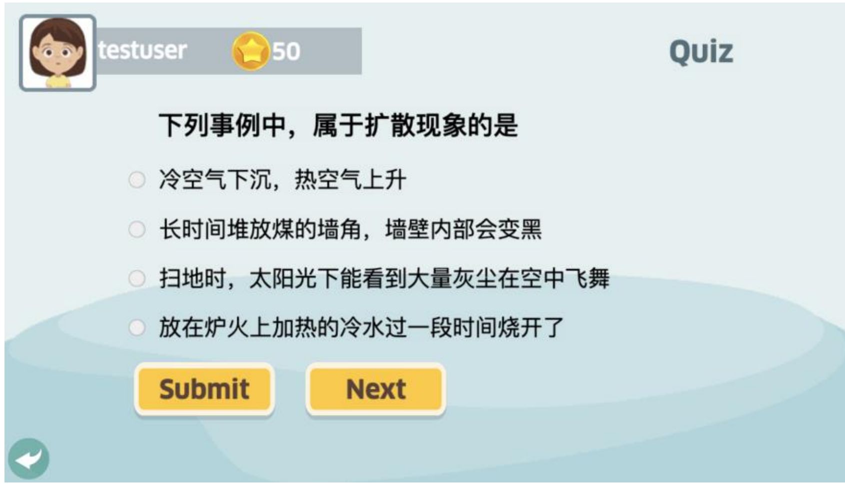

Figure A.4: Quiz page in Chinese version game

Figure A.5: Knowledge tree page in Chinese version game