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Adaptive Virtual Assistant for Virtual Reality-based Remote Learning

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Abstract

This research describes the development of an adaptive virtual assistant in an immersive virtual reality (VR) serious game aimed at teaching engineering students manufacturing concepts. For undergraduate manufacturing education, students need to learn product design and manufacturing systems that require well-coordinated analysis of requirements and hands-on practices in complex manufacturing assembly lines. While it is often not feasible and practical for students to participate in real factory environments, simulations are created to offer a flexible alternative of digital learning. With the advancements in immersive technologies, VR opens new opportunities for teaching and learning manufacturing, and enables remote learning from any physical location. In this research, we describe the elements of a serious game built using the Unity game engine with VR technology that allows students to practice the concept of craft production.

Prior research has shown that adapting learning material to suit individual student needs increases motivation and student successes. While learning remotely using an immersive virtual environment, a student is often working in an independent manner. Seeking help often requires the student to leave the virtual environment and break immersion. In this research, we propose an adaptive virtual assistant in the game environment to support the student learning process. By tracking student actions in the game environment and building a model of the student using reinforcement learning, the virtual assistant can learn and adapt to the student's preference in the types of assistance to provide. We show the adaptation of the virtual assistant through simulated experiments of typical student preferences.

1. Introduction

The current educational system is facing many barriers for students in diverse socioeconomic backgrounds (e.g., the unequal distribution of academic resources in different regions, limited accessibility to in-person academically diverse education due to physical or financial reasons) [1]. Providing accessible and more affordable education opens the door for many students. Remote learning that bridges these barriers together with virtual reality (VR) technology is well suited for providing an immersive learning experience for students in need. VR has many advantages for learners, including a completely immersive experience without disruptions and real-time simulations of environments beyond the traditional classroom setting.

In this research, we explore VR-based remote learning in the context of a manufacturing environment for engineering students. Familiarity with manufacturing environments is an essential aspect for many post-secondary engineering students. These students need to learn product design and manufacturing systems that require well-coordinated analysis of requirements and hands-on practices in complex manufacturing assembly lines. However, such environments in the real world are often difficult to access for students, and creating them in an educational institution is expensive and needs various resources that not every institution can afford. For this reason, simulated physical environments where the process is approximated using scaled-down representations are usually used in education. However, such physical simulations alone may not capture all the details and flexibilities of a real environment. Therefore, a simulated VR environment is well suited for this learning purpose.

We integrate VR, gamification with reinforcement learning to provide a holistic remote learning experience. We create a VR learning environment simulating a manufacturing paradigm called craft production. The VR learning environment is built in the Unity game engine with the Oculus Rift S VR system for navigation and motion tracking. In the VR environment, students see through the headset a factory composed of a series of workstations. For the task, students are asked to design and assemble toy cars using plastic components. A set of customer requirements are given to the students that they should satisfy. Finding the most effective solution becomes a part of this problem-solving task. The learning environment is further enhanced with gamification. To better support students in this learning process, we design a virtual assistant who acts as the student's partner in the tasks. The virtual assistant is driven by a reinforcement-learning-based AI and adapts to the student's various needs for assistance.

2. Relevant Literature

2.1 Virtual Reality

VR has emerged as a modern technology that simulates the real-world experience in an immersive virtual environment. This is combined with the advances in computational power and the maturation of game engine technologies, allowing students to interact with virtual objects in ways never possible before. Therefore, VR can serve as an enabling tool to mimic the physical learning environment. While researchers have examined VR usage in educational settings ever since its invention [2], much more research is needed in specific subject areas [3]. A virtual environment built in VR is flexible to changes in manufacturing systems, thereby providing students with the ability to learn manufacturing technologies hands-on, from anywhere they have access to VR devices [4]. Past research has shown the success of VR in engineering education such as the training of the reconfigurable manufacturing system, a prominent concept of Industry 4.0 [5], manual assembly process [6], industrial additive manufacturing [7], and team-based manufacturing [8].

2.2 Gamification

An advantage of using games for education is interactivity. Digital video games have been used in educational settings for the purpose of learning [9], training [10], assessment [11], and experience [12]. Using games for education promotes interactivity, engagement and increases motivation [13]. Gamification has also been shown to have a positive effect on the response rate of user feedback [14]. This fast-growing trend is aided by the vast improvement in hardware capable of rendering increasingly realistic and high-definition virtual environments. Through the use of VR technology, users are able to experience learning environments that were never before possible. Because virtual environments are interactive and the content of these virtual environments can be changed and adapted as the user is going through them, researchers can utilize this to explore the full advantages of digital learning supported by artificial intelligence (AI).

2.3 Reinforcement Learning

Reinforcement learning is an area of AI where an AI agent learns and adapts based on feedback it receives from performing actions. It iteratively improves its own model based on the feedback in the form of positive and negative numerical rewards.

Reinforcement learning has become a huge topic of recent gaming research [15]. AlphaGo and its successors [16] have achieved worldwide fame. Pinto and Coutinho [17] designed and evaluated a fighting game combining reinforcement learning with Monte Carlo tree search. Florensa et al. [18] used reinforcement learning to tackle the circumstance where there was a need for an agent to perform multiple tasks. In their paradigm, tasks were generated automatically, and the reinforcement learning agent automatically learned and performed those tasks. More recently, Hare and Tang [19] deployed reinforcement learning in a learning game to select different sections based on player knowledge.

3. Research Methodology

The proposed research develops a gamified VR learning environment together with a virtual assistant to enhance student understanding of manufacturing concepts. A learning environment is first developed to simulate a manufacturing system where students can assemble toy cars with plastic components. Second, this VR learning environment is enhanced with gamification elements, including a tutorial, scoring, levels, and scoreboard. Third, a virtual assistant is created to be the student's helper on the tasks. The virtual assistant can learn to adjust to the student's preferences on the amount and types of assistance. We evaluate the effectiveness of the virtual assistant by running experiments on simulated scenarios of student preferences, demonstrating how the virtual assistant effectively adapts its behavior according to students' feedback.

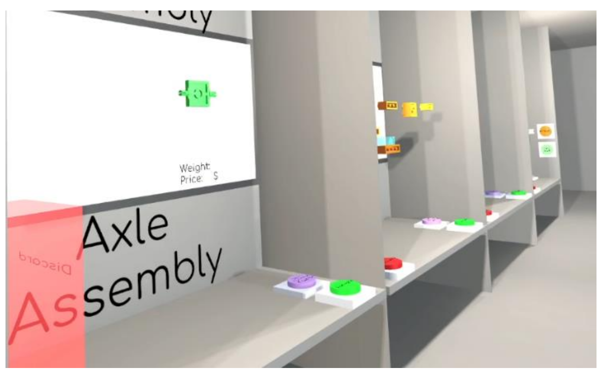


Figure 1. Side-by-side workstations in a VR learning environment. Each workstation allows for the assembly of certain car parts, such as axle, sides, or wheels.

3.1 VR-based Manufacturing Learning Environment

In this research, a VR learning environment is developed to help engineering students gain hands-on training on manufacturing craft production concepts. The VR learning environment was built in the Unity game engine and worked with the Oculus Rift S VR headset and wireless controllers for navigation and motion tracking. Through the headset, students were presented with a virtual environment with a series of workstations (Figure 1). They were able to interact with the virtual environment and objects with wireless controllers.

The goal of this learning environment is to provide hands-on training to engineering students grasping craft production concepts. The task given to students involves the assembly of toy cars according to a set of customer requirements as shown in Figure 2. Students need to minimize the total cost of car toy assembly while satisfying customer requirements, such as weight requirements, and cycle time (total time to completion) requirements. The assembly task consists of four main functions: design, sourcing, manufacturing, and inspection. An example completed car is shown in Figure 3.

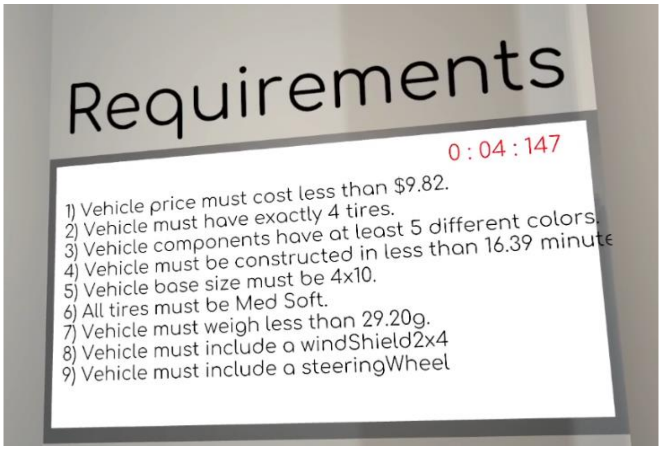


Figure 2. Example customer requirements for the toy car assembly.

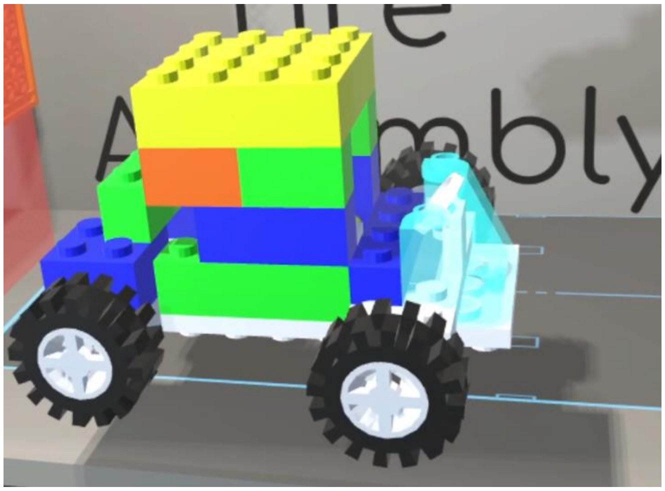
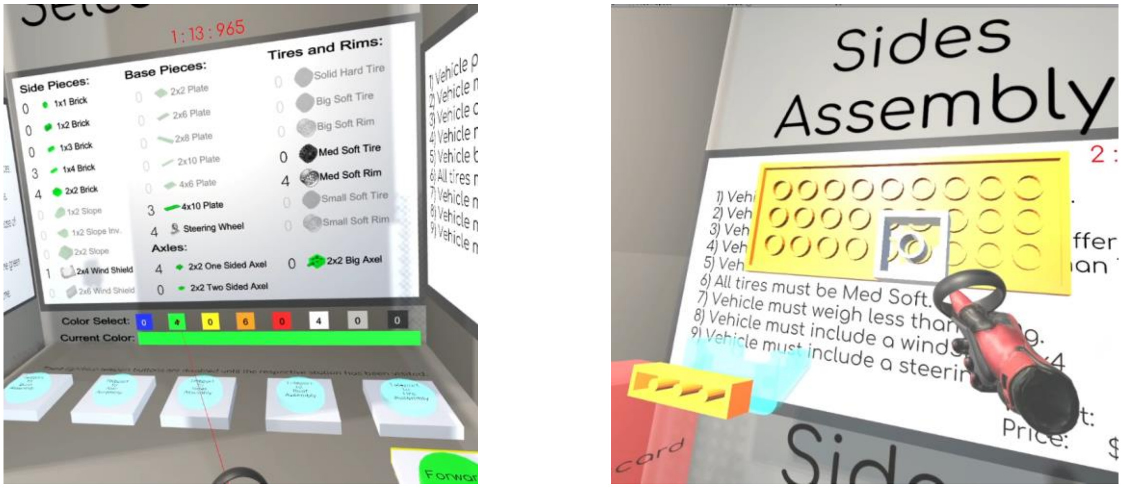


Figure 3. Example completed toy car.



(a) (b)

Figure 4. Example workstations in VR learning environment. (a) The component selection station. (b) The sides assembly station showing a student's virtual hand manipulating plastic components.

Table 1. A list of workstations and the corresponding tasks.

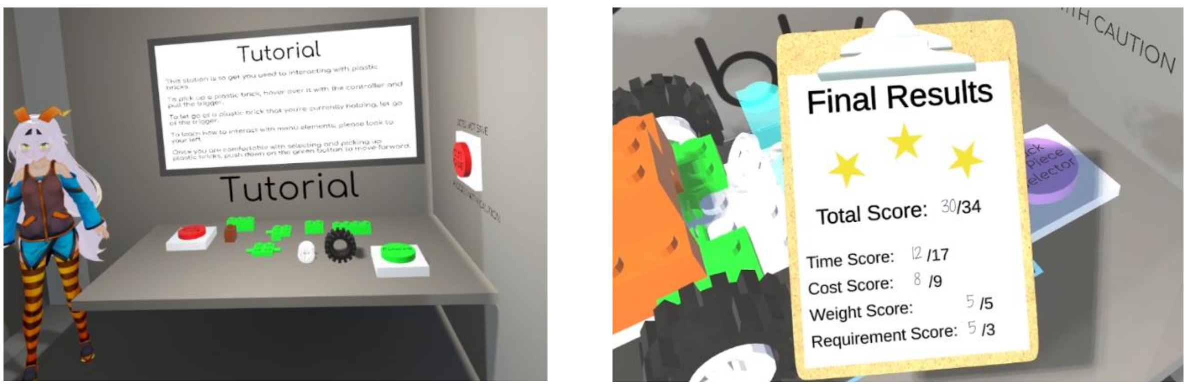
Workstation	**Task**
Requirement	Student is given the requirements
Component Selection	Student picks the components for car assembly based on requirements
Base Assembly	Student assembles the base of the car
Axle Assembly	Student assembles the axles of the car
Sides Assembly	Student assembles the sides of the car
Roof Assembly	Student assembles the roof of the car
Tire Assembly	Student assembles the tires of the car and completes the assembly process

Once the students enter the VR learning environment, a virtual assistant provides instructions on how to interact with the virtual environment. There are seven workstations in the VR learning environment (Table 1). The requirement station is the first workstation where students are shown a set of customer requirements (see Figure 2). After understanding the customer requirements, students move to a component selection station (see Figure 4 (a)) and select the components by pointing at them and pressing a button on the wireless controller. Each selected component appears in subsequent assembly stations. While students can come back later and choose other components, selecting the correct components requires students to understand the design aspects of craft production. Students can complete the assembly process by going into the base, axle, sides, roof, and tire assembly workstations. Figure 4 (b) shows the sides assembly station with some chosen components. Students can switch between seven workstations during the assembly process, but frequently switching the workstations is not an effective method to solve the problem, and students need to take into account the limit on cycle time.

3.2 Interactive Gamified Learning

Gamified elements are added to the virtual learning environment to provide an engaging experience. Common game elements include scoring, game levels and leaderboards [20]. These elements provide feedback on player performance in the tasks. Games also deploy tutorial game levels so that players can start playing without having to read instruction manuals.

A tutorial game level is commonly used in games as an introduction to the game mechanics, where players are asked to perform simple tasks under the guidance of the game world itself. The tutorial level allows players to learn how to play the game and get familiar with the game mechanics without facing the pressure and challenges of a regular game task. This is especially important for us since our target audience, undergraduate engineering students, may not be familiar with using VR. Using a similar concept, we created a tutorial workstation as the starting point of a task. In the tutorial workstation as seen in Figure 5 (a), a virtual assistant provides instructions to the student on how to navigate in VR using the controller on their hands, how to pick up a component, and how to use buttons to go to different workstations. This provides an opportunity for students who are unfamiliar with VR in general to get used to the VR mechanics.



(a) (b)

Figure 5. (a) The tutorial station with a virtual assistant teaching the student how to use VR. (b) A scoring card is provided to the student upon completion of the task.

We created a scoring system for the manufacturing assembly task. Figure 5 (b) shows a scoring card when a student completes a task. The scoring card provides scores on different measures depending on the requirements given, and one to three stars based on the total score. This provides feedback in a format that is not alienating to the student, while encouraging students to improve their skills.

In terms of game levels, we created nine levels of difficulties in our learning environment in order to provide a natural learning progression. These can be selected from the starting screen (Figure 6). Our level design follows the design principle of flow channel [21], where the challenge level of the game increases proportionally with respect to the player’s skills. The first level of the learning environment starts with three requirements that the player must fulfill, and the number of requirements gradually increases as the player completes each level. The player must take additional manufacturing concepts into consideration each time the player moves on to the next level, completing the next task.

Finally, a leaderboard exists on the starting screen, where students can see the top scores achieved by any student at each level, and their own best score at each level. This gives students a sense of accomplishment in achieving top scores, and a motivation to improve their scores.

Figure 6. The starting screen of the VR environment. A leaderboard showing the top scoring students is displayed on the left, and the level selection panel is displayed on the right.

3.3 Adaptive Virtual Assistant Interface

The VR immersive learning environment has pros and cons. One study shows that working in VR increases loneliness [22]. This is perhaps not surprising since the student is immersed in the virtual environment, which is completely detached from the rest of the world. If the student encounters a problem or would like to receive some help, it is difficult to get help in VR. Normally, the student would have to break immersion, take off the VR headset, and then seek help. To address this challenge, we implement a virtual assistant inside VR. As a student works on the tasks, the virtual assistant is standing by to support the student. The virtual assistant can support students by providing hints and reminders.

The purpose of the virtual assistant is to help the student as the student completes the problem-solving task. The assistance materializes in the form of on-screen text provided to the students at various decision points during the task. Support from the virtual assistant can be categorized into two categories, hints and reminders. Hints can be generated when students make mistakes in the tasks, such as when an obvious wrong plastic component was chosen for a task. A reminder can be generated when a student is at risk of failing to achieve a requirement, such as when the toy car being assembled is getting close to the maximum weight allowed. Since our requirements are generated automatically with some randomness each time a student starts a task, hints and reminders must also be created according to the current set of requirements. We set a β-threshold for each numerical requirement. When the threshold is reached, a decision point is triggered. An example numerical requirement is “weight must be less than 30g.” With β set to 0.9, the threshold is reached when the current weight of the toy car reaches 27g (0.9 x 30g). A decision point is triggered when certain conditions in the current task are satisfied (e.g., when 75% of the time limit has passed, a reminder decision point is triggered), or when the student explicitly turns and looks to the virtual assistant for help.

Figure 7 shows an example interaction between the virtual assistant and the student. The hint from the virtual assistant appears as a text bubble on top of the virtual assistant, and the controller on the student's hand turns into a wheel with four possible responses. The student can select a response and then continue with their task. The student can also simply turn away from the virtual assistant without responding, and the response wheel will disappear.

Figure 7. Example interaction between the virtual assistant providing a hint, and the student selecting a response.

The responses "This Was Helpful" and "This Was Unhelpful" provide the feedback on this specific hint or reminder, while the responses "Show Me More!" or "Show Me Less" allow the virtual assistant to learn the student's preferences using reinforcement learning, as described below.

Because of the differences in student background knowledge and preferences, having the right number of hints is important in helping the student along while not being intrusive. The virtual assistant must make the decision on whether to show a hint to the student or not, or which hint is shown, when a decision point is triggered.

3.4 Adaptive Virtual Assistant AI with Reinforcement Learning

One important aspect of the virtual assistant is the ability to adapt to different student needs. Some students are confident in completing the tasks that constant interruptions by the virtual assistant would be a disruption. Other students may require more help as they are still learning the new concepts and figuring out how to utilize these concepts in problem-solving tasks. Therefore, the virtual assistant must be able to recognize student feedback (or the lack of feedback), and adapt accordingly. While prior research such as Zhao et al. [23] has proposed using player modeling, we deploy reinforcement learning to effectively accomplish this goal.

Reinforcement learning is an area of machine learning where an AI agent is not told what to do and has to discover the appropriate actions to maximize a notion of a numerical reward. In reinforcement learning, there are a set of world states $s \in S$, a set of actions $a \in A$, an unknown reward function R(s,a) → r that outputs a reward *r* for each state *s* and action *a*, and an unknown state transition function T(s,a) → s' that takes a state *s* into the next state *s'*. The goal of reinforcement learning is to discover a policy, which is a mapping from states to actions that maximizes the expected future reward.

We deploy Q-Learning [24], a common reinforcement learning algorithm where the agent keeps state-action values Q(s,a) and uses these values to choose the best action to take in each state. The Q(s,a) values are updated through a trial-and-error process and the action with the highest Q(s,a) value is considered the best action to take. Often the state space is large and explicitly storing Q(s,a) values in tabular form is not feasible. Therefore, approximation methods, ranging from linear combinations to deep convolutional neural networks have been used to approximate Q(s,a). Since we aim for effective adaptation, we deploy Q-Learning with linear approximation on the virtual assistant. Our reward values range from -5 to +5 (Table 2), and there are three actions to the virtual assistant: provide a hint, provide a reminder, and stay silent.

Table 2. Actions from a student, its corresponding reward given to Q-Learning, and the rationale behind each reward.

Student action	Reward given to Q-Learning	Rationale
Student responds to the hint/reminder by selecting "Show me more!"	+5	Explicit responses result in the largest positive reward
Student responds to the hint/reminder by selecting "Show me less"	-5	Explicit responses result in the largest negative reward
Student looks at the hint/reminder for more than 2 seconds and turns away without a response	+3	No explicit response, but student reads what the assistant provides
Student looks at the hint/reminder for less than 2 seconds and turns away without a response	-3	No explicit response, and student did not read what the assistant provides
Student ignores the provided help	-2	Student does not want to interact with assistant
Student does not look for help when the assistant remains silent	+3	Student does not want to interact with assistant and assistant correctly remains non-intrusive
Student looks for help when the assistant remains silent	-3	Student wants to interact with assistant

4. Experiments and Results

We evaluate the virtual assistant by running experiments with a set of simulations representing different typical student responses and analyzing the results. The results show that the virtual assistant successfully adapts to the responses of these hypothetical student behaviors. We experimented with the follow typical student preferences:

1. Student prefers hints and reminders from the virtual assistant
2. Student prefers to receive hints, but not reminders

3. Student prefers no help from the virtual assistant
4. Student starts with one preference, but changes to a different preference

For each type of preferences, we created a simulation where an AI-controlled student responded to the virtual assistant according to the chosen preferences. We performed the simulation five times per preference and recorded the Q(s,a) values that determined the behaviors of the virtual assistant.

Figure 8 shows the result of a simulated student who is receptive to the help provided by the virtual assistant. This student always provides the response "Show me more!" to hints and the virtual assistant learns to be helpful. The y-axis shows the average Q(s,a) value of each action over five simulated experiments – in each experiment, the action with the highest Q(s,a) value is chosen by the virtual assistant at each decision point. The Q(s,a) values are random at the beginning. We can see that the Q(s,a) values for "provide hints" and "provide reminders" quickly go up, indicating that the virtual assistant is choosing the actions to either provide hints or reminders whenever possible.

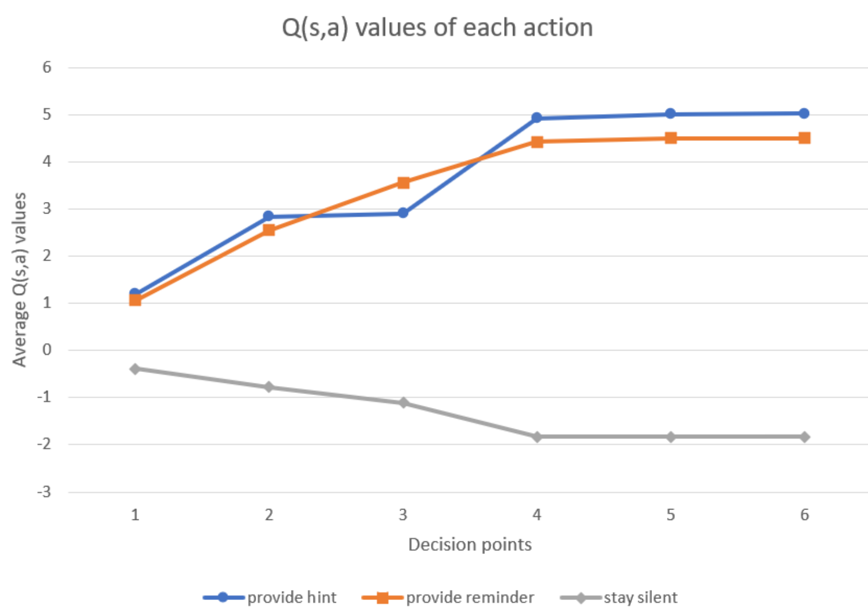


Figure 8. Learned Q(s,a) values of each action over 6 decision points where the simulated student is receptive to help.

Figure 9 shows the result of a simulated student who is not receptive to reminders, but would still like hints provided by the virtual assistant. We see that the assistant quickly learns to only provide hints (high Q(s,a) values), not reminders (low Q(s,a) values).

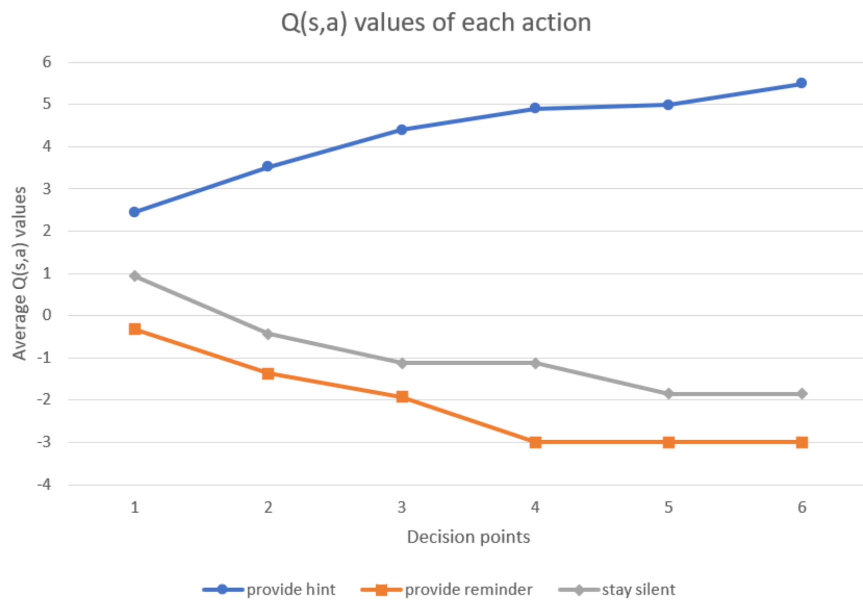


Figure 9. Learned Q(s,a) values of each action over 6 decision points where the simulated student is receptive to hints, not reminders.

Figure 10 shows the result of a simulated student who is not receptive to the help provided by the virtual assistant. This student always ignores any help provided by the virtual assistant, and the virtual assistant quickly learns to not disturb the student. The action with the highest Q(s,a) value is "Stay silent."

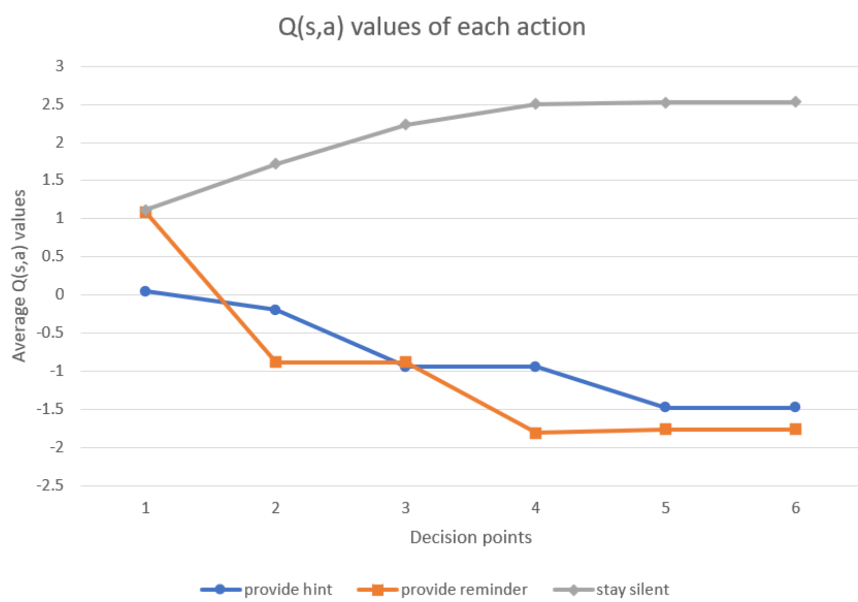


Figure 10. Learned Q(s,a) values of each action over 6 decision points where the simulated student is not receptive to help.

Figure 11 shows the adaptivity of the virtual assistant. This student responds with "Show me less" in the first game level, causing the virtual assistant to stop providing help, and then responds with

“Show me more!” in the second game level. This could be due to the fact that the second level is more difficult, resulting in the student requiring additional help. In this simulated scenario, we assume 10 decision points are triggered during the first level. We can see that the virtual assistant quickly learns to start providing help during the second level when the student’s behavior changes.

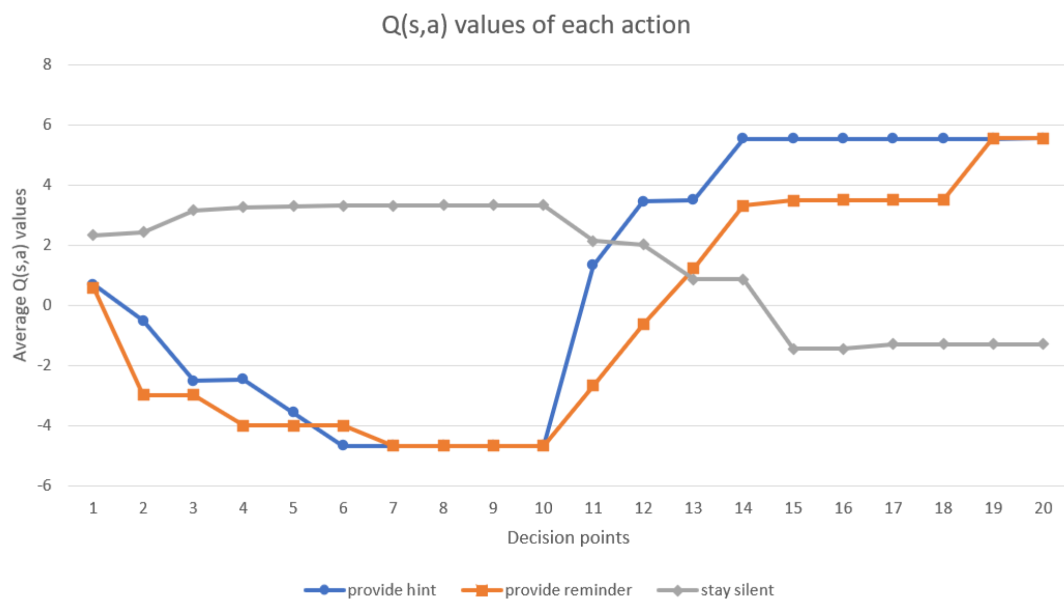


Figure 11. Learned Q(s,a) values of each action over 6 decision points where the simulated student is not receptive to help during the first 10 decision points, but changes mind to ask for help.

5. Conclusions

In this research, we developed a VR remote learning environment to perform tasks in a manufacturing craft production scenario. Remote learning environments can be integrated into course curriculums and provide hands-on training to engineering students, allowing them to apply their knowledge from any location away from the classroom.

We integrated gamification with reinforcement learning-based adaptive virtual assistant who can provide help as students complete the problem-solving tasks. By tracking student actions in the game environment and building a model of the student using reinforcement learning, the virtual assistant can learn and adapt to the student’s preference in the types of assistance to provide. We showed the adaptations of the virtual assistant through simulated experiments of different hypothetical student responses. Experimental results showed that the virtual assistant effectively adapts to student preferences, whether the student requires lots of help in completing the tasks, little help in completing the tasks, or changes their needs mid-way. An adaptive virtual assistant is an innovative method to support student learning in a remote VR environment where other forms of help are not readily available. Adaptive virtual assistants can be deployed in many types of learning environments for different subject areas.

Our future work will focus on improving the virtual assistant to work in more complex environments. The ultimate goal is to create a virtual assistant that can act as a partner to the student in the VR environment, enabling a collaborative group environment. Collaborative problem-solving, working alongside a partner to solve a problem, is an important transferable skill. We also plan to recruit engineering students to participate in user studies and collect their actions, responses, and feedback on the adaptive virtual assistant for further analysis.

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