A Personalised Virtual Reality Learning Environment

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July, 2024

Submitted in partial fulfilment of the requirements for the degree of Master of Science in Artificial Intelligence.

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Acknowledgements

First and foremost, I would like to thank my supervisor Professor Matthew Montebello for providing the guidance, knowledge, and feedback required to make this dissertation and its research possible. I am also grateful to all the researchers whose work is referenced in this dissertation, as their work provided an excellent basis for my own.

Additionally, I am extending my gratitude to my family members, especially my parents for their support and care throughout my studies. This dissertation would not have been possible without them.

Finally, I would like to thank all those who contributed towards the dissertation in any way, be it through direct participation in the user evaluation sections of this dissertation, or through any feedback and support. Your time and contributions, whether big or small, allowed for this dissertation to reach its finalised state.

Abstract

This dissertation looks into using Artificial Intelligent (AI) environment customisation and recommendation and applying it to Virtual Reality Learning Environments (VRLEs) to provide a greater understanding of how this type of AI can be implemented to make VRLEs more enjoyable and personalised experiences.

Personalisation can provide many benefits in an educational process, and as such, the study and usage of systems that can automatically adjust VRLE experiences to meet preferences at an individual level, could contribute towards making future versions of Virtual Learning Environments (VLEs) more engaging and satisfying places for those using them in education.

An important part in achieving the goals of this dissertation is the production of a demo that leverages Machine Learning (ML) to change the features of a VRLE environment, specifically a VR classroom environment, and align them with individual users' preferences. This is made possible through the use of Reinforcement Learning (RL) techniques which involve taking user feedback for each VR classroom design and converting it to rewards for an RL agent. The feedback and the current state of the VR classroom is then used to generate a Learner Profile corresponding to the individual user that can be used to improve future educational experiences.

In order to evaluate the effectiveness of this demo, two implementations have been produced, one where there is no form of VRLE customisation, and one where the customisation is AI agent-based. This allows for a baseline of data points to compare and contrast with. There is currently a lack of robust standards on how to gather data points and evaluate metrics regarding user experiences in VRLEs, hence this dissertation borrows and adapts evaluation strategies from the educational games sector to address this point.

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List of Abbreviations

The following list defines the abbreviations and acronyms that are used in this paper:

1. Introduction

1.1 Motivation

As technology advances, the benefits it can provide to other fields grow with it. One such example is the use of Virtual Learning Environments (VLEs) in the educational sector. VLEs are already commonplace amongst many educational institutions but there are many aspects of them that can be built upon to make them more engaging places [1]. In the case of VLEs, a boost in engagement would mean students are spending more time in an educational environment and building a more positive association with education [2]. As such, making use of Artificial Intelligence (AI) technologies to increase user engagement in such virtual environments is a case worth looking into. This paper looks into doing so through making use of AI technologies to personalise these environments and therefore match the preferences of users on an individual level.

The type of VLEs targeted by this paper are Virtual Reality Learning Environments (VRLEs). These are VLEs that exist within Virtual Reality (VR) spaces. VR itself is a technology that has been found to increase user engagement [3], meaning there could be significant benefits reaped from progressing educational VR technologies. Additionally, whilst VR is often still considered a niche, it has seen plenty of growth in recent years and even massive investment from some of the largest technology companies such as Meta and Apple. This is due to the potential VR technologies have when it comes to playing an integral role in how people of the future interface with technology. Unfortunately, despite this growth and investment, there is still a relatively small amount of research on VRLEs themselves, meaning their potential is still very much untapped, despite all that they could offer. As such, furthering research and experimentation with AI technologies in this domain is imperative as it could have a dramatic impact on how engaging and intuitive VRLE environments are once VR technologies become more integral to daily life.

1.2 Proposed Solution

This dissertation looks into the effects that combining AI based customisation and VRLE systems can have on user engagement. This is achieved through a piece of software that makes use of AI technologies to customise a VRLE environment to tailor the experience to students on an individual level. The software is then used to investigate how users react to different parts of the experience.

The main AI technologies leveraged by this paper in order to solve these problems are those of Reinforcement Learning (RL) agent-based environment customisation and Learner Profiling. In this system RL agents make use of student/user feedback to determine how the virtual environment should be personalised. The users are prompted with a feedback section at the end of every VRLE session, and the data collected from this is used to generate the reward value for the RL agent. This allows the RL agent to develop an understanding of the preferences of individual users as they spend more time in the VRLE, and therefore get better at personalising the VRLE environment for individual users.

The same user feedback, along with the state of the VRLE and RL agent, is stored and used to generate Learner Profiles. Each user has a Learner Profile associated with them, and the contents stored in these are easy to adjust. Learner profiling in this way not only allows for educators to get a better insight into their students, but also provides data that can be useful for implementing additional layers of educational content recommendation in the VRLE setting, which could further boost educational engagement and satisfaction.

The RL agents mainly focus on customisation and alteration of the 3D virtual environment itself, meaning a method of representing the state and action space to the agent needed to be developed. Additionally, several evaluation strategies have been implemented or adapted from other fields with more robust evaluation standards. Both quantitative and qualitative results have been deemed valuable in the insight they can provide for this dissertation and any future work in AI enhanced VRLEs, and as such processes to collect both have been leveraged.

1.3 Aim and Objectives

The main aim of this project is the development and evaluation of an AI tailored VRLE classroom that provides insight into how VRLEs can be made more engaging places for end users through the use of AI agent-based personalisation. To reach this aim, the following set of objectives have been defined. To reach this aim, the following set of objectives have been defined. They are an important factor in guiding the scope and evaluation of this paper.

- O1 - Set up a customisable learning environment that is accessible through the use of VR Technologies.
- O2 - Implement an RL agent that is able to alter the environment to match user preferences based on user feedback.
- O3 - Generate and fine tune Leaner Profiles that can be employed for educational content recommendation.
- O4 - Investigate the effects that a VRLE making use of RL agent-based environment customisation has on a user satisfaction and engagement.
- O5 - Propose recommendations and best practices based on which elements of the custom VR environments had the greatest effect on the users.

1.4 Summary of Contributions

This dissertation has contributed towards the area of AI in Education in at least four distinct ways where AI and VRLE technologies intersect. The first major contribution is related to the software developed in association with this dissertation. It takes the form of a VRLE classroom where an AI agent is able to change the environment to tailor the design for individual users. Such an implementation is the first of its kind and promises to further project the use of AI within the VLE by employing VR.

The software also includes a flexible learner profile system, the second major contribution, where files storing information on each user can be generated. By default the information gathered relates to user preferences regarding the AI environment customisation and AI agent, however the implementation was designed to be adjustable so that developers could adjust and fine tune them to account for their datasets and needs. This dissertation includes a breakdown of how this can be done. The source code for the VRLE implementation is already being used by other research projects in the same field.

The third contribution is implemented within the VRLE, whereby a system was proposed and implemented, referred to by this dissertation as the CCID system. This is a methodology for labelling and representing the state space of potential classroom designs to an AI agent. This dissertation leverages this system to represent 256 classrooms, however with the right adjustments this system can be adapted to support significantly larger state spaces.

There is a lack of standardisation regarding evaluation approaches for measuring engagement and satisfaction within the field of VRLE research. Therefore, the fourth contribution relates to the proposal and usage of a more standardised evaluation system based on research done in the field of educational games. This evaluation system has been documented in this dissertation to allow for ease of replication and comparison of results by other studies.

This dissertation brings these four contributions together while investigating the benefits and downsides of AI agent-designed classrooms, and has developed guidelines on how they can be implemented in the future to boost user engagement and satisfaction even further.

1.5 Document Structure

The structure of this research paper is broken down as follows:

- The first chapter is a standard overview of the whole project that sets the objectives of the paper.
- The second chapter is a breakdown of the technologies that are most relevant to this project, as well as a look into and critique of related works and how they used these technologies.
- The third chapter describes the methodology used by this paper, describing the approach taken during development of the VRLE and AI software designed for this project. Evaluation methodology is also discussed in this chapter.
- The fourth chapter contains a breakdown of the different types of results collected regarding this dissertation's software. Each type of results gathered is split into distinct sections.
- The fifth chapter contains an evaluation of the results of the prior chapter and discussion of the implications.
- The sixth and final chapter includes any final remarks regarding this dissertation. The aims and objectives are revisited, with limitations encountered being discussed to help facilitate future or follow up studies.

2. Background & Literature Overview

2.1 Virtual Reality Learning Environments

2.1.1 VLEs vs VRLEs

VLEs are educational environments that exist in a digital space with the goal of providing enhancements to the learning experience [2]. They can be used to offer many types of educational services such as providing access to student resources and assignment pages, giving recommendations on educational material, and allowing for class discussion both between students and lecturers. As such VLEs have become a common part of the experience provided by educational institutions. VRLEs are often looked at as a possible future iteration of the modern VLE. This is as VRLEs follow the same principals and tend to provide the same services as more traditional VLEs but apply these to VR environments.

Access to VRLEs is currently more limited than that of traditional VLEs due to the hardware requirements for accessing such a system. VRLE environments require the use of a VR headset in order to better track user movement and provide them with a first-person Three Dimensional (3D) space that they can explore and interact with at a level that is not traditionally possible.

2.1.2 Strengths and Use-cases of VRLE Systems

Due to their enhanced level of immersion and interaction, VRLEs can also be the best place to provide educational simulations for fields where hands on work can be especially beneficial. One example of this [4] allows medical students to practise suturing in a VR environment which helps beginners improve whilst avoiding the risk that could emerge from practising in real world scenarios. An additional benefit of this is that the only costs involved are the initial purchase of the VR setup itself.

VRLEs bring with them the advantages of VR technology which means that they can provide more immersive experiences and therefore boost student engagement [5]. One example of this is allowing students to virtually put themselves in places related to what they are studying to allow them to better understand what it is they are learning about, or appreciate it to a degree that would only otherwise only be possible by physically going to the location [6]. This advantage of VRLEs allows students to virtually visit and interact with different environments in a way that provides a more realistic and intuitive understanding of the space that is not possible through the use of more commonplace VLE experiences.

2.2 Virtual Reality in Education

2.2.1 Educational Virtual Reality Systems

In recent years, VR technologies have often been experimented with and used to provide educational experiences [5; 7]. They can provide students with with quick and easy access to experiences that may otherwise be very difficult or very costly to host otherwise. A systematic review of VR in education [8] defined four categories of educational VR applications: training, simulation, distance learning, and limited resource access.

One example of a simulation application [6] is combining VR with Google Earth technologies in a geography class to allow students to almost instantaneously digitally visit the locations being discussed in class. This was done as part of a study on student perceptions of VR in the classroom to enhance the learning experience and was carried out over the course of an entire year to understand the long term student perceptions of the technology. After the full year of in class VR sessions were complete, students continued to have a positive perception of VR technologies and were interested in seeing future implementations of educational VR. Results however did not contain a large distinction between the VR users and non users, implying in-class VR should not be considered a replacement for traditional lectures but rather be a tool to enhance them.

Training applications are used to allow users to develop and practice practical skills in VR environments. Many aviation companies for instance, provide staff with access to VR aircraft maintenance training [9]. A system like this can allow staff to see and interact with the different components of an aircraft in a manner that is significantly safer and more flexible than one that would involve using physical aircraft parts.

VR technologies have also been deployed to enhance online classes. One example of this is a study [10] which investigated the effects of using VR to host e-commerce classes. When comparing the performance of students taking these classes through traditional online learning methods, with those of students who took part in the classes through a VRLE, it was found that the latter group were able to maintain higher concentration levels, and scored better when tested on the subject matter. The main downside of VR distance learning highlighted in this study is that such classes can require longer preparation times and higher technical knowledge from the educators hosting the classes. With thisin mind, studies on educational VR applications should not only focus on how the learning experience can be enhanced, but also how the teaching process can be improved.

Another interesting VR in education application was used as part of a case study on library system VRLEs. A system [11] was set up to allow users to search for and browse the contents of ebooks. This would fall under the category of applications that enhance access to limited resources. Users also had the ability to talk to a library reference expert who would also log in via a VR headset to offer support. While a novel concept with potential, the paper about this case study mainly included information on how to implement such a system and how it can be streamlined, and did not include any evaluation metrics or methods of gauging the value that the system provided to its user base. A point like this is valuable to address as it can not only show the value of a particular approach but also provide deeper insight into why it was valuable and how that value can be reapplied and enhanced further. As such, this dissertation's evaluation focuses on addressing these points.

2.2.2 Virtual Reality and Augmented Reality in Education

Augmented Reality (AR) technologies allow digital objects and information to be inserted into the physical world [12]. AR educational technologies overlap with VR technologies in that both are attempting to enhance the educational experience and boost user engagement through the use of virtual environments. The main difference between them is that while VR technologies immerse the user in a completely virtual environment, AR technologies attempt to bridge the gap between what is virtual and what is real by inserting virtual elements and enhancements into the the real world environments [13]. One can visualise this via a diagram like that of Fig. 2.1 in which the spectrum of Mixed Realty (MR) technologies is a gradient between real world environments and completely virtual environments, with VR technologies being at one end and AR technologies landing in the middle.

The most common AR experiences are typically done through the use of a smartphone where the user can see virtual elements added to the camera feed on their device. AR implementations however, can also provide more immersive experiences on VR headsets themselves or specialised versions of VR headsets called VR glasses. These options mean that the barrier of entry for AR experiences is significantly lower than that of VR.

AR having a lower barrier of entry than VR means that it is preferable in situations

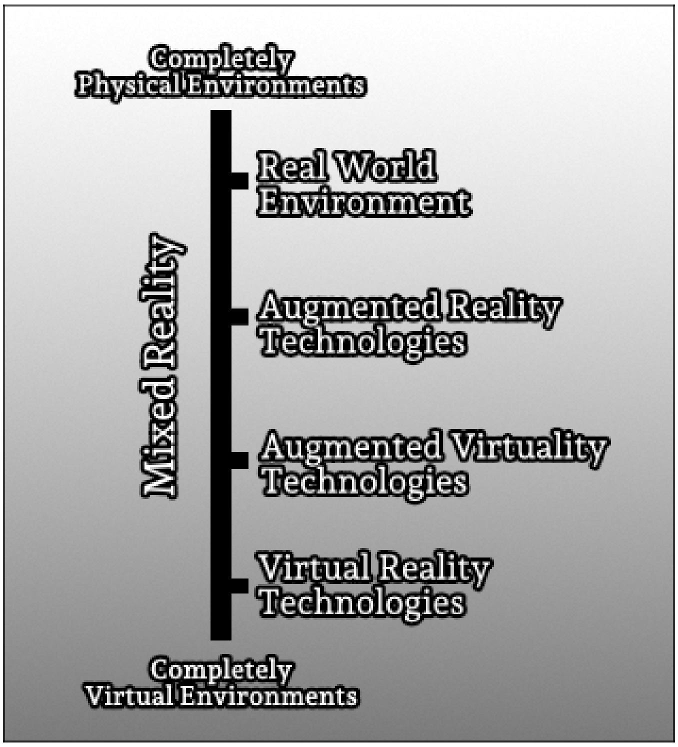


Figure 2.1: Gradient of Mixed Reality technologies that fall between between real world and completely virtual environments.

where one can benefit from being able to view a specific virtual object in an unrestricted three dimensional space rather than a full virtual environment. For instance it can be used by medical professionals and students in order to navigate a 3D scan of a human skull [14] in a more detailed manner than would be possible without AR technologies when preparing for a surgery. Since the focus here is specifically on a single virtual object, that being the 3D scan, the benefits of using VR technologies over AR ones are outweighed by the conveniences of AR.

Aside from being used as a tool for professional use, AR can also be used to provide unique educational experiences, such as displaying virtual recreations of historical buildings or artefacts over real world environments [15; 16] or enhance how students can view and compare animal and plant cells [17].

2.3 Metaverse Technologies

2.3.1 Overview

The term metaverse originated in the 1990s from a science fiction novel where it was coined to represent a combination of the words meta and universe. It was used to describe a 3D digital universe comprised of immersive virtual worlds which users can enter and interact with through the use of avatars [18]. Whilst the technology to achieve this did not exist when the concept of the metaverse was conceptualised, in modern times technology is allowing metaverse experiences to finally be actualised and implemented. In recent years there has been a significant increase in discussion (Fig. 2.2) and investment into metaverse technologies from major players in the technology space.

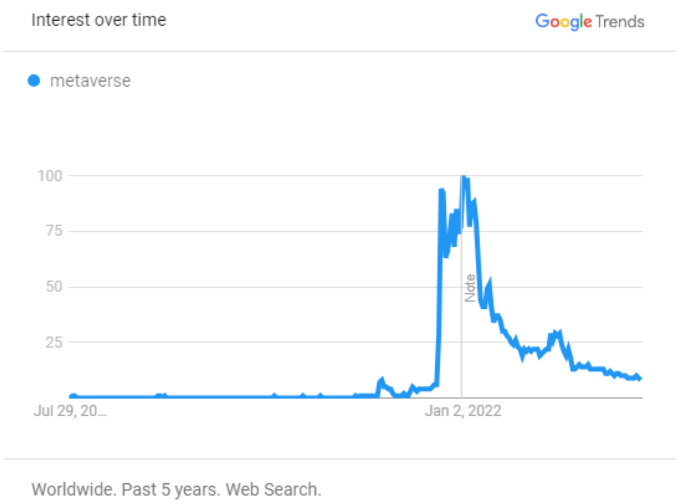


Figure 2.2: Google Trends graph showing the increase in searches for the term "Metaverse" over the last 5 years.

VR technologies have found themselves very closely associated with metaverse technologies. This is as the advantages of VR align well with what metaverse technology is trying to accomplish. VR allows for greater immersion in virtual worlds that metaverse technologies are striving to achieve [19]. Additionally, VR headsets usually come with some form of body tracking functionality which can be used to enhance user avatars by allowing for significantly more natural and realistic movements that reflect the real world actions of the users.

2.3.2 Educational Metaverse Applications

Despite the dramatic increase in interest in metaverse applications, only a small sample of research done on metaverse technologies has been related to educational applications [20]. Education is a critical field that needs to keep up with current technologies to further advance and optimise learning experiences, and as such more researchers should be encouraged to invest their time and talents into educational metaverse applications. That being said, the research already done in the field shows great promise in how metaverse technologies can revolutionise educational experiences.

One study [21] investigated using metaverse technologies in order to alleviate the downsides of remote education. Remote learning can often be necessary, but doesn't allow for the same level of student engagement and as a result can often lead to a reduction in student participation [22]. The study [21] compared students that were learning through a VR and metaverse remote learning platform with traditional video call remote learning. Comparisons were made using student retention and knowledge acquisition tests, and found that in general students scored higher on both when making use of the VR and metaverse approach. It also confirmed that VR and metaverse based education helps provide students with a significantly higher feeling of spatial presence when learning remotely.

Metaverse educational technologies can also often be considered as an evolution of VR educational technologies. This is as it is not uncommon for concepts from VR educational technologies to be enhanced and transformed into metaverse technologies. This can be seen for instance in one paper [23], which broke down how remote lung cancer surgery training was achieved through metaverse technologies. VR educational technology allowed medical students to remotely view and learn about lung cancer surgery via immersive 360 degree video, and metaverse technologies were leveraged to add in social elements, allowing for lecturers and other students to meet in virtual classrooms where they all had shared access to the 360 degree surgery videos. This approach not only reduced the negative effects associated with remote learning, but was also able to allow more immersive demonstrations than would be possible in a traditional classroom setting.

2.3.3 Metaverse Platforms

In recent years several platforms have either evolved to incorporate more metaverse-esque elements or have been designed from the ground up around the concept of metaverse technologies. This section gives a brief breakdown and explanation on some of the more prominent examples, or examples that are particularly relevant to this paper. A table is available (Tbl. 2.1) that shows a comparison of the platforms' avatar Level of Detail (LOD), as well as some information about their capabilities.

- VRChat [24]:

  - One of the most well know VR platforms. It acts as VR social media platform allowing anyone to join public or private virtual worlds where they can talk, interact, and add each other to their friend lists.
  - VRChat is a relatively open platform which allows users to upload their own 3D models to use as avatars or virtual worlds. Unfortunately, whilst being able to make and import custom avatar models is significantly more control than what is offered by most other platforms, VRChat does not have a built in avatar customiser, meaning that the best one can do if they do not know how or do not want to import their own models is use pre-made avatars that do not reflect their real world bodies.
  - Additionally, whilst it is very popular, VRChat is not as commonly used as other metaverse platforms for serious applications like education or work related tasks. Instead, it is mainly used as a platform where one can meet with and make new friends, as well as share VR experiences with them.

- Axon Park [25]:
  - The slogan "Welcome to Your New Virtual Campus" gives a good insight into the strengths of the Axon park platform. It provides interactive three dimensional VR words in which students and educators can meet to participate in, host, or design educational activities. They also advertise implementation of AI technologies in their metaverse worlds.
  - Currently users are able to base an avatar off a photo or template. This avatar acts as the default but developers can also define avatar customisation on a per virtual world basis, i.e. developers are able to choose if they are going to provide users with their own avatar customisation and to what LOD.
  - It is a relatively new platform that was started in 2019 and is still being actively developed. As such, at the moment of writing, it is still not completely open and requires getting in contact in order for developers to make use of the platform. At this moment they do not have a Software Development Kit (SDK) for external development available.

- Spatial [26]:
  - This platform is dedicated to encouraging people to be creative in collaborative VR environments. The platform also supports AR environments which allow users to virtually meet in a real world environment that can include virtual elements such as virtual screens, notes, or 3D models. Spatial also makes use

of Non-Fungible Token (NFT) technologies. Not only can NFTs be displayed but they can also be used as tickets required to enter certain virtual worlds, and even the virtual worlds themselves can also be minted into NFTs, allowing them to be sold and rented.

  - Users are required to create an avatar during the setup of their account and can make use of templates as a starting point. The options given allow users to design an avatar that matches their real world appearance. The platform also allows virtual worlds to be developed via a plugin called Spatial Creator Toolkit that connects to the Unity game engine. This allows virtual world developers to include custom quests, avatars, and vehicles in their virtual worlds.
  - While being able to develop environments in unity through the Spatial Creator Toolkit is incredibly handy, it does not mean that spatial world developers are able to make use of all the tools and features of the unity game engine. Most notably custom C# scripts and certain types of visual scripting nodes are not supported, meaning that more unique virtual world features might not be possible to implement.

- Roblox [27]:
  - Despite not being a VR compatible platform, Roblox is often considered a metaverse platform. It is significantly older than the other platforms discussed in this section, having been launched in 2004. As a result its feature set can be considered more mature than most platforms.
  - The Roblox platform contains some of the most open and customisable virtual world development options amongst metaverse platforms. Through an optional free program called Roblox Studio, virtual worlds can be built completely from scratch using custom assets and code. Developers are even able to override systems such as the platforms default animations, avatars, and control inputs. This gives developers the ability to create virtual worlds that are both highly specialised and distinct.
  - Similarly to VRChat however, Roblox is not commonly used for serious applications. Instead it is mainly used as a metaverse platform where users can develop and play a variety of different games together within virtual worlds. Additionally, whilst its virtual world customisation is very open, its avatar customisation is significantly more limited; requiring users to use a currency system to buy customisation options that would allow their avatars to match their real life appearances.

- Horizons Worlds [28]:
  - Created by Meta, the same company that develops the Quest VR headsets, Horizons Worlds provides users with free VR worlds where they are able to meet with friends or new people, attend virtual events, and play some games together in VR.
  - Whilst they provide an avatar customisation system that does allow for a level of customisation high enough to allow users to create avatars that align with their real world appearance, the visual quality of the avatars themselves is noticeably less high than what is offered by some of the other platforms mentioned such as Spatial. Virtual world development on Horizons Worlds is relatively unique. Users are able to develop the same virtual world simultaneously whilst remaining in VR, essentially turning the act of creating metaverse experiences into a metaverse experience.
  - The ability to develop virtual worlds whilst remaining in VR is used very well. Users are even able to use a drag and drop system, as well as visual scripting. This allows for an enjoyable and streamlined virtual world development and testing experience at the cost of a level of accuracy and fine detailing that is more achievable through more traditional virtual environment development tools.

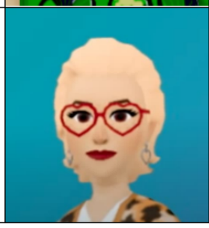
Platform	Avatar Example	Built in Avatar Customisation	Built in World Customisation	Custom Script Execution
VrChat		Custom characters can be imported from external sources	Can be done through plugins with unity	Supports a custom Visual Scripting system
Axon Park		Robust customisation	Can be done through Unreal Engine 5	No current support for external development
Spatial		Robust customisation	Can be done through plugins with unity	Supports a custom Visual Scripting system
Roblox		Customisation with some caveats	Robust Customisation	Supports LUA scripts
Horizons Worlds		Robust customisation	Robust Customisation	Supports a custom Visual Scripting system

Table 2.1: Table showing a comparison of avatars and some features available in different Metaverse platforms. Each avatar image is either taken from official sources or a direct screenshot from usage of the platform.

2.4 Personalised Learning Systems

Personalised Learning systems are systems put in place to optimise learning experiences in a way where they can adapt and tailor to individual users' preferred learning environments, pace and styles [29]. Whilst personalised learning does exist in a more traditional manner, advances in technology have allowed this to be done through much more efficient means. Traditional personalised learning has generally required educators to put effort specifically into tracking each students progress and tailoring for them. Personalised e-learning technologies allow software to automate parts of this process, which has resulted in increased accessibility for educators to implement personalisation into the learning process. That is not to say that there are no challenges when developing personalised e-learning systems however.

2.4.1 Challenges of Personalised Learning Systems

As was identified in one study [30] there are several types of challenges that must be considered during the development of these systems. These included integration challenges which define the challenges involved in training or educating students and teachers on how to make best use of the e-learning systems, as well as providing them with resources and technical support for when things go wrong. It also defines challenges types such as "Content-Oriented versus Student-Oriented" which are about dealing with e-learning technologies causing teachers to be encouraged to focus on providing content for each week rather than on educating the students, and pedagogical challenges which are about how e-learning should not just be a way to deliver normal learning content, rather it should be a way to enhance the learning experience at cognitive, behavioral and physiological levels. The paper [30] also notes that these systems should try to accommodate for a variety of learning styles and preferences.

These insights provide valuable information on the common pitfalls that personalised systems can encounter and have therefore been taken into account in the writing and development of the implementations associated with this dissertation. It is important that these challenges are considered when a general plan for what a personalised learning system will try to achieve is decided on. This dissertation keeps integration challenges in mind by ensuring that classroom personalisation is offloaded to an AI agent rather than onto teachers. Additionally, any inputs required from students to train the AI agent are kept straight forward. Learner profiling also helps in keeping a focus on student-oriented teaching since it can keep educators more informed on the likes and needs of the students when they are planning classes. Furthermore, by leveraging a dynamic and personalised VRLE, this dissertation is able to tackle pedagogical challenges by focusing on accommodating for more preferences and providing classroom tailoring on an individual level that would not be possible in a normal learning environment.

2.4.2 Development of Personalised Learning Systems

Learner profiles and Machine Learning (ML) agents are valuable tools in the development of these personalised e-learning systems. These tools can be implemented to facilitate the automation of learning personalisation. Learner Profiling systems are focused around building a set of data for each individual learner that encompasses information that relates to their learning experiences such as what educational preferences and goals they have, what keeps them motivated more, what areas they find more troubling, and so on [31]. This data can be gathered through explicit means such as user surveys, as well as through observational means such as tracking how much they interact with e-learning systems and the types of content they access through them. ML agents can then be used to cycle through and process the data present in the learner profiles in order to optimise for the settings that need to be enabled in an e-learning environment to best match a particular student.

2.5 Reinforcement Learning

2.5.1 Overview

One type of ML agent that does not require a large data source ahead of time is a RL agent. Rather than training on a data set, RL agents are placed directly in the environment where they are able to perform actions and adapt to it based on a trial and error technique. Throughout this the agents are looking for what actions and contexts allow it to maximise the rewards they receive and minimise the penalties. This type of mapping between the context of the environment and actions that should be taken is referred to as the agent's policy [32].

The nature of this strategy applies itself well to areas where specific data on the environment will be unknown ahead of time. As such, RL agents are advantageous when it comes to being applied to gaming and robotics. Video games usually already contain win and lose conditions or score systems that can be directly mapped to the rewards and penalties of a RL algorithm. This is typically true of both competitive and collaborative games [33]. Since robotic systems have to deal with real world environments, conditions will never be identical and so, due to their ability to adapt and use policies to deal with new scenarios, RL techniques are some of the best systems for handling robotic automation and path-finding [34]. In both of these scenarios, the environments encountered can vary and the agent may even need to deal with environments or scenarios that change dynamically in real time. These advantages of RL systems have lead some studies to research and apply them to personalised learning where systems may need to dynamically adapt to learners and educational environments.

2.5.2 Application to Personalised Learning Systems

RL technologies are often applied to personalisation systems such as advertisement and product recommendations [35]. Such implementations are commonplace as RL is capable of tailoring recommendations to users, even when data on a particular user is relatively scarce compared to what is required to effectively use many other AI technologies. This benefit also appears when dealing with personalised learning systems.

When RL technologies are applied to personalised learning systems they can surpass what is possible when using simpler optimisation algorithms. An important factor in this is the dynamic, ever changing nature of educational settings; preferences and abilities can change dramatically over time and the explorative nature of RL algorithms gives them an advantage when compared to more static optimisation systems [32]. Additionally, the number of factors taken into account in personalised learning can be quite large and individuals may have very different requirements. As such, a system based on RL that is capable of developing complex policies whilst handling a wide range of scenarios is ideal.

One study [36] ran several RL agents in order to determine which types of RL were best applicable to recommendation in personalised learning implementations. This study found that in the context of personalised learning systems, Q-Learning based RL agents were generally able to develop strategies that out-performed the other agents'. Whilst the use-case in this paper was not identical to what is being done in this dissertation, it still supports the usage of RL technologies being a viable strategy, and provides useful foundations on how that can be implemented.

2.5.3 Q-Learning

There are multiple variants of RL technologies. One such variant is Q-Learning, which makes use of a Quality value (Q-value) to determine what action should be taken next to maximise positive outcomes. Each state and possible action combination are given their own Q-value. Therefore when an action needs to be selected, the Q-Learning agent can see which action has the highest Q-value. If multiple actions are equally viable then the agent may choose randomly between them [32]. It should also be noted that, generally, the Q-values are discovered by the agent through trial and error rather than given to the agent ahead of time. Q-learning allows for RL agents to develop policies and strategies

$$\underbrace{New\ Q\text{-}Value(S,A)}_{\text{New Q-Value at current State and Action}} = \underbrace{Q(S,A)}_{\text{Q-Value}} + \overset{\text{Learning Rate}}{\alpha}[\underbrace{R(S,A)}_{\text{Reward}} + \overset{\text{Discount Rate}}{\gamma}\ \underbrace{MaxQ'\ (S',A')}_{\text{Max Predicted Reward at next State and Action}} - \underbrace{Q(S,A)}_{\text{Q-Value}}]$$

Figure 2.3: Bellman Equation

that lead to better long term rewards, but can often struggle when the number of possible states i.e. the state space is relatively large.

The Q-Values themselves can be calculated through the use of the Bellman Equation (Fig. 2.3). This equation is used by Q-Leaning agents to update the Q-values associated with each state and action pairing as it explores and adapts to its environment [37]. As is observable in the equation, a default value for the Q-values needs to be initialised ahead of time by the developer, since getting the new updated Q-value requires making use of an already defined Q-value.

2.6 Virtual Environment Customisation

When setting up a virtual environment, one can choose to create a static or customisable environment. A static environment is one where all users encounter the same environment and no alterations, manual or automatic, can be made. A customisable environment is the opposite. The environment itself can be changes in a variety of ways depending on the user or other conditions.

There exists a variety of systems that can be employed to handle customisation of an environment. One paper [38] proposes an elegant way to categorise these systems into three main approaches. These are specifically designed to be inclusive of all systems used to generate custom environments for a three dimensional space for end-users.

The three approaches are pre-programmed, agent-programmed, and user-programmed approaches. When one is developing a virtual environment with customisation elements, it is valuable to keep these approaches in mind as they help ensure a level of consistency in how the customisable elements of the environment are handled. VRLE environments fall under the definition of a three dimensional virtual environment for end-users, and as such these strategies remain the main considerations for custom environment generation.

2.6.1 Pre-Programmed Environment Customisation

Pre-programmed approaches contain rules regarding environment generation that are explicitly set by the developer of the environment ahead of time, as such they often take the form of static decision trees [38]. When this approach is taken, the environment customisation is completed before the users ever interact with the system, meaning from a user standpoint the environment is static in form and function. The main advantage of this approach is that it allows designers to perfectly tune the environment to provide the exact type of experience that they intend their users to have.

There are unfortunately some notable disadvantages of pre-programmed systems. Mainly, that because of their static nature, they are very limited when it comes to accounting for user preferences and have no systems in place to automatically align with new demands over time. Additionally, pre-programmed environments may have an inverse effect on user engagement, as users may not feel like anything about their experience in the environment is unique.

2.6.2 Agent-programmed Environment Customisation

Agent-programmed approaches make use of AI agents to generate the environment based on policies that are defined by the AI algorithm itself [38]. This is typically done by having the agent try to optimise for the user based on past trends, behaviours, and preferences. As such one can consider this a data driven approach to environment customisation. The policies that define the state of an agent-programmed environment can be dynamically changed over time by the agents. The goals and limitations of the agents are defined by the developers ahead of time.

While this approach generally does not allow for developers or users to fine tune the environment to provide a very specific experience, it comes with a high degree of environment flexibility. Through this paradigm, a large variety of users can have environments that align with their demands, with relatively little input from them or the environment developers.

2.6.3 User-programmed Environment Customisation

User-programmed is when the users themselves are able to define the rules for the environment customisation [38]. One popular method of achieving this is by providing a User Interface (UI) that streamlines the rules of the environment into a series of toggles and/or sliders. This gives users fine control over their environments whilst minimising the barrier to do so.

One way of further streamlining this approach is to provide the users with templates for the environment, with each template being predefined but still modifiable. Templates help reduce the amount of work a user needs to put in to have a more tailored experience as users can just tweak the template rather than start everything from scratch. It should be noted however that even through template systems, the amount of time a user is required to invest to have an environment that aligns with their specific needs is still significantly higher than that of agent-programmed environments. This barrier could lead many users to just select the default settings and not interact with the customisation elements. Additionally, these systems are static over time, meaning that users will need to invest more time to keep the environment updated if their needs or demands change.

2.7 Evaluation Criteria

At the time of writing, evaluation of educational VR environments suffers from a lack of robust systems and standardisation. Since the goals of this paper involve investigating the effects that AI agents can have on user satisfaction and engagement in VRLE environments (O4), evaluation methodologies which measure user satisfaction and engagement values in similar projects have been looked into as a foundation.

2.7.1 Evaluation for VR systems

Evaluation systems for VR systems can take on a variety of forms. These include surveying users about VR experiences, measuring software analytics through video game industry tools [39], and/or tracking bio-metric data during VR experiences [40]. For this dissertation surveying users is being chosen as the main source for determining standardised engagement and satisfaction scores. Externally measuring user satisfaction and engagement can lead to large variance and subjectivity that can be easier to handle with surveying the users directly. Additionally, software analytics tools work best in situations where there are active users on a deployed platform which users can access whenever they want, which is not the case for this dissertation. Bio-metric tracking is a novel and interesting evaluation method that can be insightful in evaluating VR training systems [40], but is not ideal for the types of metrics being targeted by this dissertation.

One study that made use of survey evaluation and shares some overlap with this dissertation focused on the evaluation of gamification elements in educational VR spaces [41]. It involved the implementation of game design techniques into an educational VR space in order to understand the effect that elements such as high-score systems, achievements, and timers have on educational VRLE spaces. This study implemented two versions of their VR environment, with only one of them making use of the gamification features they hypothesised would increase motivation.

The study [41] contains significant overlap with this dissertation, with both attempting to measure the positive effects that specific additional features can have on VRLE spaces. The main distinguishing factor being that this dissertation is looking into measuring satisfaction and engagement in regards to AI customisation whilst the study measures motivation in regards to gamification elements. The study made use of a custom made questionnaire to measure the user motivation. Having two versions of the VRLE is an effective evaluation methodology as it allows for the results to isolate the additional features to the environment. The main part of this evaluation plan that could be improved is the nature of the questionnaire itself. Whilst it serves the purpose of the study, it seemingly neither follows, nor is based upon a specific model or standard. Since educational VR environments are still very lacking when it comes to standardised evaluation systems, it could be beneficial to take a look into how a similar but more robustly researched field handles measuring user motivation, engagement, and satisfaction in similar scenarios.

2.7.2 Educational Games Evaluation

Evaluation of educational games shares several similarities with the evaluation of educational VR experiences. This is not only because there is a technological overlap between the two but also as they often have similar end goals, that being to increase the satisfaction and engagement of those being educated. Unfortunately, there is also an overlap in the lack of standardisation on evaluation methods. Whilst educational games have more research done on them, it was still noted in a 2017 study [42] that 81% of research papers on educational games investigated did not follow a specific evaluation model. Despite this, educational game evaluation is still significantly more robust then educational VR evaluation and so taking a look into the most popular evaluation models used by the remaining 19% of papers can give insight on how advances in evaluation techniques for educational games can be adapted to VR educational software.

The most popular evaluation model identified was the MEEGA model [43]. This model was significantly more popular than any other, being used around 60% more frequently than the second most popular model known as EGameFlow [44]. The MEEGA model breaks down evaluation into several standardised categories of questions, with each category being designed to gauge a specific metric. The metrics are Motivation, User Experience, and Learning. Users are given questions before and after using the educational game and are able to answer every question by picking a value on a 5 point scale, and the results can be compiled into a score for each category and a standardised overall score.

Since the release of the MEEGA model however, some researchers [45] have pointed out flaws and proposed a more robust version referred to as MEEGA+.

The MEEGA+ model [45] builds on the MEEGA model to be more comprehensive and provide a greater level of reliability. It follows the same categorical standardised question structure as its predecessor but rather than having three categories, provides two main categories: Player Experience and Usability, that can be broken down into nine and four sub-categories respectively. These sub-categories can be seen in Fig. 2.4 . They allow for the same standardised questioning and scoring system as the MEEGA model but provide a greater level of evaluation information.

This dissertation adapts aspects of the MEEGA+ model and reapplies them to VRLE applications. In doing so, a more standardised methodology for evaluating VRLEs is developed. This approach allows for quantitative results to be gathered that can be directly compared with those of studies leveraging the same evaluation system.

2.8 Summary

This chapter provides a breakdown of the main technologies and research papers related to this dissertation. It discusses several use cases of these technologies, mainly from the perspective of applying them to e-learning, as well as references other works to give insight into how they leveraged these technologies and what was learned that can be used to best achieve this dissertation's goals.

The main technologies covered were VLEs and VRLEs, VR and metaverse technologies, personalised learning systems, RL systems, and virtual environment customisation. For each of these technologies, research papers that overlap with this dissertation or provide relevant information on how the technologies can be implemented to align with this dissertation were reviewed. The relevant takeaways of these papers were taken into account and the areas where they lacked were discussed and taken note of to be addressed in this dissertation. The main area which similar papers lacked in was providing robust result gathering and evaluation methodologies. Consequentially, this chapter also looked into how educational game applications handle evaluation systems so that this dissertation can adapt them to VRLEs.

Overall, it was noted that whilst there are a variety of research papers on VRLE technologies, there is a general lack of standardisation when it comes to evaluation and relatively little research on this dissertation's niche of using AI agents to tailor their designs to make them more engaging for users. This dissertation therefore aims to help fill the gap in these areas through leveraging the main insights on what technologies provide the best advantages for personalised VRLEs, applying them to AI agent-based environment customsation, and providing a more robust evaluation and insight gathering system based on work done in similar, more established fields.

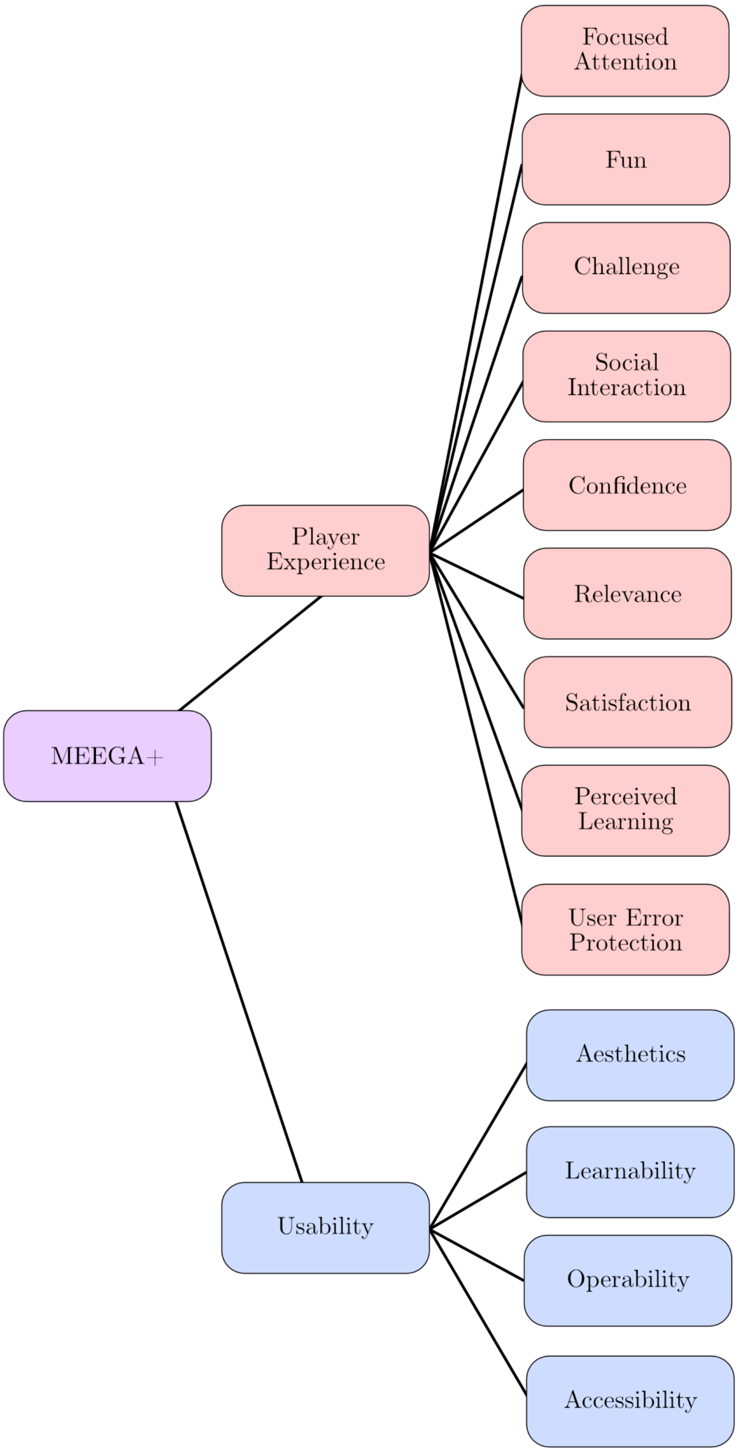


Figure 2.4: Breakdown of the MEEGA+ Evaluation Model Categories.

3. Materials & Methods

3.1 Target Demographic

The target demographic of most VLE and VRLE studies and systems is students and/or people who were recently in education. This demographic is also applicable to this dissertation. The reason students are the ideal target for these types of studies is that they are the people who would most benefit from VRLE systems and are also most familiar with the modern standards and experiences of educational and VLE technologies. The students targeted by this dissertation are adult students, specifically in the 18 to 23 age range, who are pursuing studies at a university level or equivalent.

3.2 General Overview

As part of this dissertation, a piece of software has been produced that allows users to put on a VR headset and access a VRLE classroom. The features and design of this classroom are dynamically changed by a RL agent that is aiming to personalise the classroom setup to align with the preferences of each individual user. The software tracks the changes and states of the classroom environment, the preferences of the users, and debug information for the RL agent, and compiles them into learner profiles that can then be accessed as individual files corresponding to each user. This information can be seen in Fig. 3.1, which is a Data-Flow Diagram (DFD) of the software.

A second version of the software was also produced to provide results for comparison with the first version. This alternate version of the software is a more standard VRLE classroom. This version's classroom contains no AI agent customisation and so has a completely static design. This version of the software acts as a baseline during this dissertation's testing process so that the effects of AI environment customisation on VRLEs can be isolated more effectively. The DFD for this version can be seen in Fig. 3.2. As can be seen, this version follows a much simpler structure and lacks all AI related components.

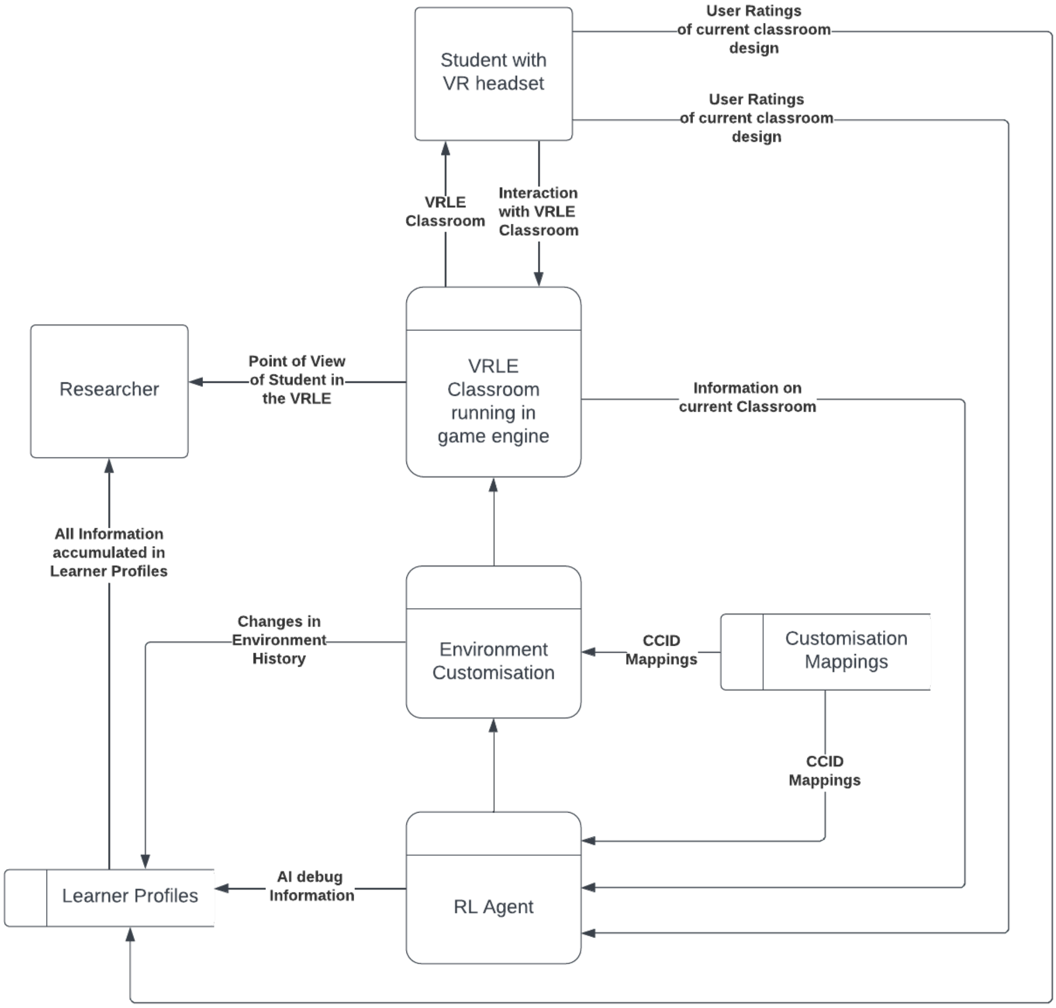


Figure 3.1: Data Flow Diagram showing a high level overview of this dissertation's personalised VRLE software implementation.

With these two versions of the software, one of the main metrics being measured is that of engagement. This dissertation follows the definition of engagement proposed in a 2014 study [46], which defines engagement as a self reported combination of Focused Attention, Satisfaction, Aesthetics, and Usability. These sub-metrics can be gathered in a standardised manner by following the MEEGA+ [45] evaluation model.

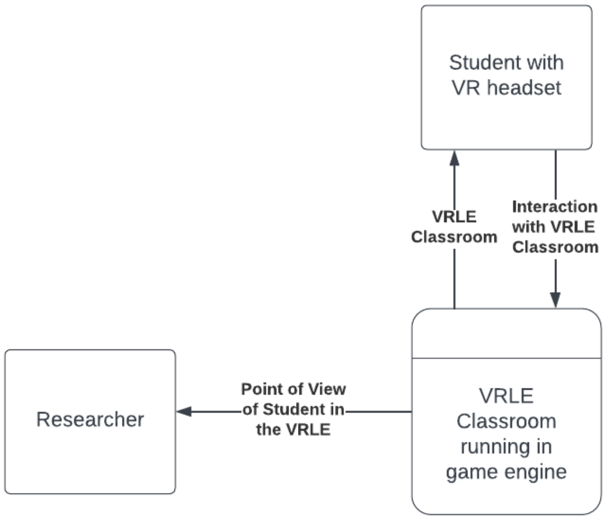


Figure 3.2: Data Flow Diagram showing a high level overview of the more standard static version of this dissertation's VRLE software implementation.

3.3 Software and Versions Used

This section goes over the software used for the development of the VRLE application related to this dissertation. It defines the exact version of the software used in order to streamline the process of replicating and building upon the application. The Software used can be seen in the following table (Tbl. 3.1):

Operating Systems	Software	Version
Windows 10/11	Visual Studio 2022	17.0.4
	Unity Hub	2.4.5
	Unity Game Engine	2022.1.13.f1
	Unity Oculus XR Plugin	3.0.2
	Unity OpenXR Plugin	1.4.2
	Oculus App	60.0

Table 3.1: The main software used to develop this dissertation's VRLE application.

3.4 VR Platform Selection

The initial plan for this dissertation was to make use of a VR and/or metaverse platform, such as those specified previously in Fig. 2.1. As such comprehensive research was done on several of these platforms.

The advantages associated with making use of these platforms include reduced development time for this dissertation's VRLE. This is as they remove the need to manually set up VR input handling and can also provide pre-built VRLE space that could be directly enhanced with AI elements. These platforms also come with features such as built in online meeting functionality, that while not necessary to this dissertation, would allow the VRLE to be closer to one that would be released to the public.

After significant research and discussion with some of the metaverse platform developers however, it was decided that making use of these platforms would not be a viable option for this dissertation. As of the time of writing, the goals and development features of the metaverse platforms did not align well with the goals of this dissertation. Whilst the platforms looked into all offer a good level of environment customisation whether built in or through external tools, the scripting capabilities offered are currently too limited in what they allow for code to be implemented that has AI agents dynamically change an environment as is required by this dissertation. The exception being the Roblox platform which could potentially support this as it has the most flexibility and openness when it comes to scripting, but it is the only one of these metaverse platforms that is not VR based, and as such is also not a viable option for this dissertation.

As such, out of necessity, the scope of this dissertation had to be expanded to devote more time to set up and implement a VR space for the VRLE at a lower level than previously expected.

3.5 Setting Up a Virtual Reality Space

3.5.1 Game Engine Selection

Since it was decided that a metaverse platform would not be used for this dissertation's VRLE space, the tools required to manually set up the VR space needed to be selected. Making use of game engines provides significantly more flexibility and avoids the problems encountered with using metaverse platforms for this dissertation. Due to this, the options in the game engine space were investigated.

The main contenders in the game engine space are the Unreal Engine, the Unity Engine, and the Godot Engine. Out of these, the Unity Engine was chosen. This is as, at time of writing, it was observed that the Unity Engine has the most robust VR asset library and tool-set, as well as the most active development community when it comes to VR development. Many of the most popular VR games are also made in the Unity engine such as Beat Saber and SuperHot VR. This level of popularity ensures that significant documentation and support exists on VR development in Unity.

3.5.2 Implementation

With the engine selected, the virtual space and its VR handling had to be implemented. To ensure compatibility with as many VR headsets and controllers as possible, as well as allow for more time to be allocated to other parts of the software, the use of open source VR templates and Unity plugins that could streamline this process was investigated. The main goal of this investigation was to find and adapt a system that provides input handling for multiple types of VR headsets to allow them to work identically when used to visit the virtual space.

An open source template, specifically the FFOS Unity VR Template [47], was selected. This template includes a compatibility layer between the unity engine and VR hardware, providing an easy way to read and standardise motion and button inputs from a variety of VR headsets and controllers. It also includes hand tracking and basic VR movement handler systems that allow developers to quickly set up either VR analogue stick movement or VR point to teleport movement. The source code provided in this template is open, editable, and modular, meaning the main benefits of coding such a system from scratch, i.e. having flexibility and a finer level of control, are still applicable, whilst the implementation and debugging time is significantly faster than that of a built from scratch system.

First person analogue stick based movement was selected for the VR space. This analogue stick based movement is more realistic than teleportation based movement and therefore can provide a greater immersion level. Teleportation based VR movement tends to reduce motion sickness when moving, as well as allow users to traverse larger areas faster. Whilst these are strong benefits, they are not very applicable to a classroom VR space, since such areas have a relatively small size and do not typically require students to move around regularly. The first person point of view was selected since it is most accurate to real life when compared to other VR camera setups.

The main VR headset targeted is the Quest 2 headset. Its portability allows for a streamlined testing experience since the headset can easily be taken to any location and requires little setup compared to VR headsets that require external tracking. This Quest line of headsets is also, at the time of writing, the most popular VR hardware on the market, meaning that targeting it could be valuable in the long term. Despite this targeting, the

Valve Index headset was also used when developing this dissertation, and as expected, due to the benefits of the VR template [47] mentioned previously, no issues were found when switching between using a Quest and using a Valve Index.

3.6 Setting Up the Educational Environment

The educational environment that users would interact with in VR was built specifically for this dissertation and is modelled after a traditional classroom, complete with the usual layout and furniture associated with one. The assets and 3D models used were either produced from scratch, or extracted from asset packs purchased on the Unity Asset store. The default version of this environment can be seen in Fig. 3.3.

Figure 3.3: The default VRLE classroom developed for this dissertation.

This educational environment was also set up with the idea that an AI agent would be able to make changes to it. The AI agent would have the ability to change the following environmental features:

- Floor Colour
  - The colour of the classroom's floor.
- Class Decorations
  - Themed decorations that can be found around the virtual classroom, mainly on the desks present.

- Background Colour
  - The colour of the sky in the virtual classroom environment.
- Background Decorations
  - A large decoration/s present in the sky, in the direction that an educator would stand.

Figure 3.4: The customisable elements of the custom VRLE classroom, with each type of customisable element being labelled by a different colour.

The features are labelled visually for reference in Fig. 3.4. Each of these 4 features has 4 variants, meaning the AI agent customising the environment is dealing with a state space of 256 possible classroom setups. Fig. 3.6 shows some examples of these classroom setups and the variety that this system allows for.

3.7 Reinforcement Learning System

3.7.1 Selection of the AI Agent

The main goal of the agent is for it to design and optimise the setup of the virtual classroom to provide a tailored experience for every student, essentially acting as a recommendation layer for different elements of the virtual classroom. RL agents work well with

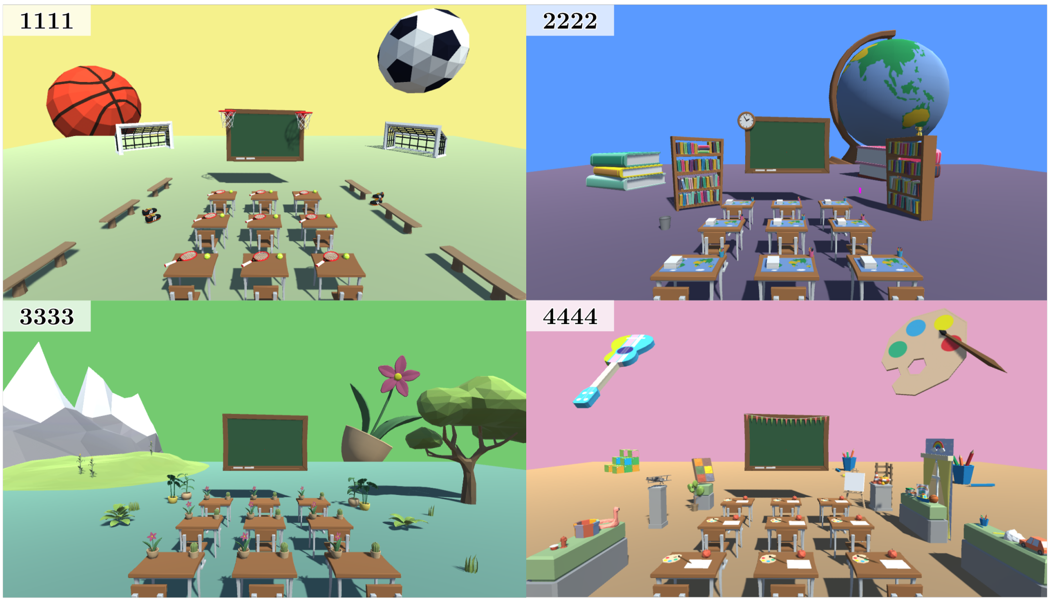


Figure 3.5: The four main VR classroom environments created for this dissertation. Each one is labelled with its corresponding classroom configuration ID. Each one is themed as follows: 1111 is sports themed, 2222 is educational themed, 3333 is nature themed, and 4444 is art themed.

these types of tailoring and personalisation systems [35] since they can quickly adapt to unique users even when information is not known about the specific user ahead of time. Another benefit of using RL technologies is that they can be set up to maintain a degree of exploration even when they have already found viable strategies. This is advantageous when dealing with student personalisation systems since it can keep things fresh and adjust to the dynamic nature of student preferences [32]. Additionally, RL is scalable and allows for generalisation. Educational personalisation is very complex, and this dissertation only covers a small fraction of the possible factors that can be taken into account. Leveraging RL technologies here could then provide better reference for future work. These advantages led to RL agents being selected for this dissertation's implementation.

There are however multiple types of RL that can be implemented into an agent for this task. Fortunately, a recent study [36] provided a comparison of several types of RL agents and their applicability to recommendation systems in the field of personalised learning. This recent study recommended the use of Q-Learning based RL agents when implementing educational customisation systems due to their performance when adapting and creating long term customisation strategies, even when the agent's starting state is initially random and no information on the learner being targeted is known in advance. Whilst the

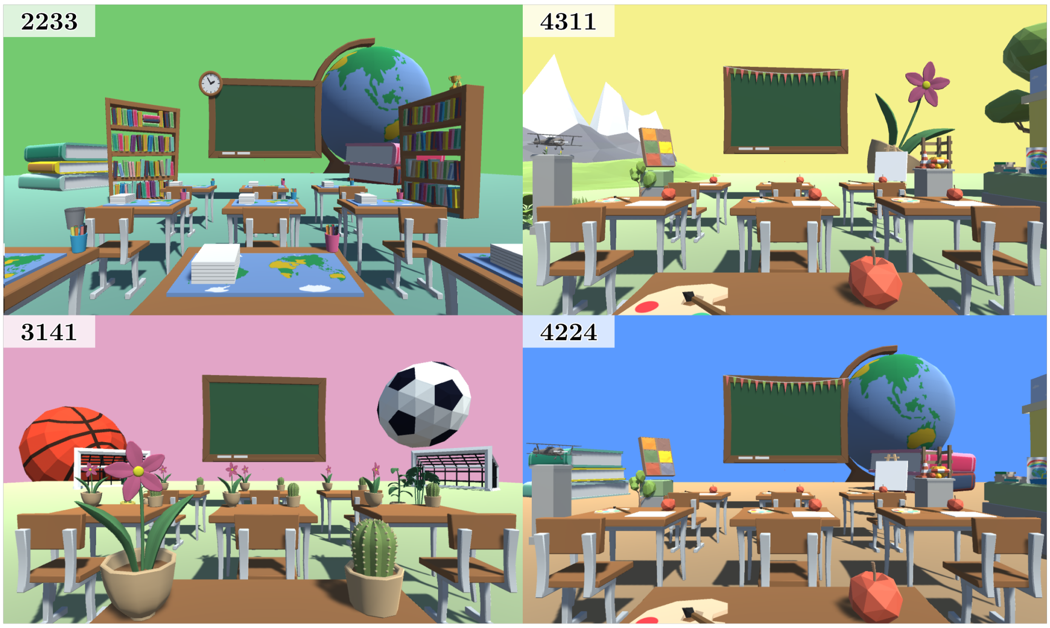


Figure 3.6: Some examples of the classrooms that can be generated in this dissertation's software through choosing and combining different elements of the four handcrafted classrooms in Fig. 3.5.

study was focused on educational content recommendation, as opposed to educational environment customisation, the advantages of Q-Learning systems are still applicable to to the latter.

There are of course some downsides to Q-Learning agents. Some of the main disadvantages being slowdown in convergence when dealing with relatively large state spaces, and an inability to handle continuous state spaces where states and/or actions are not discretely defined. These disadvantages however should not cause any significant hindrance to this dissertation's software implementation since a discrete environment with a state space that is limited to a size of 256 states is being used.

Due to Q-Learning being well suited for the scenario, it was chosen as the driving force behind the AI agent that handles environment tailoring and customisation in this dissertation's dynamic VRLE software. With it selected the finer details on how the agent would interact with the system needed to be decided on.

3.7.2 Representation of the Environment

3.7.2.1 Creating the CCID System

In order to have the AI agent tailor the VRLE environment to match individual students, a methodology for how the AI agent would be able to represent and interface with the student and the environment needed to be developed. In regards to the environment, this was achieved through having the agent traverse a state space where each position in the space is a unique classroom variant. Naturally, the positions closest to each other represented classrooms with similar features. The actions available to the AI agent would allow it to traverse this space, one classroom variant at a time.

Due to the classroom variants having 4 editable features, and those features having 4 options each, each classroom variant can be defined by a 4 by 1 array as follows [feature_1, feature_2, feature_3, feature_4]. For example, [2,3,1,4] would be a classroom where the floor colour (feature_1) is the second of four possible colours, the class decorations (feature_2) is the third of four possible options, the background colour (feature_3) is the first of four possible colours, and the background decorations (feature_4) are the forth of four possible options.

The 4 digits of this array can simply be stored as a four digit integer referred to in this dissertation as a Classroom Configuration Identifier (CCID). For instance, the aforementioned [2,3,1,4] classroom can simply be defined by the CCID 2314. At a source code level, the system stores the current classroom definition as an integer first and fills an array values based on it. This is simply done so that depending on context the array values or the integer can be called directly rather than regularly casting one into another. This configuration number system can be seen with visual examples of the classrooms in Fig. 3.6, where the numbers on the top left of each classroom represent their correlating CCIDs.

Whilst limited to a size of 4 features in this dissertation's implementation, the CCID system could be reapplied to any number of editable classroom features through simply increasing the size of the array or integer storing the CCID. Additionally, the number of variants per feature could be increased by changing the numerical base for each feature. For instance, with 4 features and a base of 4, as is the case with this dissertation's VRLE, the maximum CCID is [4,4,4,4] or 4444, whilst a VRLE with 6 features and 12 variants would have a maximum CCID of [12,12,12,12,12,12] or 121212121212.

With this method of representing individual classroom designs selected, the AI agent still needs a way to traverse from one possible design to the next. RL systems are usually given a set of actions that they can perform within a given environment. In this case the individual actions need to be able to allow the agent to go from one classroom variant to another closely related one.

3.7.2.2 Representing the Environment and Action Space

Since the classrooms can be represented by a 4 by 1 array just as coordinates for a Four Dimensional (4D) space can, then all the classrooms can be defined by a 4D space where each position in the 4D space is a classroom. In this scenario the AI agent would have actions which allow it to move 1 step in any direction of the 4D space. Whilst this method is the easiest to implement since the arrays representing a classroom do not have to be altered in any way to represent a 4D space, it is not ideal for this dissertations implementation.

The reward system for the agent has a dependency on user inputs (More information in Section 3.7.3). Because of this, any systems that can reduce the environment and/or action space complexity would also result in less user inputs required before the agent is able to develop an idea of that particular user's classroom preferences. With this in mind, reducing the dimensions of the 4D environment would be beneficial to the User Experience (UX) of any students making use of the software.

Since the environment is discrete and has straightforward bounds on the number of possible states, dimensionality reduction can be applied by mapping each possible 4D coordinate to a position in a lower dimensionality space. This can be seen in Tbl. 3.2 where the 256 possible CCIDs are mapped to different positions in a Two Dimensional (2D) table. This table was manually handcrafted by this dissertation's main researcher, with each CCID in the table being positioned so that it is surrounded by similar looking classroom environments. The CCIDss of the four original distinctly themed classrooms are placed as far away from each other as possible and elements from a themed classroom are progressively introduced as a position in the table approaches the position of the correlating distinctly themed classrooms. By leveraging this table, the agent can traverse a 2D environment where its coordinates in the 2D space directly correlate to a position on the table.

Reducing from a 4D representation to 2D representation was chosen as 2D reduces the complexity of the environment significantly when compared to 3D and 4D. Additionally, a 2D environment still allows the 4 main VRLE classrooms from Fig. 3.5 to be equidistant from each other. This would no longer be possible if the dimensionality was further reduced to One Dimensional (1D), and as such doing so would actually be counter productive as it would significantly increase the number of actions the agent would need to take to get to some classroom types, and thus also significantly increase the number of inputs the user needs to make before the agent starts developing working strategies.

Due to the dimensionality reduction, the action space required for the agent simply needs to provide a list of actions that can traverse all positions of a discrete 2D space. As

1111	2111	1211	1121	1112	1212	1221	1122	2211	2112	2121	2221	2212	2122	1222	2222
3111	4111	4211	4121	4112	4212	4221	2411	1322	3112	3121	3221	3212	3122	3222	4222
1311	4311	1411	1223	1123	1412	1421	1422	2311	2312	2321	2214	2114	2322	3422	2422
1131	4131	1321	1141	1231	1242	1241	1142	2231	2132	2131	2142	2232	2342	3242	2242
1113	4113	1413	1312	1114	1214	1224	1124	2213	2113	2123	2223	2421	2324	3224	2224
1313	1213	1431	1341	1314	1414	1243	1423	2314	2134	2323	2423	2432	2412	2124	2424
1331	3114	1132	1143	1232	1342	1441	1234	2143	2332	2431	2141	2234	2241	4223	2442
1133	3411	1433	3141	1134	1432	1324	1144	2233	2413	2341	2243	4232	2344	4322	2244
3311	1233	3211	1323	3312	3214	3142	3322	4411	4231	4123	4421	2414	4122	2144	4422
3113	1332	3314	3321	3414	3124	3223	3412	4321	4114	4213	4323	4412	4423	2441	4224
3131	3431	3143	3123	3132	3232	3421	3241	4132	4312	4141	4241	4214	4234	4342	4242
3331	2331	3231	3134	3332	3432	3442	3342	4431	4331	4341	4441	4243	4142	1442	4442
3313	2313	3213	3323	3413	3424	3423	3324	4413	4314	4313	4324	4414	4124	1424	4424
3133	2133	3233	3441	3341	3234	3243	3244	4133	4134	4143	4432	4332	4144	1244	4244
1333	2333	2433	2343	2334	2434	2443	4233	3144	1334	1343	1443	1434	1344	1444	2444
3333	4333	3433	3343	3334	3434	3443	3344	4433	4334	4343	4443	4434	4344	3444	4444

Table 3.2: Two dimensional table where each position in the table represents a possible VRLE classroom variant.

such, the actions are simply as follows: Move Up, Move Down, Move Left, Move Right.

Fig. 3.2 shows the finalised table that the RL agent uses to understand the environment it is traversing. This interactivity is also shown in Fig. 3.1 where this table is stored in the "Customisation Mappings" component. The coloured gradients on Fig. 3.2 show a visual approximation of how far a VRLE classroom variant is to the agent from one of the four main designs shown in Fig. 3.5.

It should be noted that this table is not always perfect due to the distortion that can happen when reducing a 4D environment to a 2D mapping. The main issue caused by the distortion is that on occasion, some classrooms that are equally different are not an equal number of steps away from the agent. This issue however is significantly reduced as the number of actions that the agent takes within an episode is increased. Additionally, the mapping table itself was handcrafted to account for these distortions and minimise them as much as possible. In conclusion, the benefits of mapping the representation of the environment from 4D to 2D significantly outweigh the negatives when it comes to this dissertation's implementation and as such this is the system used in the finalised software.

3.7.3 User Input and Reward System

The RL agent used in this dissertation is specifically a Q-Learning agent, therefore the Bellman Equation (Fig. 2.3) was used as the Q-function. With this system in place, the agent associates a Q-value with every state and action combination that it encounters, and uses that information to determine its future actions. Since in this case the agent needs to adapt to real people's preferences, the rewards used to help define a Q-value need to be based, at least to some degree, on the thoughts of the individual people.

To provide a link between user sentiment and Q-values in this implementation, a user input system was built into the VRLE that allows for users to submit a 1 to 5 rating for every classroom that the RL agent sets up. These ratings are then converted into reward values used to generate corresponding Q-value. Specifically, ratings of 1 and 2 represent negative rewards of -1 and -0.5 respectively, a rating of 3 represents a neutral reward value of 0, and ratings of 4 and 5 represent positive reward values of 0.5 and 1 respectively.

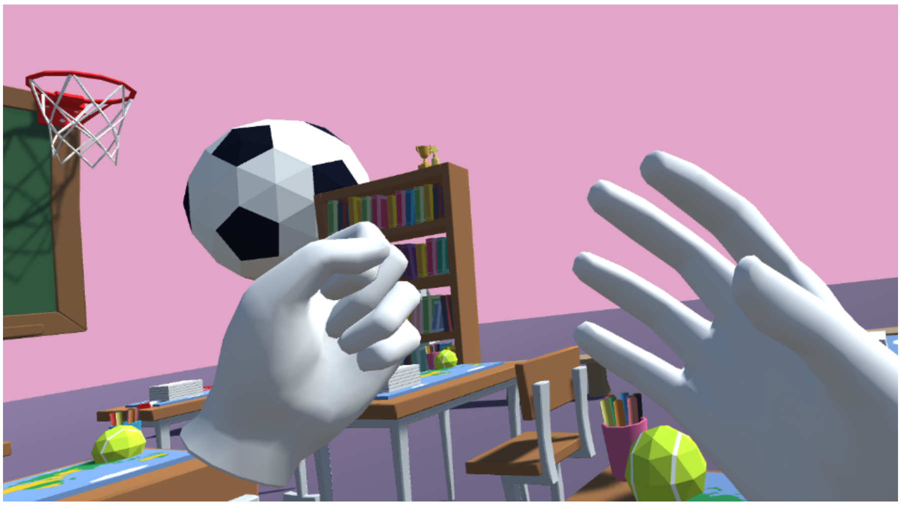


Figure 3.7: Hand tracking system.

Two user input methods for these ratings have been set up. The first being a simple keyboard input method, where when being within one of the VR classrooms a score of 1 to 5 can be submitted by pressing the corresponding number on a keyboard. The second input method however is in the VRLE itself; users can see a set of buttons on the desk they are positioned at when they first enter the VRLE. These buttons are labelled 1 through 5 and as hand tracking was set up for this environment (shown in Fig. 3.7), they are able to simply push one of the buttons to submit a rating. This submission system can be seen in Fig. 3.8 and Fig. 3.9.

Naturally, steps had to be taken to prevent confusion and exploits in regards to the VR rating system. The main steps taken are as follows:

- Only allow one button to be pressed at the same time. Users can press a button with each hand or even two buttons with a single hand. When this is done accidentally, it can lead to errors.

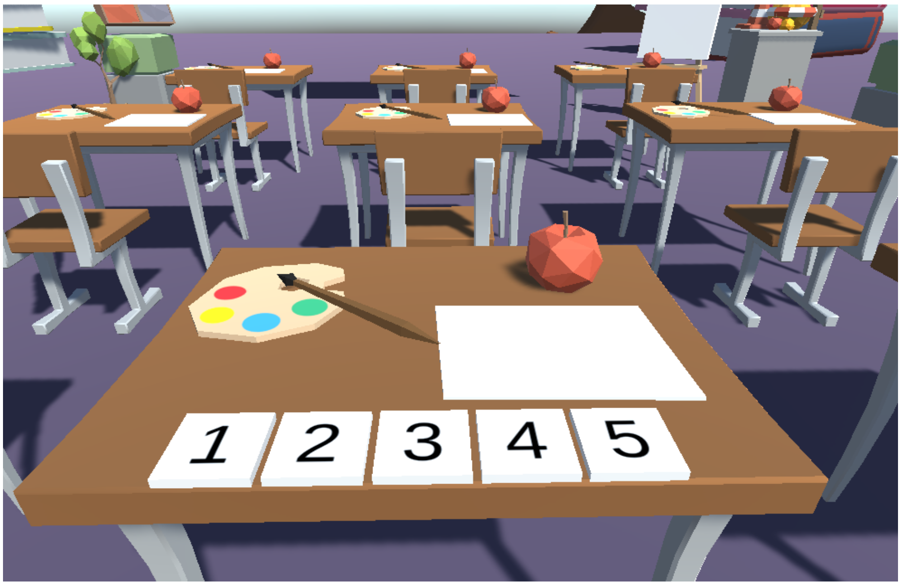


Figure 3.8: Buttons in the VR classroom that can be clicked to submit a 1 to 5 rating of the current classroom's design.

- Space the buttons well and ensure the size is reasonable given the scale of the VR hands. This can prevent users from accidentally pressing the wrong buttons.
- Highlight which button is being pressed. A lack of clarity in this regard can cause confusion especially during situations mentioned in the first point. For this implementation the button being pressed is highlighted in green as seen in Fig. 3.9.
- Ensure that the button cannot be pressed rapidly by accident. A hand shaking a bit when pressing the button, whether caused by a tracking error or because the user was actually shaking, should not be considered as multiple inputs.
- Send the rating once the user has released the button as opposed to when they initially press down on it. This reduces accidental inputs and gives the user more time to understand that they have pressed the button they intended to select.

Another factor to consider is the subjectivity of the scores. When dealing with a 1 to 5 rating system, different participants may have different ideas on how positive or negative each score is and how the classrooms should be rated. To negate this effect a rubric can be leveraged to standardise the way classrooms are scored. The rubric proposed by this dissertation can be seen in Tbl. 3.3.

The agent considers each classroom design it sets up for each user as a step in an episode, and so this system can be set up for a real educational course through having

Figure 3.9: A user submitting a rating of the classroom. The rating button flashes in green to indicate to the user that the score has been submitted.

each student submit a single rating at the end of every lecture in the VRLE. Initially the agent will start being very experimental with the classroom designs, however, with each passing lecture the agent will start to gain an understanding of each student's preferences and so lean more into designs which they prefer. As one can imagine, a system like this requiring some degree of user input every episode, does not have the luxury of being able to wait hundreds or thousands of episodes before progress is seen. Therefore intentional parameter tuning is necessary.

3.7.4 Parameter Selection

Many of the parameters used for the RL agent in this dissertation's implementation were manually picked and fine-tuned specifically for this use case. The following table (Table 3.4) shows more specific information on the parameters used for the RL agent:

3.8 Learner Profiles

3.8.1 Implementation and User Classification

This dissertation makes use of a Learner Profiling system in its implementation for two main reasons:

Factors	Very Negative (Score of 1)	Negative (Score of 2)	Neutral (Score of 3)	Positive (Score of 4)	Very Positive (Score of 5)
Aesthetics	Unattractive and uninviting	Some visually appealing elements but overall unattractive	Moderately attractive design	Visually attractive and appealing design	Highly attractive and appealing design
Immersion	Feels very flat and unrealistic	Feels disconnected from reality	Moderate immersion	High level of immersion	Very Immersive
Environmental Decorations	Objects are poorly designed and placed	Some objects are well designed, but many are poorly placed or designed	Some objects contribute positively to the design	Most objects contribute positively to the design.	All objects contribute positively to the design of the environment
Cohesiveness	Environment is chaotic and mismatched	Some parts of the environment match, but it feels disjointed	Decorations are moderately cohesive. There is sense of unity	Good sense of unity and theme consistency	Great sense of theme and unity

Table 3.3: Rubric for standardising participant scoring of VR classroom designs.

Parameter	Value	Explanation
Steps Per Episode	16	Defines the number of times the agent can take an action within an episode. The value selected allows for the agent to traverse to any possible position in the state space when starting from the a position close to the middle of its environment.
Learning Rate	0.5	Defines the rate at which the Q-values are updated based on the results of current actions. The value selected allows the Q-values to change fast enough that the user can see results relatively quickly whilst the agent still works effectively.
Discount Rate	0.98	Defines how much the agent will prioritise longer term rewards. Allows the agent to balance future rewards with the more immediate rewards.
Starting Epsilon	1	Defines the probability that the agent will experiment by selecting a random action. This value will go down over time.
Minimum Epsilon	0.1	Defines the minimum value that the epsilon can reach Allows for a small but still useful amount of experimentation once this value is reached
Annealing Steps	200	Defines the number of steps taken for the starting epsilon to reach its minimum value. The value selected allows the agent to experiment

Table 3.4: Table showing the parameters used for the RL agent.

- Storing user information learned within the VRLE that can then be used to fine tune further educational experiences and content.
- Providing an additional layer for AI agent action history storing and debugging.

The current setup is relatively straightforward, leveraging C#'s System.IO namespace, Comma-Separated Values (CSV) files are generated and populated directly from within the Unity Engine that the VRLE environment is running on. Whenever a new user starts running the program, a new Learner Profile CSV is created. Each new CSV file is also labelled numerically, with the highest number being the newest Learner Profile.

The CSVs are updated regularly whilst the VRLE software is in use, with the CCID and the user rating of the current classroom design being stored. Because the classroom designs themselves are made up of themed elements as seen in Fig. 3.5 and the CCIDs show how much of each theme is present within a given classroom design, information on a user's sentiment towards each of the themes can be easily derived. This means not only that the Learner Profiles store information on how users can be classified based on the themes they prefer, but also on the themes they are least inclined to or lukewarm on. This type of system can provide great value for educators in understanding the students they are teaching, both on an individual level and, if the data from multiple Learner Profiles is accumulated and compared, on whole classrooms of students.

Aside from student related information, traditionally associated with Learner Profiles, this dissertation's implementation also stores tracking and debugging information related to the AI agent that customises the classrooms to meet individual student's preferences.

Learner profiles are designed to be easy to add onto to tweak what i being saved to them and how frequently it is updated

3.8.2 Debugging Information

The learner profiles are enhanced with logs on status and debug information from the RL agent. This is done to allow for a greater level of transparency when either analysing the results of the agent, fine tuning parameters, or trying to debug issues.

Since the CCIDs of every classroom customised by the agent are stored along with the user rating, then not only is the history of all the actions taken by the agent stored by default, but the list is already sequential, meaning that information on the status of the RL agent at any time can be added with minimal changes to the structure of the CSV file.

The agent logs its current status into a given learner profile CSV at the end of every episode. This information contains an array of the current Q-table and Q-Values it has developed. It also contains values such as the reward value associated with each step and episode, as well as the current epsilon which defines the probability that the agent will experiment and pick a random action. This information, combined with being able to derive any action taken by the agent at any step, provides a valuable tool for those developing a system similar to this, or those trying to understand what is happening under the hood of such a system.

The debug functionality specified can be easily disabled or enhanced based on the need. Keeping the learner profiling system adjustable is important since there is notable room to build upon. Additionally, different developers and educators may have different requirements on what needs to be logged.

3.8.3 Adding onto the Learner Profiles

The logging system for the learner profiles is based on the well documented System.IO C# namespace. As such the logging mechanisms are kept simple and readable to those who may be interested in modifying the existing learner profiles.

To disable any of the currently logged information, developers can simply comment out any of the following code snippets (Fig. 3.10 and Fig. 3.11) with no repercussions:

```
//Add the state and reward stats to the learner profile
using (StreamWriter writer = new StreamWriter(fileName, true))
{
    writer.WriteLine("Step: " + getCurrentState() + ", " + reward);
}
```

Figure 3.10: Learner Profile Logging - CCID and User Rating Value.

```
//Add the state and reward stats to the learner profile
using (StreamWriter writer = new StreamWriter(fileName, true))
{
    writer.WriteLine("Episode End: " + getCurrentState() + ", Total Reward:" + currentEpisodeReward + ", Epsilon: " + e);
    writer.WriteLine("Avg. Q-Values: " + "[" + string.Join(", ", GetAverageQValuePerState()) + "]");
}
```

Figure 3.11: Learner Profile Logging - AI Agent related information.

To add any new parameters or information to the logging system, developers can simply make use of the same format as the code snippets and switch out the parameters for other values. If the information they are adding is static, for instance a student's name, it is ideal to put the logging for this after the filename for the current learner profile is generated in the Start() function of the script (See Fig. F.1 for more information). On the other hand, dynamic information should be logged either within the Step cycle of the script (as is the case with the CCID logging; see Fig. 3.10), or within the Episode cycle (as is the case with the Q-Table logging; see Fig. 3.11). Whether a dynamic value is logged within the Step cycle or Episode cycle should be dependent on how often the value changes and the level of precision required in monitoring those changes.

Separating the learner profile loggers into Start, Step, and Episode categories in this way allows for developers to better control how much precision they want when tracking student and AI agent information. It also means the learner profiles generated can be significantly more well organised, with all static details specified in the first few lines, followed by a timeline of the dynamic ones. Naturally, this results in less clutter since values that are not changing are only included once, and values that do not change often can be included less often than those that are more dynamic.

The effort put into ensuring the learner profiles are easy to understand and adjust has already proven useful as, at the time of writing, another study being done intends on making use of this dissertation's VRLE software. This study specifically intends on adding additional parameters to the learner profiling system so that it aligns with their student classification data-set.

3.8.4 Ethical Considerations

When storing user data, it is important to keep best practices and ethical considerations in mind. Whilst this dissertation's learner profiling system does not store data points that include very sensitive information about participants, this still applies. Irrespective of what user data is stored, good standards should be followed. Additionally, future projects that reference or build upon this dissertation may include systems which store more sensitive data.

Learner profiles generated by this dissertation's implementation are stored in CSV files, with a new file being generated for each unique participant. The files themselves are anonymised so that no information is present that could be used to identify an individual person in a scenario where an unauthorised party gains access to the files. A means to allow participants to request the deletion of their data should they wish to be excluded from the study is still required. As such, each file was labelled with a participant identifier number. Participants were given their number along with an information sheet (Available in Appendix D) and consent form (Available in Appendix E). Should a participant have wanted their data removed from the study, they simply needed to give the main researcher the relevant participant identifier number and their file would have been deleted. Only the main researcher had access to the files, and they were stored in one place to be easy to delete once no longer needed.

Naturally, aside from those related to data collection, there are other ethical considerations that were taken when developing this dissertation's implementation, mainly relating to the VRLE itself. Since the VRLE contains objects and colours that are dynamically adjusted, it was important to ensure that adjustments do not happen at a rapid enough rate to cause any disorientation or trigger any photosensitive epilepsy. Some options were also put in place to enhance accessibility and reduce motion sickness; mainly, aside from only allowing participants to traverse and look around the VRLE through head tracking, they were also given the option to use controller inputs.

3.9 Evaluation Methodology

3.9.1 User Sampling

Since the objectives for this dissertation are centered around how AI customisation in VRLEs affects users, gathering participants is required for the testing and evaluation. As specified in 3.1, the demographic being targeted is University students. Since there are no additional specific criteria required for participants of this study, and the research includes focus on gauging metrics such as engagement and user satisfaction, a convenience sampling approach to user sampling was taken.

In convenience sampling, the participants are selected simply if they are easy to get a hold of and willing to participate, irrespective of the demographical proportions of other users participating. For this study, a subsection of the students taught by this dissertation's supervisor were reached out to via an email. They were given a breakdown of the objectives and benefits of this study, as well as an explanation of what would be required of them if they chose to participate.

Whilst initially it was planned to have 15 to 30 people participate in this study, it was decided that this range be changed to 5 to 10 participants. This was done to make it feasible to include more qualitative result gathering through researcher observation and focus group sessions. Getting these results not only leads to significantly more time invested in planning and evaluation from a researcher point of view, but also requires a larger time investment from each participant, meaning the amount of students willing to participate would be notably lower. The reduction in potential participants however is worth it, since the results collected from each student using this system will be significantly more targeted, informative and relevant to the goals of this dissertation.

3.9.2 Quantitative Evaluation Scores

The MEEGA+ [45] model's dimensions can be combined together to determine scores for a variety of factors. One of these, specifically engagement, is one of the main factors this dissertation is examining. The MEEGA+ model defines engagement as a combination of the following dimensions defined in Fig. 2.4: Focused Attention, Satisfaction, Aesthetics, and Usability. This definition of engagement aligns with the definition proposed by a study on engagement in digital environments [46]. As such, in order to measure an engagement score for comparison between the VRLE and the AI Agent customised VRLE, users are requested to answer questions based on the MEEGA+ models standards on measuring these dimensions.

The standardised questions of the MEEGA+ [45] model have only been modified where necessary to maintain the integrity of the dimensions it measures. The MEEGA+

model was specifically designed as a standardised questionnaire model for evaluating educational games. There is however significant overlap between educational games and VRLE systems, and as such the main changes being made for this dissertation involve modifying the language used in the questionnaire sections to refer to VRLE related terminology, as opposed to educational game terminology. Additionally, only questions which were relevant to the the dimensions needed by this dissertation have been included.

3.9.3 Qualitative Result Gathering

3.9.3.1 Researcher's Observations

The testing setup itself was designed to help streamline the researcher observation process whilst study participants were making use of the VRLE.

- The VRLE environment itself was being run from within the Unity editor as opposed to the exported executable file. This provides more flexibility during observation, since it allows for observation of not only a first person view of what the participant is seeing in VR, but also third person view adjustable by the observer.
- Through the use of a linking cable, the VRLE software could not only be executed on the laptop the observer was making use of, but the learner profile data, including the debug information for the RL agent, could be viewed in real time by the observer to allow them a better understanding of what was happening in the moment.
- The observer made use of two devices during the testing period. The first was the laptop mentioned previously that was dedicated to viewing the participant in the VR classroom, as well as viewing the learner profiles and RL agent status, and the second was dedicated to note taking. Whilst making use of two devices for these actions is not a necessity since note taking could be done on the first device as well, having a separate device means that notes can be easily taken without interrupting observation or requiring the observer to constantly context switch.
- It was ensured during setup that the observer would be seated in a position where they were physically able to see the participants when they were making use of the software. This helped the observer correlate the movements of the participant in the real world to what was happening in the VRLE, as well as allowed them to take note of any comments made by the participants during usage of the VRLE.

3.9.3.2 Participant Focus Group

A focus group was held a couple of weeks after the process of bringing in participants to use the VRLE had concluded. This focus group leaned towards a free-form session where all participants who took part in the study could voice and discuss any opinions or thoughts on their experience taking part, as well as on the idea of VRLEs that make use of the concepts and technologies explored in this dissertation.

This dissertation's researcher was also present at the focus group session in order to ensure that the session stayed on track and prompt the participants, whether it be to get them to discuss a point further, or in case a point was reached where all participants were remaining silent. The prompts used by the researcher were prepared ahead of time and can be found in Appendix I.

3.10 Summary

This chapter explores how the more practical parts of this dissertation were set up and implemented. It includes a breakdown of the software developed, explanations of why certain choices were taken, as well instructions on how to replicate or build upon it.

The chapter starts by explaining the dissertation's participant target demographic, followed by an overview of the VRLEs developed, along with information on the software and hardware technologies that were leveraged during development. An in depth breakdown is given for how the VR input handling and environments were implemented, followed by a similar breakdown for the RL technologies used to make the software's AI agent and the systems put in place to allow the agent to drive the environment personlisation. The learner profiling system is also broken down and instructions on how to effectively modify and build upon them is given.

The final part of this chapter discusses the evaluation methodologies adapted and developed to achieve the goals of this dissertation whilst maintaining standardised systems that can be easily replicated for comparison and contrast. The evaluation systems for this dissertation are split into a quantitative system which has been adapted and reworked based on research and standards in educational games evaluation, and qualitative systems that include a researcher observation setup and a participant focus group.

4. Results & Discussion

4.1 Overview

Once the customisable VR classroom was developed for this dissertation (in line with O1) and enhanced through the use of an RL agent that could manage the customisation (O2), participants needed to be brought in to evaluate the effects of this system (O3) and study how it could be practically implemented in real world scenarios (O5). A total of 9 participants took part in this study. This was within the target 5 to 10 range discussed previously in chapter 3.9.1. These participants were requested to do the following:

- Try out the default VRLE that did not make use of any AI functionality.
- Fill in a questionnaire on VR usage which is mainly based on the MEEGA+ [45] model's engagement related dimensions.
- Try out the AI enhanced VRLE that makes use of an RL agent to customise the VR classroom environment.
- Fill out a second questionnaire that is also based on the MEEGA+ [45] model's engagement related dimensions.
- Take part in a focus group session with the other participants.

Whilst participants were making use of this dissertation's VRLE software, two other systems were in place to gather as much research data as possible. The first simply being this dissertation's main researcher having access to a video feed of what each participant was seeing in VR as well as corresponding live debug information. Having these, as well as positioning the main researcher in the same room as the participants, allows for the researcher to take note of participant actions and reactions that would not be captured in the result gathering process otherwise. The second process for gathering research data whilst participants were making use of the VRLE is the generation of learner profiles for each participant. These learner profiles are tuned to allow for the collection of user data that can be used in educational content recommendation for each individual (in line with O4). However, when the learner profiles are aggregated and compared together, they can allow for unique insights on user preferences regarding different parts of this dissertation's software implementation.

4.2 Demographics

Upon opening the first questionnaire, participants were prompted with some basic questions which are designed to gather information on participant demographics, as well as information on how familiar the participants were with VR and VRLE technologies. The results were as follows:

- All participants were within the 18 to 25 age range.
- Six participants identified as males whilst three participants identified as female (Fig. 4.1).
- Participant VR usage can be seen in Fig. 4.2. It shows that the majority of participants had used VR once or twice.
- Participant familiarity with VLE technologies varied greatly. Specifics are shown in Fig. 4.3.

These results generally fall in line with what was expected, with the majority of the participants having had some experience with VR technologies without being frequent users of them. The overall VLE familiarity, at an average of 2.44 out of 5, was lower than expected when considering that all participants were university students. There may be multiple reasons for this, for instance students might only be familiar with a couple of VLEs, or feel that they do not leverage many VLE features that they have access to, and so believe there are many areas of VLEs that they are not familiar with.

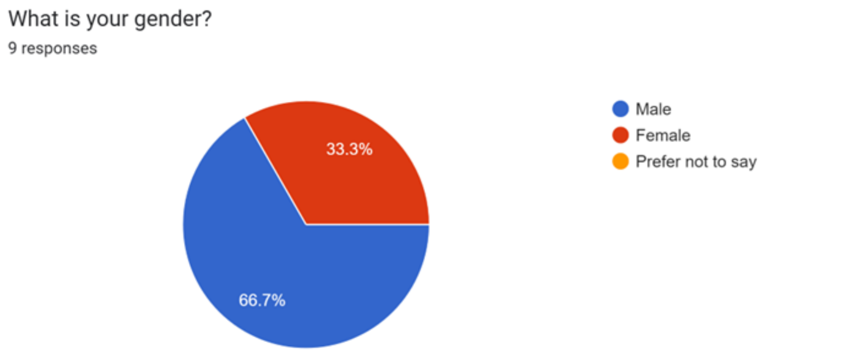


Figure 4.1: Participant Gender demographics

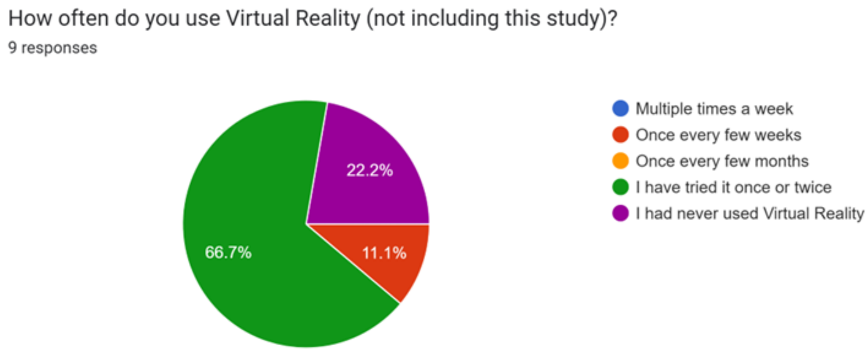


Figure 4.2: Participant VR usage

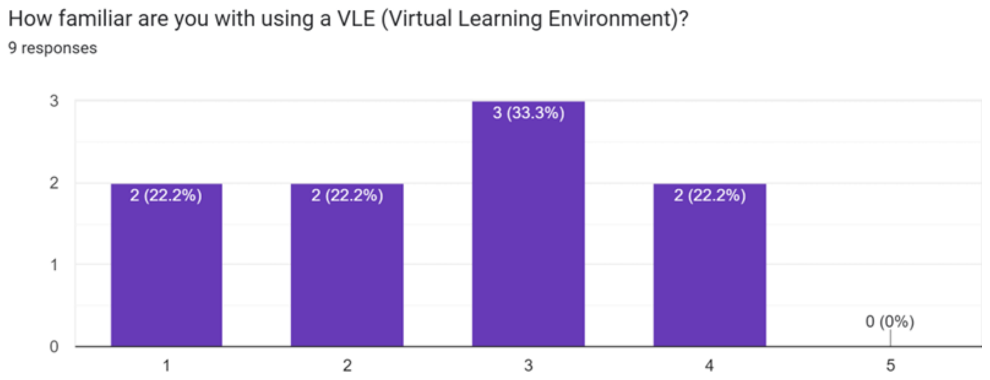


Figure 4.3: Participant VLE familiarity on a 1 to 5 scale

4.3 Engagement Scores

4.3.1 Standard VRLE Classroom

This section goes over the data, results and insights gathered from the first questionnaire given to participants after they had made use of this dissertation's default VRLE classroom. This questionnaire collects data on the dimensions of the MEEGA+ [45] model that relate to measuring engagement. As such, the following dimensions were collected: Focused Attention, Satisfaction, Aesthetics, and Usability. The individual questions asked and responses to those questions can be seen in Appendix G. The average scores for each dimension can be seen in the following diagram (Tbl. 4.1):

Dimension	Question Scores	Question Averages	Dimension Average
Aesthetics	2,3,3,3,3,4,4,4,5	3.44	3.50
	3,3,3,3,4,4,4,4,4	3.56	
Learnability	5,5,5,5,4,4,4,3,3	4.22	4.52
	5,5,5,5,5,5,5,5,5	5.00	
	3,4,4,4,4,5,5,5,5	4.33	
Satisfaction	2,2,2,3,4,4,4,5,5	3.44	3.33
	1,2,3,3,3,4,4,5,5	3.33	
	2,2,2,3,3,3,4,5,5	3.22	
	2,2,3,3,3,4,4,4,5	3.33	
Fun	3,3,3,4,4,4,4,5,5	3.89	3.61
	1,2,2,3,3,4,5,5,5	3.33	
Focused Attention	2,2,3,3,4,4,5,5,5	3.67	3.33
	1,1,2,2,2,3,4,4,5	2.67	
	1,2,3,4,4,4,5,5,5	3.67	
Operability	4,4,5,5,5,5,5,5,5	4.78	4.67
	3,3,5,5,5,5,5,5,5	4.56	

Engagement Score	3.83

Table 4.1: Default VRLE Participant Engagement Results

The maximum score each question in the MEEGA+ model can reach is a 5, as such the question averages, dimension averages, and engagement score in the table (Tbl. 4.1) are also on a 1 to 5 scale, with a higher number always being better. Each question's average score has an equal weighting on its own dimension, whilst each dimension has an equal weighting on the final engagement score. This means that dimensions which require more questions to measure do not have a larger effect on the final engagement score.

The results in (Tbl. 4.1) show that aesthetic, user satisfaction, and focused attention scores were notably lower than learnability and operability scores. This could imply that even though the vast majority of participants reported that they have only used VR at most a couple of times (Fig. 4.2), the novelty of VR technology simultaneously did not cause a significant barrier of entry for the participants nor significantly inflate the aesthetic, user satisfaction, and focused attention dimensions.

4.3.2 Personalised VRLE Classroom

This section covers the data, results and insights gathered from the second questionnaire, which was given to participants after they had made use of this dissertation's AI tailored VRLE classroom and follows the same format as the first when it comes to measuring engagement related dimensions. The following figure (Tbl. 4.2) shows the average scores for each engagement related dimension collected from the second questionnaire:

Dimension	Question Scores	Question Averages	Dimension Average
Aesthetics	3,3,4,4,4,4,4,4,4	3.78	3.94
	3,4,4,4,4,4,4,5,5	4.11	
Learnability	1,2,3,4,5,5,5,5,5	3.89	4.41
	4,4,5,5,5,5,5,5,5	4.78	
	4,4,4,4,5,5,5,5,5	4.56	
Satisfaction	2,2,4,4,4,4,5,5,5	3.89	3.81
	2,2,3,3,3,4,4,4,5	3.33	
	3,3,3,4,4,4,5,5,5	4.00	
	2,2,4,4,4,5,5,5,5	4.00	
Fun	3,4,4,5,5,5,5,5,5	4.56	4.39
	2,2,4,5,5,5,5,5,5	4.22	
Focused Attention	2,3,4,4,4,5,5,5,5	4.11	4.04
	2,2,3,3,5,5,5,5,5	3.89	
	1,4,4,4,4,5,5,5,5	4.11	
Operability	4,5,5,5,5,5,5,5,5	4.89	4.78
	3,4,5,5,5,5,5,5,5	4.67	

Engagement Score	4.23

Table 4.2: AI agent tailored VRLE Participant Engagement Results

Similarly to the results of the first questionnaire (Fig. 4.1), the operability and learnability dimensions had higher average scores than the aesthetic, user satisfaction, and focused attention dimensions. The differences between the dimension average scores in the second questionnaire however, are smaller on average than those in the first, whilst the actual values are higher. A more detailed breakdown of the differences and similarities between the two versions of the VRLE can be found in chapter 5.1.

4.4 Effectiveness of Customisable Elements

As discussed previously, the personalised VRLE classroom has four types of customisable elements that can be customised by an AI agent. These elements are the floor colour, class decorations, background colour, and background decorations. In order to understand which of these elements had the greatest effects on users (O5), the participants of this study were asked to give each element a 1 to 5 score based on how significant a role they played in their opinions of the VRLE classrooms customised by the AI agent. The following diagram (Fig. 4.4) shows the results:

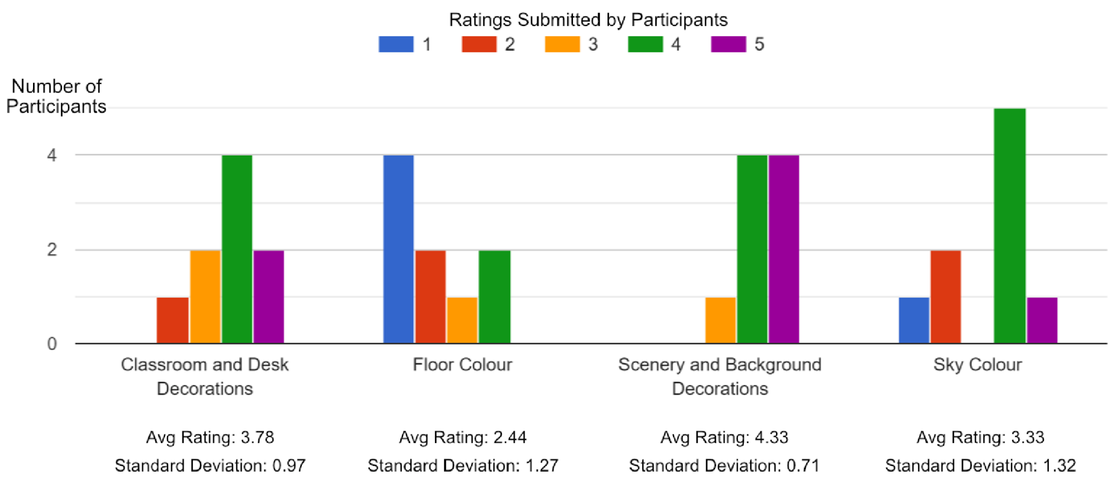


Figure 4.4: Participant 1 to 5 ratings for how important each customisable factor the AI agent could change in the VRLE.

As can be seen in the diagram (Fig. 4.4), the customisable feature considered to be decorations had a greater impact on participants, as opposed to the colours of the environment. The scenery and background related decorations specifically were the most significant customisable features to the participants by a notable margin. Additionally, these features had the lowest standard deviation, implying that these are the most important and consistent features from those the AI agent could adjust when it comes to how participants score the classroom designs.

The floor colour on the other hand was considered the least important, scoring significantly lower than sky colour, and even being the only feature which not a single participant ranked a 5 in importance. This shows that when developing AI tailored VRLE systems like this dissertation's, this environmental feature is the safest to deprioritise when it comes to selecting what an AI agent can customise. The second safest to deprioritise is the sky colour since it had the second lowest average rating. However, it should be noted that sky colour had the highest standard deviation in participant ratings, implying that whilst some participants found it ineffective, others ranked it highly on importance.

4.5 Learner Profile Analysis

The following python script (Fig. 4.5) was developed in order to efficiently parse through the learner profile results relating to CCIDs and the ratings that participants gave for each VR classroom. This script loops through each CCID encountered by a participant and finds the correlating rating that the participant gave for that classroom design. It then takes the individual digits making up the CCIDs and stores the average rating for each digit. Since each digit in a CCID is associated with one of the four main themed classrooms shown in Fig. 3.5, the average ratings returned by the python script represent user sentiment on the themed classrooms that the AI can mix and match from to customise classrooms.

Participant	Number of scores submitted	Theme 1 Score	Theme 2 Score	Theme 3 Score	Theme 4 Score
1	95	-0.189	-0.214	-0.050	-0.189
2	150	-0.116	-0.015	0.091	0.020
3	264	-0.349	-0.162	-0.062	-0.040
4	97	-0.076	0.183	-0.097	0.065
5	102	-0.167	-0.329	-0.429	-0.536
6	48	-0.510	-0.750	-0.531	-0.407
7	74	0.220	0.200	0.304	0.136
8	92	-0.112	-0.011	0.170	-0.043
9	91	-0.181	-0.119	-0.509	-0.148
Average:	113	-0.164	-0.135	-0.124	-0.127

Table 4.3: Results generated from the participant learner profile data that relates to CCIDs and classroom ratings.

The results gathered using the python script are presented in Tbl. 4.3. This table shows anonymous information gathered from the learner profiles generated for each participant who took part in the study, as well as averaged out information. The "Number of scores submitted" column of the table refers to the number of 1 to 5 ratings that each participant

```python
def calculateAverageThemeScore(input_text):

    #Define a dictionary to store the total and counts for each theme
    themeDict = defaultdict(lambda: {'total': 0, 'count': 0})

    #Split the input into by each step
    steps = input_text.strip().split('\n')

    for step in steps:
        #Remove the "Step: " identifier text split wghats left into CCID and reward value
        CCID, rewardVal = map(float, step.replace("Step: ", "").split(", "))

        #Iterate through each digit of the CCID and adjust the dictionary
        for digit in str(int(CCID)):
            themeDict[digit]['total'] += rewardVal
            themeDict[digit]['count'] += 1

    # Calculate the average for each digit
    averages = {}
    for digit, total in themeDict.items():
        count = total['count']
        total_value = total['total']

        if count > 0:
            averages[digit] = total_value / count
        else:
            averages[digit] = 0

    return averages
```

Figure 4.5: Python function used to extract average user sentiment scores for each classroom theme.

gave to the AI agent. The theme scores have a range of -1 to 1 with -1 being completely negative and 1 being completely positive. With this in mind it can be noted that the classroom theme with the best user sentiment is Theme 3, i.e. the nature theme, followed by the art theme, the educational theme, and the sports theme in that order.

4.6 Researcher's Observations

This section goes over some notes and takeaways made by the main researcher whilst observing participants making use of this dissertation's VRLE software.

- Those participants who were unfamiliar with VR technologies would often accidentally submit scores they did not intend to submit, especially when first orienting themselves or trying to get familiar with hand tracking. Participants were presented with the default VRLE prior to the one with the AI and UI to avoid this exact scenario. Despite this precaution, it was noted that those very unfamiliar with the technology often needed a minute or two to reorient themselves in a VR space, even if they had been in one a few minutes prior. One way to prevent users from accidentally interacting with the UI whilst they are reorienting themselves would be to have the UI in these types of systems only become intractable once a user has been in the VR space for a certain amount of time.

- Participants often stuck to extreme values when rating the work of the AI agent, they would for instance vote for the minimum and maximum scores and mention out-loud that it was based on a single feature that they particularly liked or particularly disliked rather than the classroom as a whole. As such, there could be value in the implementation of a system that can identify and adjust weightings for more extreme scores.

- There were occasions where the AI agent would suggest the same classroom design to participants twice consecutively even if the score it had been given was a 3 out of 5 or lower. Whilst not a common occurrence, it still caused some confusion or frustration on a few instances. Hard-coding the system to prevent this exact scenario would be ideal.

- Those unfamiliar with VR sometimes required some guidance on how to interact with UI in VR. Multiple participants attempted to keep their hands static whilst moving their entire bodies into a UI button. In scenarios like this, they were informed by the researcher observing them that they could keep their body static and reach out with their hands as if pressing a button in the real world. These situations show that it may be beneficial to provide participants who are not familiar with VR technologies with visual demonstrations of how they can interact with the VR environment.

- Participants were told to aim to submit at least 30 classroom ratings to the AI agent, however they were free to use the software for as long as they wanted. The average participant surpassed expectations by a wide margin and interacted with the classroom customisation AI for a significant time period. This is reflected in Tbl. 4.3 where it can be seen the average participant submitted 113 scores, with only a single participant submitting under 50 scores. This implies that participants were finding satisfaction in the process of rating the classrooms and seeing how the system adapts to those ratings.

- Whilst using the software some participants noted that they were changing their opinions over time, i.e. starting to like some classroom elements they had previously disregarded or vise versa. Situations like this could cause some frustration for students using a VRLE of this nature since if they start liking a feature they had previously disliked, it would be significantly harder to get the AI agent to notice due to it simultaneously recommending that feature less, whilst also requiring more interactions with that feature to counteract the negative association. One way of handling a situation like this in future implementations could be to have the values of the agent's Q-table move towards neutral if not updated over a long enough time period.

The observations noted show that it is important to focus on further improving learnability for VRLEs and reducing the chances of user error occurring. Additionally, when developing software similar to this dissertation's, one should take into account and implement systems to mitigate psychological factors that could affect the user experience being targeted.

4.7 Participant Focus Group

The focus group session was transcribed so that it could be analysed more effectively. The transcript was imported into the qualitative data analysis software Nvivo [48] where a thematic coding process was done. This involved manually marking and labelling the statements made by the participants in the focus group session. The labels were iteratively abstracted and grouped together until the general themes emerged. This was done to understand the main trends and points being made during the focus group session.

This system led to the emergence of three main themes as follows:

- **Focus and Engagement**
  This was the most commonly occurring theme and aligns well with this dissertation's aim. Participants felt that VRLEs in general could help eliminate distractions and improve focus. They also mentioned how the AI agent customisation created a feeling of engagement as they became invested in seeing how the environment would change and adapt to them. It was mentioned that a system like this dissertation's can resonate well and grab one's attention by keeping things dynamic. They also found satisfaction in seeing if they could get the AI agent to produce certain results. One participant also mentioned how they believed a system like this would create a better learning environment than the one size fits all approach that is currently the norm. Another participant noted that they believed a tailored approach like this could also help people with certain conditions or tendencies to feel more accommodated for.

- **Future Possibilities**
  Generally participants found that there was significant potential in the ways that future AI customised VRLE classrooms could be implemented and the feature sets that could be added. Participants mentioned that they would be interested in seeing both an increase in the variety of features that can be changed by the AI agent in the VRLE, as well as an increase in the factors that the AI agent could account for. For instance, one participant mentioned that they think features based on a variety of educational fields could be added and that the subject of the class being held within a VRLE at a given time could have a weighting on the AI agent's choices.

- **Online Classes**
  Participants noted that they felt like this technology could enhance the experience of online classes. They noted how it is easier to end up fidgeting, multitasking or losing focus in online classes, and that making use of VRLE technologies reduces the opportunities to do so. These findings align with the pre-existing studies discussed earlier in this dissertation (2.3.2) which looked into how metaverse and VRLE technologies can negate the undesirable effects of remote learning.

4.8 Summary

This chapter includes all the raw results generated as a result of the quantitative and qualitative result gathering methodologies developed in the previous chapters. It starts with an overview of what was requested of participants who took part in the study, as well as information on the number, demographics and familiarity with relevant technologies of those participants. The participants found all fell within this dissertation's targeted demographics.

The raw quantitative results collected through engagement measuring models adapted from the field of educational games [45; 46] were then shown. Two tables were created as a result of this, one that shows the engagement related dimensions and scores of the default VRLE classroom, and the other showing the same information for the peronalised AI enhanced VRLE classroom. The main takeaway being that, inline with expectations, the majority of engagement related dimensions saw positive changes from the AI enhancements added to the VRLE.

Additionally, the quantitative results were used to show the level of impact that the different customisable elements of the AI enhanced VRLE had on the participants. The learner profiles were used to get similar results for the themes that the elements making up the classrooms could be selected from. A python script was used to analyse the learner profiles and extract user sentiment for each theme. This showed an overview of which of what varients of the environmental elements were preferred by participants.

The qualitative results gained from the researcher observation system and the focus group session were also discussed. These show a combination of practical notes and advice that can be applied to future studies or AI enhanced VRLE applications, as well as the results of the thematic coding process done on the transcript of the focus group session, which showed the main themes and points brought up by participants during the focus group session.

5. Evaluation

5.1 Comparison of Default and AI Enhanced VRLE

This section contrasts the data, results and insights gathered from the first questionnaire with those from the second. The first questionnaire was given to participants after they had made use of this dissertation's default VRLE classroom. This default VRLE environment (can be seen in Fig. 3.3) was designed to act as a ground truth to be used to compare with the AI customisation based counterpart. The questionnaire focuses on gathering information regarding user satisfaction and engagement and is based on how these are measured in the MEEGA+ model [45]. The second questionnaire was given to participants after they had made use of this dissertation's VRLE enhanced with AI customisation, and measured the exact same values.

Table Tbl. 5.1 provides a good insight into the differences between the results of the two questionnaires. The Delta column of the table shows how each dimension measured changed between the first and the second questionnaire. Green coloured cells denote a positive change once the AI agent was introduced, whilst red denoted a negative change. As such, it is immediately apparent that the AI agent customisation that this dissertation is centered around exploring has much more of a positive effect than a negative one. The only dimension that was affected negatively was Learnability which is not surprising when one considers that the AI enhanced VRLE requires users to perform additional steps when compared to the default VRLE.

The Fun and Focused Attention dimensions saw the greatest boosts in value from the AI enhancements to the VRLE. This aligns with how participants who took part in the study often spent significantly longer in the AI enhanced VRLE and, as discussed previously, interacted with the AI systems significantly more than they were required to do. The dynamic nature of AI agent-based VR classroom generation seems to have kept the environment feeling fresh and produced an experience where participants found joy in seeing the classroom become more tailored to them over time.

The Aesthetics, Satisfaction, and Operability dimensions also saw benefit from the AI

	Default VRLE		AI Enhanced VRLE		
Dimension	Question Averages	Dimension Average	Question Averages	Dimension Average	Delta
Aesthetics	3.44	3.50	3.78	3.94	0.44
	3.56		4.11		
Learnability	4.22	4.52	3.89	4.41	-0.11
	5.00		4.78		
	4.33		4.56		
Satisfaction	3.44	3.33	3.89	3.81	0.47
	3.33		3.33		
	3.22		4.00		
	3.33		4.00		
Fun	3.89	3.61	4.56	4.39	0.78
	3.33		4.22		
Focused Attention	3.67	3.33	4.11	4.04	0.70
	2.67		3.89		
	3.67		4.11		
Operability	4.78	4.67	4.89	4.78	0.11
	4.56		4.67		
	Engagement Score	3.83	Engagement Score	4.23	0.40

Table 5.1: Table showing a comparison of the participant engagement and satisfaction data between the default VRLE and the AI enhanced VRLE.

enhancements to the VRLE, albeit not to the same degree as the Fun and Focused Attention dimensions. The increase in the Aesthetics dimension is expected due to the AI enhancements leading to more tailored and varied visuals for the VR classroom. The increase in the Satisfaction dimension implies that users found the feature set of this VRLE more interesting, satisfying and recommendable to others than the feature set of a more standard VRLE. The only dimension that did not fall in line with expectations was the Operability dimension since it was presumed that this would see a slight decrease along with the Learnability dimension, as opposed to the slight increase seen. The main difference between the Learnability and Operability dimensions in the MEEGA+ [45] model is that the Learnability dimension focuses on measuring how easy it is for users to understand what is needed from them to use the features of the software, whilst Operability focuses on evaluating the difficulty involved in controlling the software. As such, these results indicate that the addition of this dissertation's AI environment customisation made participants feel like they required more investment to understand what was happening, however, the addition of the VR buttons required to interact with the AI agent did not dissuade the participants.

The Engagement Score is an evenly weighted accumulated score based on the dimensions measured. As such, it saw an increase of 0.4 when the AI agent customisation was introduced. This puts the final Engagement Score of the AI enhanced VRLE at a 4.23 out of 5. This increase falls in line with the hypothesis that making use of AI environment customisation would allow for a more tailored, satisfying and engaging VR classroom experience.

5.2 Expectations Vs Realities

This section covers some situations encountered during this dissertation's methodology, testing, and evaluation that were not expected to cause issue either because they were not accounted for or as precautions were in place but needed to be stronger. These are points that future studies in this field can take into account to streamline their research.

- Several steps were taken to prevent users from pressing the wrong buttons in the VR environment and submitting the wrong scores to the AI agent. The buttons were made large and spaced out, the colliders of the hand and the buttons were simplified to to prevent double inputs, only a single button could be pressed at a given time, and the button being pressed would turn green to indicate that it was active. There were however still multiple instances noted where participants would press the wrong button by accident. This was often due to them losing track of their non dominant hand in the VR space and not realising they were pressing another part of the UI with it, or because they would press the wrong button whilst moving towards the intended button. Whilst this is not a massive detriment since these mistakes often happen when participants are still getting used to the VRLE and so restarting the software and the AI aren't detrimental, it can still cause unnecessary issues and therefore steps should be taken to negate it. Possible solutions include only having VR buttons activate after they have been held down for a few seconds rather than instantly, and/or require the user to be able to manually toggle which hand can interact with the VR UI at any given time.

- During the researcher observation process, it was noted that some participants would say they changed their mind on a particular customisation feature and so would start voting differently when encountering it. Whist this is not a massive issue in regards to affecting the performance of the AI agent, it could cause some frustration with users since the AI agent would require more time to change an association with one of these customisation features when compared to one it has no associations made with. This scenario was not accounted for during the development of the software and as such no system was implemented to help with it. As mentioned previously, this could be negated in future implementations by allowing the AI agent's Q-values that have not been updated after a specific time period to trend towards being neutral.

- The results of the Learner Profile Analysis showed that, on average, participant sentiment regarding all 4 themes that the AI agent was mixing and matching from when selecting features for the custom VR classrooms, was negative. This could simply be an indication that participants vote a more extreme score when they dislike a particular element then when they like one. If this is the case, it could be beneficial to give any positive reward values passed to the AI agent a higher weighting than negative reward values.

5.3 Overall Evaluation Discussion

The results gathered from this dissertation align well with what was expected. Overall, those who participated saw higher levels of satisfaction and engagement when using a VRLE that was tailored to them using an RL based AI agent. On average, participants struggled slightly more to learn how to make use of the tailored AI enhanced VRLE but all other measurements taken showed that the AI enhancements were beneficial to the user experience.

The feedback participants gave to the AI agent so that it could tailor the VRLE accordingly also provided an extra layer of insight. This feedback was stored as part of the Learner Profiles and the analysis on them (Fig. 4.5) allowed for an overview of sentiment regarding classroom themes that the AI agent could reference while tailoring the VRLE. The results showed that the the nature themed classroom elements were associated with the greatest participant sentiment, followed by the art elements, the educational elements, and the sports elements. This ranking can be used by similar or follow up studies to understand what themes and environment specifics to prioritise and which to build on or improve.

Investigating which elements of the AI tailored VRLE had the greatest effect on the participants and making recommendations on best practices (O5) could provide invaluable information for streamlining and improving research and implementations of future AI tailored VRLE. To achieve this, as part of the second questionnaire given to participants after they had finished using this dissertation's AI enhanced VRLE software, participants were asked to rank the different types of customisble features used in the AI enhanced VRLE. A ranking (Fig. 4.4) was then created based on these results that provides insight into which features of VR classrooms had the most impact. Additionally, due to the rigorous researcher observation process taken during participant usage of the default and AI enhanced VRLEs, a list of takeaways and recommendations was created (Fig. 4.6) that can be a valuable asset in future research where AI customisation meets VRLE technologies. Additionally, the focus group allowed for more light to be shed into these areas as well as for more qualitative data to be gathered that added more context to the quantitative results.

The implementation and these corresponding results align with the main aim of this dissertation, i.e. to provide insight into on how AI agent-based personalisation can increase engagement levels. Multiple types of insights, based on both quantitative and qualitative results, have been found that support this aim, and each of this dissertation's objectives have been met.

5.4 Summary

This chapter follows up on the previous through evaluation and analysis of the results gathered from this dissertation. It includes a comparison of the engagement related dimensions between the default VRLE classroom and the AI enhanced one, with the default acting as the baseline to gauge the effects that the AI enhancements had on the participants. It was noted that all dimensions except for the Learnability dimension saw a positive change when AI agent-based customisation was introduced.

Also included in this chapter is a section on which expectations were not met throughout this dissertation's implementation, testing, and evaluation. This refers specifically to situations where unexpected issues arose. These were noted to allow for documentation to exist to help future studies avoid the same pitfalls. The final section of this chapter looks at all the result types, both quantitative and qualitative, gathered from the previous chapter from a more holistic viewpoint. The implications of the different result types and how they relate to one another, as well as to objectives of this dissertation, were discussed. It was deemed that the insights and results gathered align with the aim and goals of this dissertation.

6. Conclusions

6.1 Revisiting the Aims and Objectives

The aim and objectives of this dissertation have been met. The aim itself was to research and provide insight into how VRLEs can be made more engaging for end users through the use of AI agent-based personalisation. The first objective (O1) set out to achieve this was the setting up of a customisable learning environment that is accessible through VR technologies. This was achieved through making use of the Unity game engine to design four differently themed VR classrooms made up of several elements and colours that can be mixed and matched with each other through changing a code referred to as a CCID. VR technologies were implemented through the use of an open source VR template [47] that allowed for support of multiple VR headsets and control styles.

The second objective (O2) was to implement an RL agent with the ability to alter the VR classroom environment to match the preferences of individual users based on their feedback. This objective was achieved through a Q-Learning based AI agent that was able to interface with the CCID system to both map the state space of possible classrooms to a traversable two dimensional environment with the AI agent's position in the environment defining how the current VR classroom is designed.

The third objective (O3) was to generate and fine tune learner profiles that can be used for educational content recommendation. This system was designed to gather and store information on each user who interacted with the AI enhanced VRLE. It was designed to be modular and flexible to allow it to be easily adjusted by developers to meet a variety of different needs. The data gathered in these profiles was also used to gain a deeper understanding of participant sentiment regarding the classroom themes that the AI agent could mix and match features from. This acts as an example of how a system like this can be used practically for understanding and enhancing educational experiences. Additionally, the learner profiles were enhanced to store AI agent action history and associated debugging information. This served as a valuable asset for fine tuning the agent and investigating issues.

The fourth objective (O4) was to investigate the effects that RL agent-based environment customisation in a VRLE has on user satisfaction and engagement. Due to the lack of standardisation in educational VR environments on gathering these metrics, standards and models from educational video games were investigated and adapted by this dissertation. This allowed for user satisfaction and engagement scores to be collected in a way that both aligns with research in other fields and allows for easy replication and comparison by future studies. With this established, and two VRLE software implementations created, one being a standard VRLE classroom, and the other having RL agent-based environment customisation, this objective was reached.

The fifth and final objective (O5) was to propose recommendations and best practices for similar implementations based on which elements of the customised VR environments had the greatest effects on the participants. Two approaches were taken to tackle this and provide insight from different perspectives. The first was making use of the learner profiles generated when participants were making use of this dissertation's software to gain an understanding of user sentiment for the different themes that the customisable environmental elements followed. This allowed for an understanding of which themes worked better or worse for the VRLE. The second approach involved directly asking users to rate the importance of different categories of the environmental features adjusted by the AI agent. This provided insight into what should be prioritised within implementations similar to this dissertation's based on what participants actually noticed and felt. Additionally, researcher observations noted whilst participants were making use of this dissertation's software, as well as insights from this dissertation's focus group session, provided additional recommendations and best practices that can be followed.

6.2 Critique and Limitations

Despite the aim and objectives of this dissertation being reached, there are still areas where limitations were hit and therefore improvements can still be made. The initial implementation plan for this dissertation's software involved making use of a metaverse platform to host the VRLEs on. This however was not feasible as after research on and discussion with the metaverse platform holders, it was deemed that the requirements of this dissertation did not align with the feature sets and level of control currently available. As such this dissertation's VRLEs were developed within a game engine and metaverse enhancements such as online functionality and allowing all students to be within the same VRLE were not included.

Another part of the initial plan for this dissertation involved the addition of a third

VRLE type to compare and contrast with the default VRLE and the AI designed VRLE that were implemented. This third VRLE would have allowed the human user access to the same options that the AI agent has within the VRLE, therefore allowing them to manually select how the environment is customised. This would have allowed for a more in-depth analysis of the value and ideal use cases of AI agent-based VRLE customisation and meant that more of the 3D environment customisation types defined previously [38] would have been compared.

A limitation of the current AI agent implementation is that the number of customisable VRLE features and options for each feature could be significantly increased. The current implementation gives the AI agent the ability to change 4 features, each with 4 variations. Whilst this does lead to a total of 256 possible unique VRLE designs, at an individual feature level the number of options could be considered quite limited. One participant specifically noted that they felt the number of colours available for the sky colour feature could have been larger as they did not like any of the options available. Allowing for more options per feature would remedy issues like this and increase the appeal for a greater number of users. Additionally, increasing the number of feature categories would allow for a finer level of tailoring to the users of the VRLE, since currently some features contain options that could be broken down into finer categories.

It was noted that the testing experience for this dissertation's VRLEs could be streamlined by including surveys in the VR environment itself as opposed to this dissertation's approach of having participants remove the VR headset and fill out the questionnaires on their phones after they are done using a particular VRLE. Having the questionnaires included in the VRLEs was actually considered for this dissertation and a toolkit [49] was found that could facilitate this. This was left out of this dissertation's implementation due to it making use of different systems to handle inputs from the VR hardware. Additionally, the toolkit could have introduced dependencies which would have gone against the choice made in this dissertation to maximise compatibility with as large of a variety of VR hardware as possible.

Whilst these limitations were the result of intentional choices made to either minimise scope creep, enhance other higher priority factors, or minimise factors that could convolute the testing and result gathering process, there are still ways in which, especially with the hindsight gained from this dissertation, future research and implementations can address these limitations whilst minimising the downsides associated with tackling them.

6.3 Future Work

This dissertation is only a step towards understanding the ideal ways to leverage AI agent customisation to create more engaging VRLEs. There are still many ways that future research can build upon this dissertation. This section covers some ways that this can be done. The first way that future work can build on this dissertation is by implementing and investigating the effects of adding metaverse features to AI agent enhanced VRLEs. This could take the form of having multiple users exist within the same VR classroom and be able to interact with each other, whilst each seeing different decorations and content depending on their learner profiles and targeted AI customisation. A future study along these lines could also take the engagement and satisfaction results relating to the two VRLEs developed for this dissertation and compare engagement and user satisfaction to versions built with metaverse features.

Future implementations similar to this dissertation's VRLE should focus on increasing customisation options available to the AI agent whilst still retaining the relatively quick convergence times associated with this dissertation. This dissertation's AI agent can present users with 256 possible classroom designs. Whilst this is a substantial amount, it implies that the four customisable features can only have four variants each which may not be enough to design classrooms that maximise engagement and satisfaction for some people. With the current Q-Learning approach, increasing the scope of the classroom customisation directly correlates with increasing the amount of VR classrooms that users have to rate before the AI agent develops a good understanding of their classroom preferences. As such future research could investigate how different RL technologies such as Deep Q-Networks (DQNs), or even other types of ML technologies altogether, being used to drive the AI agent customisation, could affect end users. The CCID system developed in this dissertation can even be altered as described previously (3.7.2) to handle expanded customisation options.

Another way that future research can gain more insights on AI enhanced VRLE technologies is to make use of the systems developed for this dissertation over the course of a longer time period. Such research could even host real classes over a semester held within the different VRLEs. This would explore longer term effects and impressions created by AI agent customisation in VRLEs.

As of the time of writing, some research is already being done by another party that is planning to leverage the VRLE software and insights from this dissertation to investigate educational content recommendation systems in VRLEs.

6.4 Final Remarks

This dissertation set out to explore how making use of AI personalisation technologies can make VRLEs more engaging places for education. Whilst the scope of the project has grown and shifted over time, this always remained constant and many insights on the topic were gained. As a result, this dissertation not only showed that AI agent designed VRLEs can boost satisfaction and engagement, but also developed and documented techniques for AI enhanced VRLE development, showed how engagement evaluations from more established fields can be adapted to VRLE research, and shed insight into what can be done for these technologies to be pushed even further. AI tailored VRLEs may be relatively newer and unestablished technologies but great potential has been shown.

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A. Media Content

The USB drive attached included with the physical version of this dissertation is comprised of two main parts as follows:

- A PDF copy of this dissertation
- A folder containing the source code and executable files developed for this dissertation

For information on how to make use of the latter component please refer to the installation instructions in Appendix B and the user manual in Appendix C.

B. Installation Instructions

This section briefly goes over the requirements needed to get the software associated with this dissertation running. The process is as follows:

- Connect your VR headset of choice to the device that will be running the application. Ensure that the corresponding VR headset software is installed, for instance making use of a Quest headset will require the Oculus app be installed on your pc, whilst the Index headset will require steamVR is installed.
- Download the application from the associated git repository or google drive link:
  - `https://github.com/polple/Personalised_VRLE`
  - `https://drive.google.com/drive/folders/1d6EKuYK6X5L7-ga-607UZHuR4lmvzI2l?usp=sharing`
- Extract the contents of the downloaded compressed file
- Import the project into the Unity engine to modify it, run in Unity, or to make your own builds.
- Run the "VRLE_AI.exe" file in the "Personalised_VRLE/Builds" folder to run the AI enhanced VRLE, or run the "VRLE_Plain.exe" file at the same location to run the default classroom VRLE.

C. User Manual

- Connect your VR headset of choice to the device that will be running the application. Ensure that the corresponding VR headset software is installed, for instance making use of a Quest headset will require the Oculus app be installed on your pc, whilst the Index headset will require steamVR is installed.
- Run the "VRLE_AI.exe" file in the "Personalised_VRLE/Builds" folder to run the AI enhanced VRLE, or run the "VRLE_Plain.exe" file at the same location to run the default classroom VRLE.
- If you are running the VRLEs from within the Unity editor then you first need to open the project in Unity and then select "VRLE" in the "Scenes" folder to load the AI enhanced VRLE classroom, or "VRLE_Plain" to load the default one. Press the start button in the Unity editor.
- Put on your VR headset and controllers.
- You can move around by either walking around physically if you have enough space, or by using the analogue stick on the left hand controller.
- If you are in the AI enhanced VRLE, you will be able to see 5 buttons on the desk closest to where you were when you put on the headset. These buttons are labelled 1, 2, 3, 4, and 5. Physically reach out and press one of these buttons in order to submit the number on the button pressed as a rating of how much you like the design of the VR classroom you are in.
- After the score is submitted, an animation will play and the AI agent will redesign the classroom taking your previous feedback into account.

D. Volunteer Information Sheet

Information Sheet – 27/12/23

Title of research project:

A Personalised Virtual Reality Learning Environment

Purpose of the research study:

This study is on investigating the usage of AI customization to enhance Virtual Reality Learning Environments. Two pieces of software have been produced; a standard VR classroom, and one where an AI agent attempts to modify and redesign the classroom based on each individual user. With a comparison of the experience of using these, the study aims to understand the effects that AI customization can have on engagement and satisfaction in VR learning spaces, as well as form ideas on what steps can be taken in the future to continue to evolve the field.

Research team:

Lead Researcher:	*Supervisor:*	*Co-Supervisor:*
Paul Psaila	**Prof Matthew Montebello**	X

What will be required from you during the experiment/study:

- You will need to install and try out the first version of the Virtual Reality Learning Environment (VRLE) software associated with the project.
- You will need to answer the questions from the first survey.
- You will need to install and try out the second version of the Virtual Reality Learning Environment (VRLE) software associated with the project.
- You will then need to answer the questions in the second survey.
- A focus group session will then be held to discuss the VRLE application.

Time required

20-30 minutes

Risks and benefits

There are no known risks associated with this particular research

Confidentiality and participation

Your name and other personal information will **not** be published in the research results nor know to any third parties. Your test scores and personal opinions will be published, but they will **in no way** be associated with your identity. You will be given a unique ID value by the lead researcher to input at the start of the first and second survey

Participation in this study is voluntary and does not in any way impact your final course/certification results. There is no remuneration for the study.

How to withdraw from the study

Kindly note that you are free to exit this study at any time. If you choose to do so, kindly inform the lead researcher in person or via e-mail

If you have any questions about this study, please contact:

paul.psaila.19@um.edu.mt

Figure D.1: Volunteer Information Sheet

E. Volunteer Consent Form

Consent Form – 27/12/23

Title of research project:

A Personalised Virtual Reality Learning Environment

Research team:

Lead Researcher:	*Supervisor:*	*Co-Supervisor:*
Paul Psaila	**Prof Matthew Montebello**	X

Participant identification number for this study:

Kindly tick (√) the boxes to confirm you consent to participating in this study:

1	I confirm that I have read and understand the information sheet dated 27/2/23 explaining the research project and I have had the opportunity to ask questions about the project.	☐
2	I understand that my participation is voluntary and that I am free to withdraw it any time without giving any reason and without there being any negative consequences. Furthermore, should I not wish to answer any particular question or questions, I am free to decline. Contact number of lead researcher is +36579238677	☐
3	I agree for the data collected from me to be used in future research.	☐
4	I agree to take part in the above research project.	☐

Signatures

______________________ *Name of participant*	Paul Psaila ______________________ *Name of lead researcher*
______________________ ________ *Signature* *Date*	______________________ 27/2/23 *Signature* *Date*

Figure E.1: Volunteer Consent Form

F. AI Agent and Learner Profile Startup Code

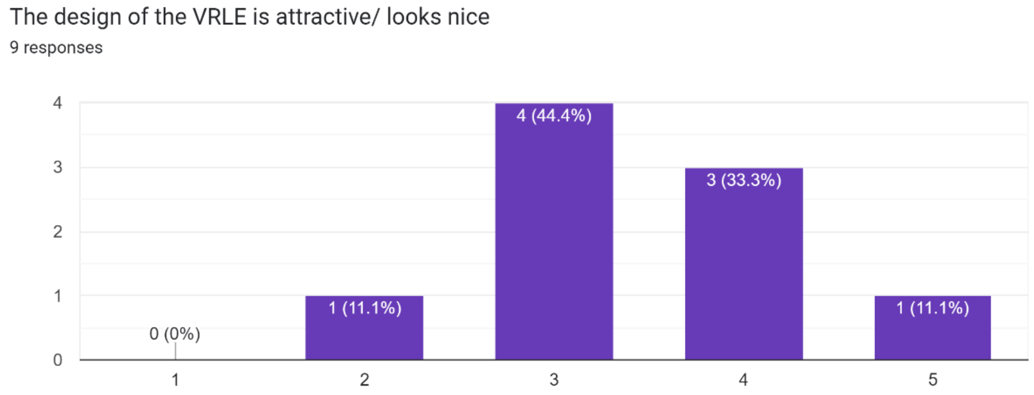
```
// Start is called before the first frame update

void Start()
{
    //Mark that a new learner profile is created and get the current profile number
    profileNum = PlayerPrefs.GetInt("profileCount", 0);
    profileNum++;
    PlayerPrefs.SetInt("profileCount", profileNum);
    PlayerPrefs.Save();
    string subfolder = "LearnerProfiles";

    //If subfolder isn't there then make it
    if (!Directory.Exists(subfolder))
    {
        Directory.CreateDirectory(subfolder);
    }

    //Create the final filename
    fileName = Path.Combine(subfolder, "learner_Profile_" + profileNum.ToString() + ".txt");

    //Set last state to the starting state
    lastState = getCurrentStateNumber();

    //Intialise the Q-Table based on the current environment and possible actions
    QTableInit(stateSpaceSize, actionSpaceSize);

    //Send starting state to the Q-Table
    SendState(getCurrentStateNumber(), 0, episodeIsDone);
}
```

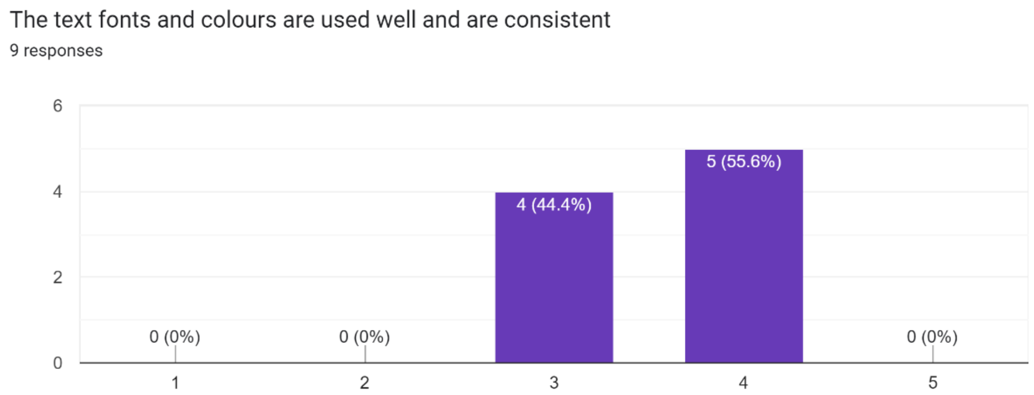
Figure F.1: AI Agent and Learner Profile Startup Code

G. Standard VRLE Questionnaire Questions and Results

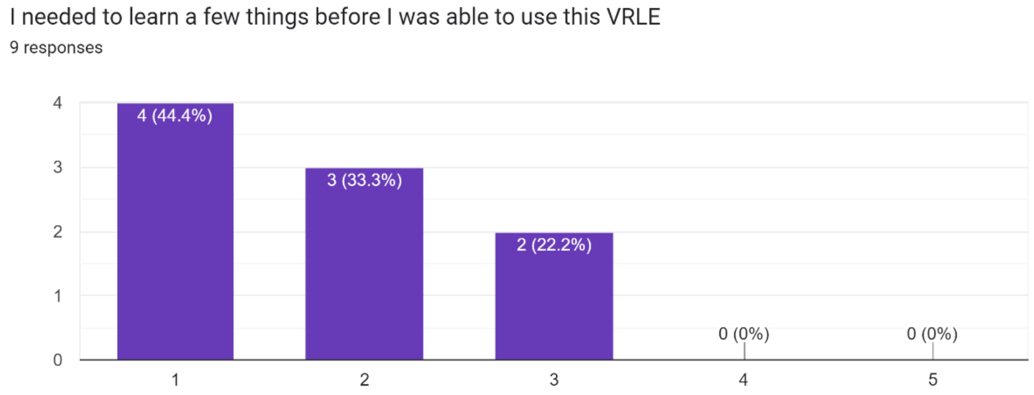
The contents of this appendix show the questions given to measure engagement and responses of those who participated in this dissertation's software testing after they had made use of the default VRLE environment.

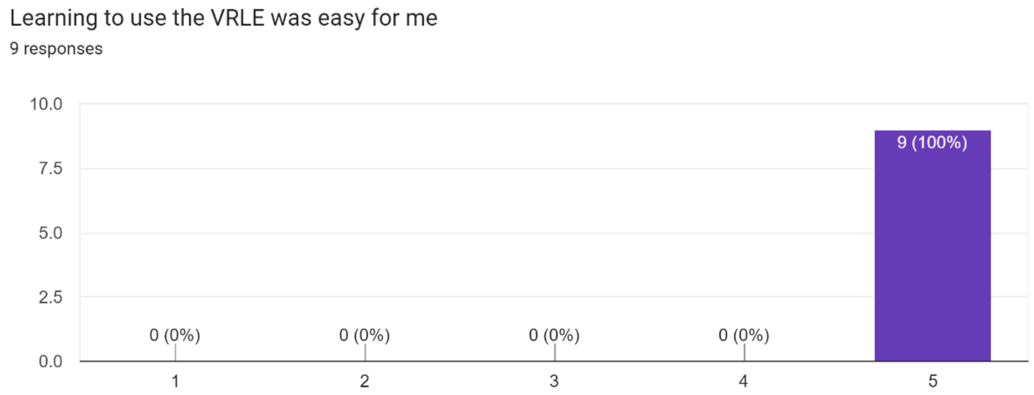
Aesthetics Questions and Scores:

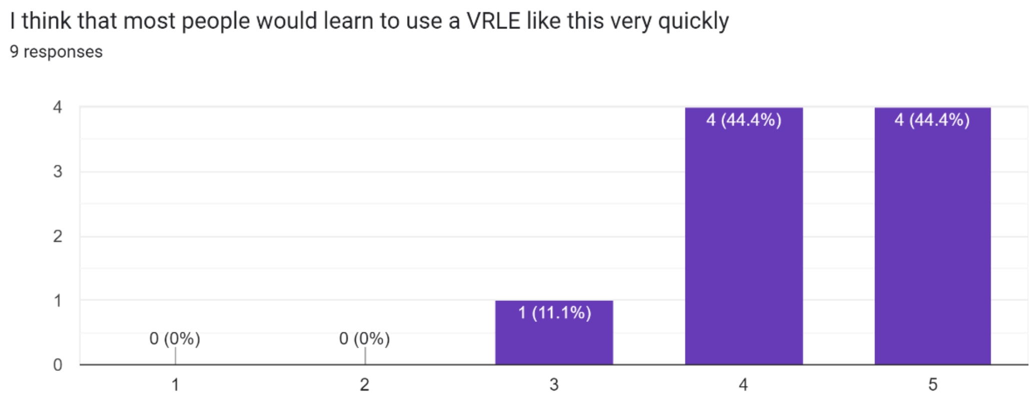




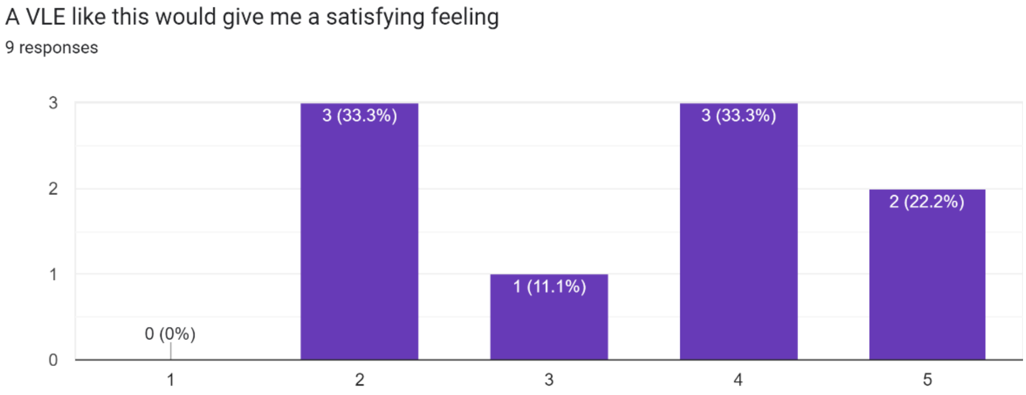
Learnability Questions and Scores:

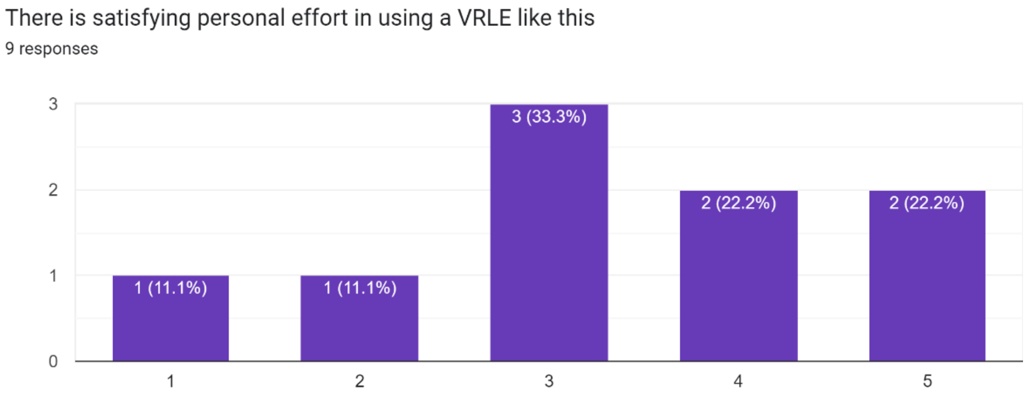






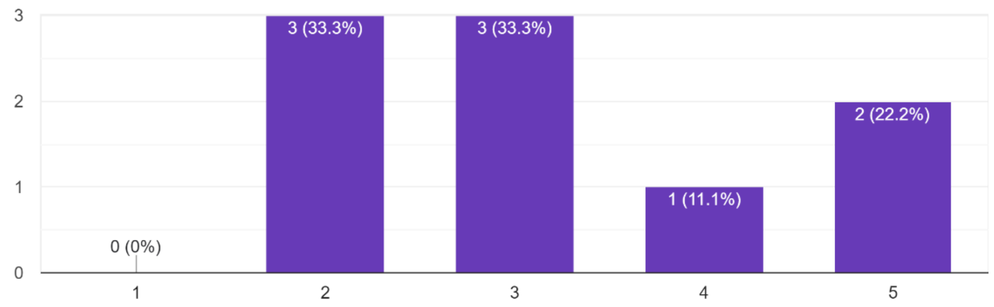
Satisfaction Questions and Scores:





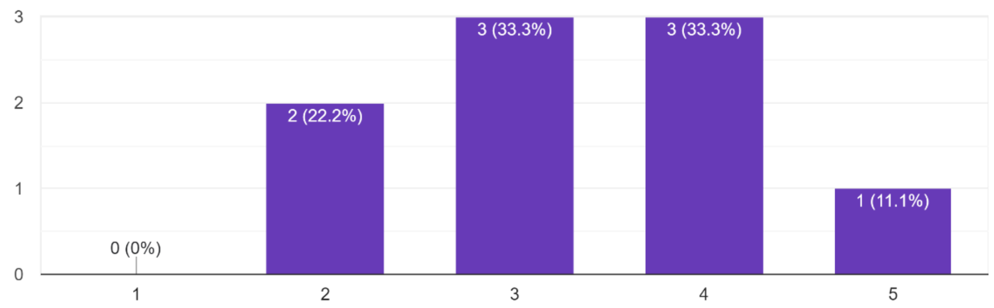
I feel satisfied with the features a VRLE like this has

9 responses

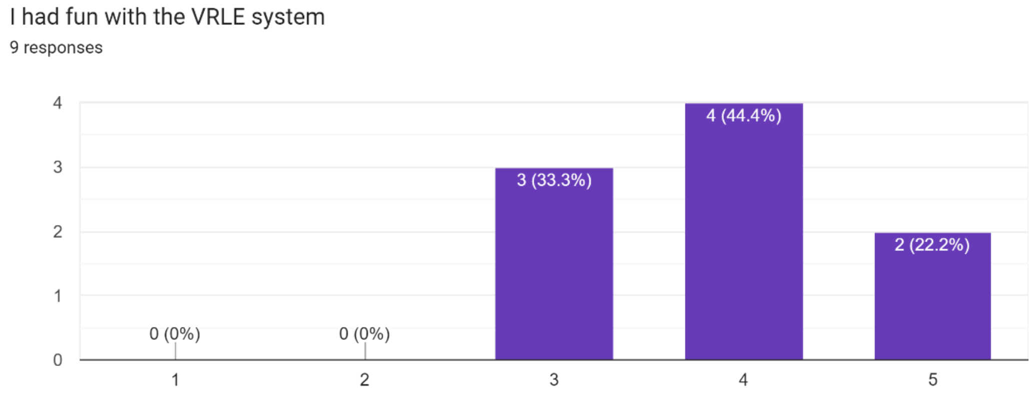


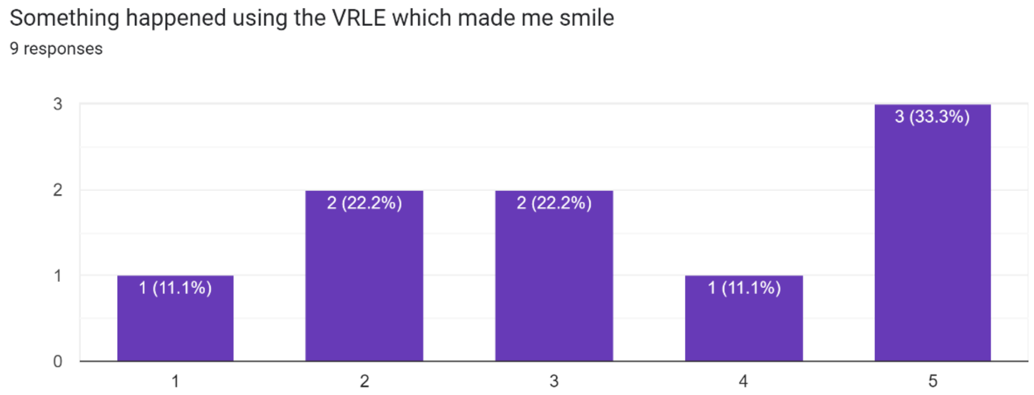
I would recommend using a VRLE with these elements to others

9 responses



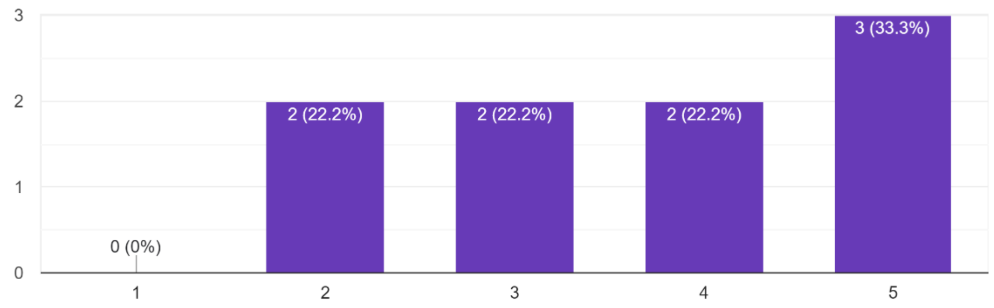
Fun Questions and Scores:



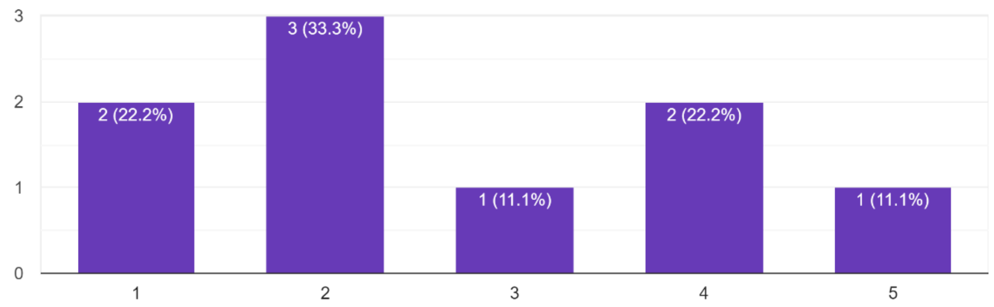


Focused Attention Questions and Scores:

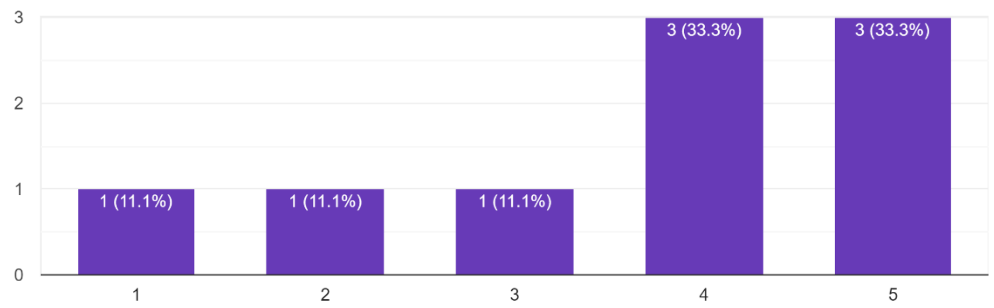
There was something interesting at the beginning of the using the VRLE that captured my attention
9 responses



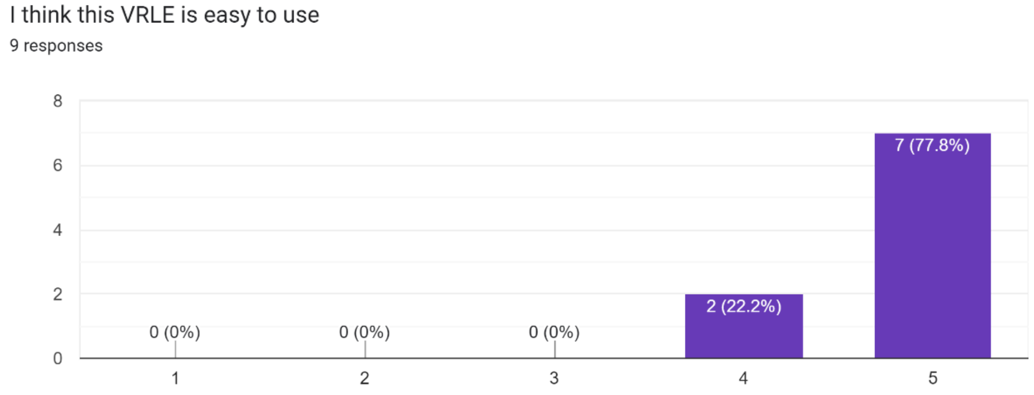
I was so involved in using the VRLE that I lost track of time
9 responses

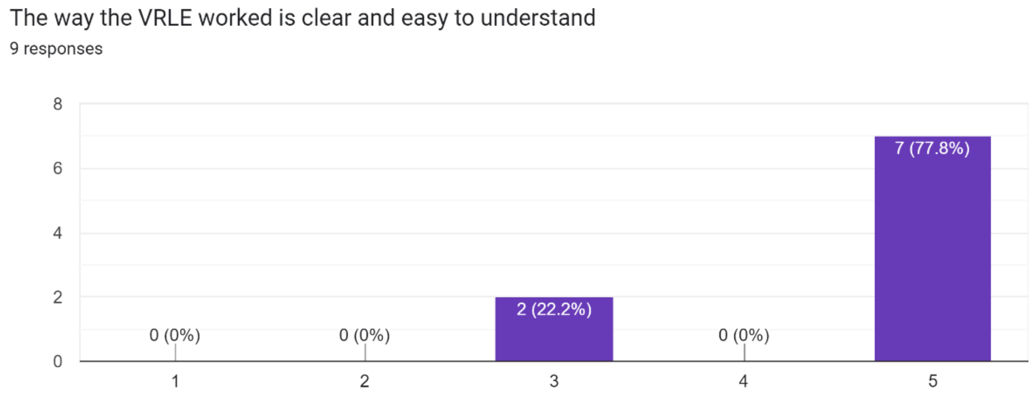


I forgot about my immediate surroundings while using this VRLE
9 responses



Operability Questions and Scores:



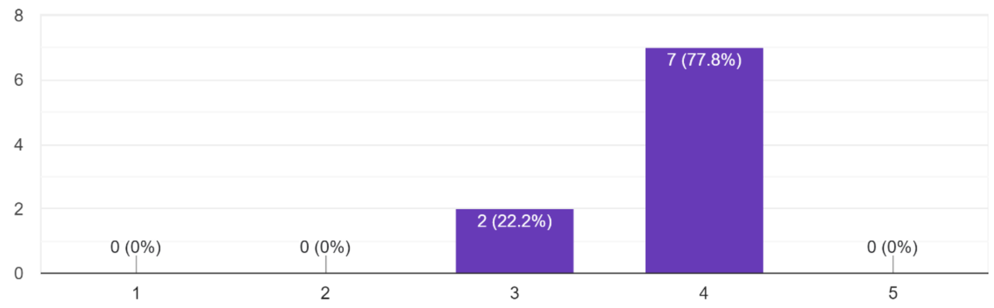


H. Standard VRLE Questionnaire Questions and Results

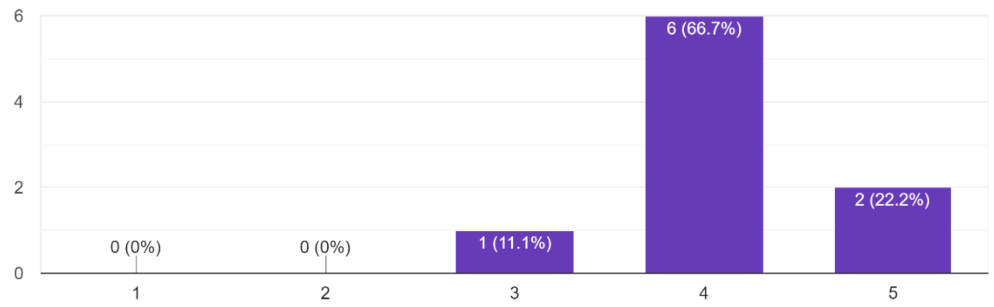
The contents of this appendix show the questions given to measure engagement and responses of those who participated in this dissertation's software testing after they had made use of the AI enhanced VRLE environment.

Aesthetics Questions and Scores:

The design of the VRLE is attractive/ looks nice
9 responses

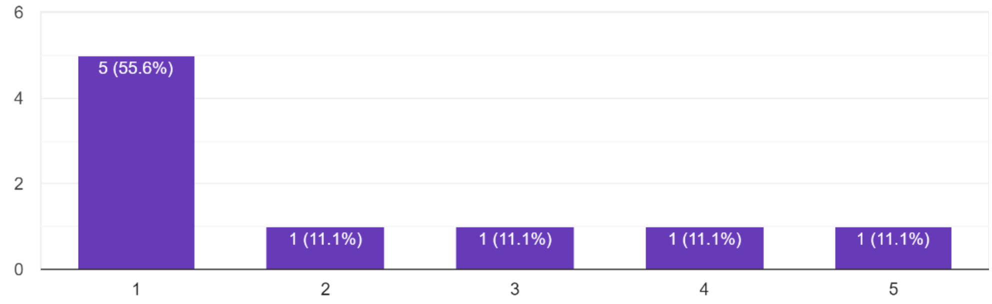


The text fonts and colours are used well and are consistent
9 responses

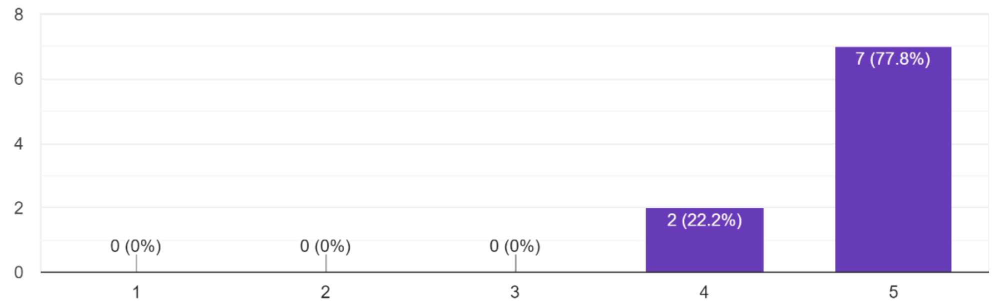


Learnability Questions and Scores:

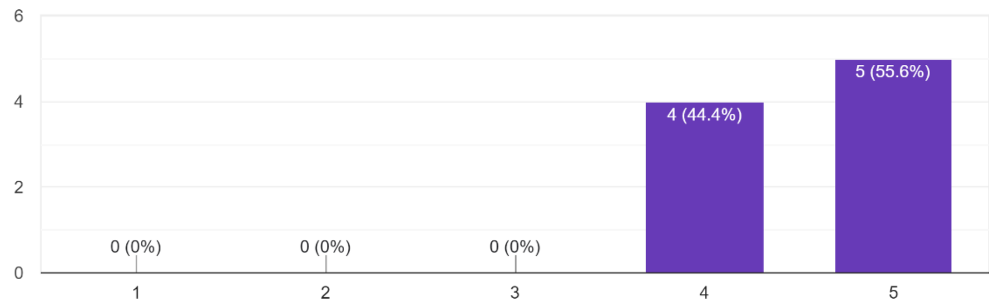
I needed to learn a few things before I was able to use this VRLE
9 responses



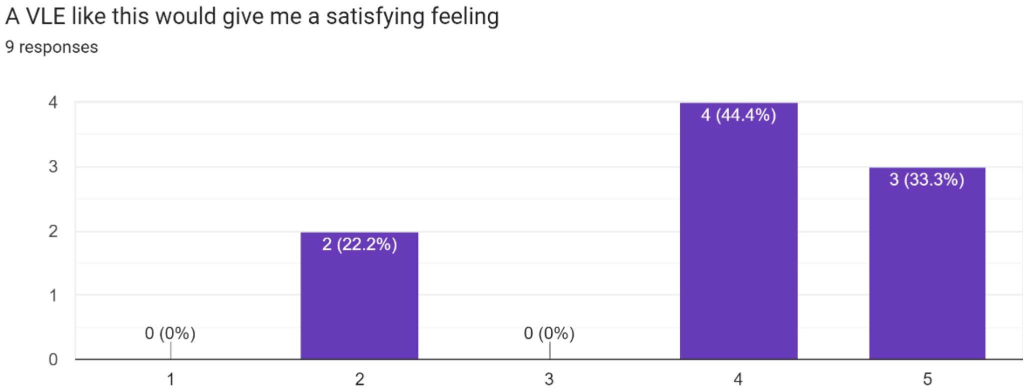
Learning to use the VRLE was easy for me
9 responses

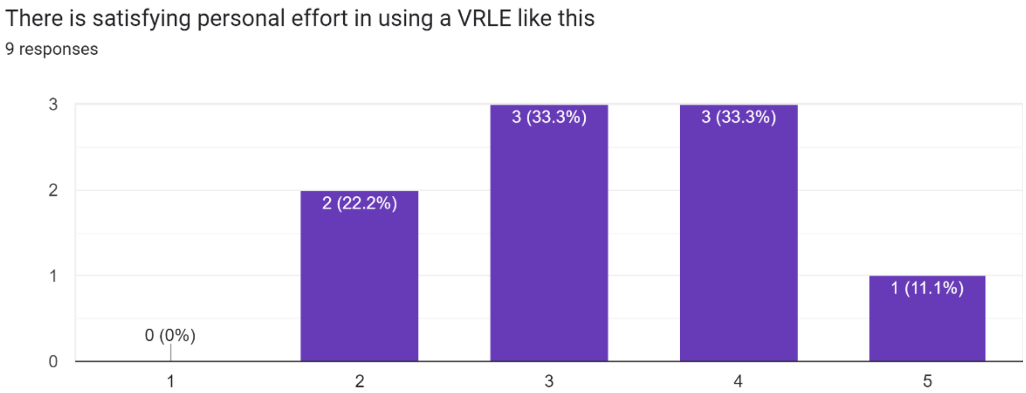


I think that most people would learn to use a VRLE like this very quickly
9 responses



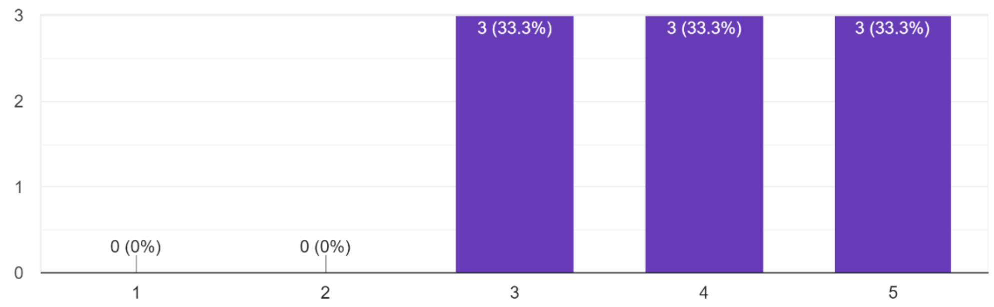
Satisfaction Questions and Scores:





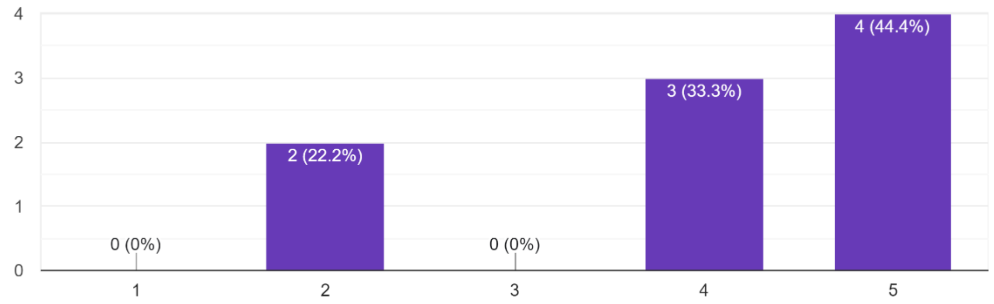
I feel satisfied with the features a VRLE like this has

9 responses

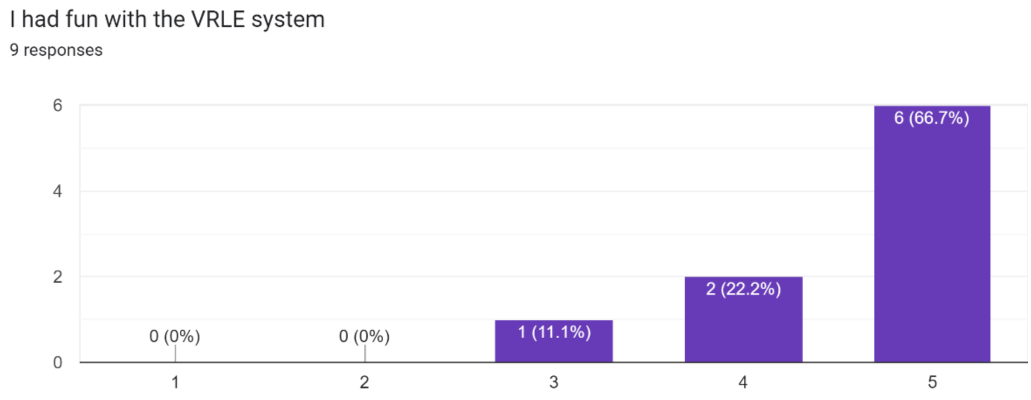


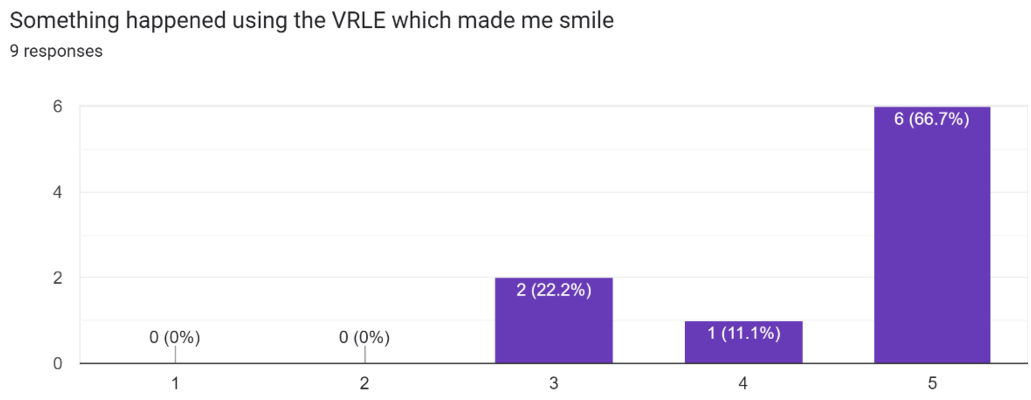
I would recommend using a VRLE with these elements to others

9 responses



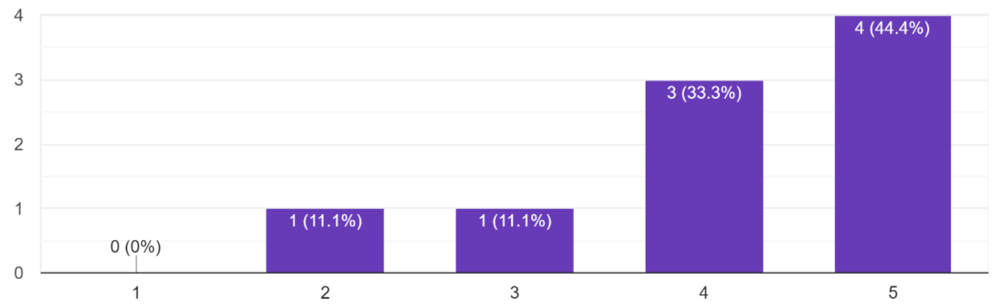
Fun Questions and Scores:



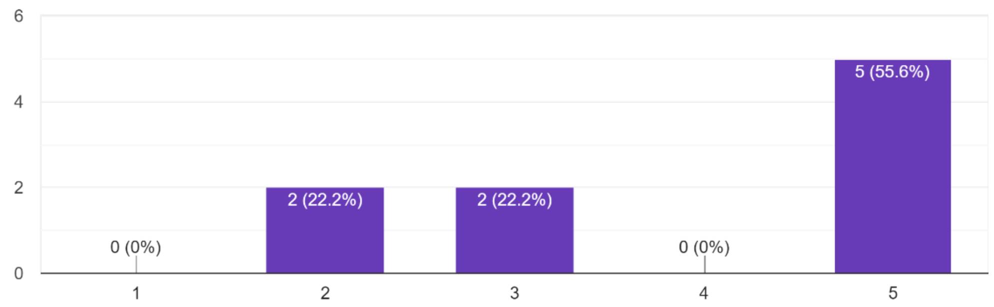


Focused Attention Questions and Scores:

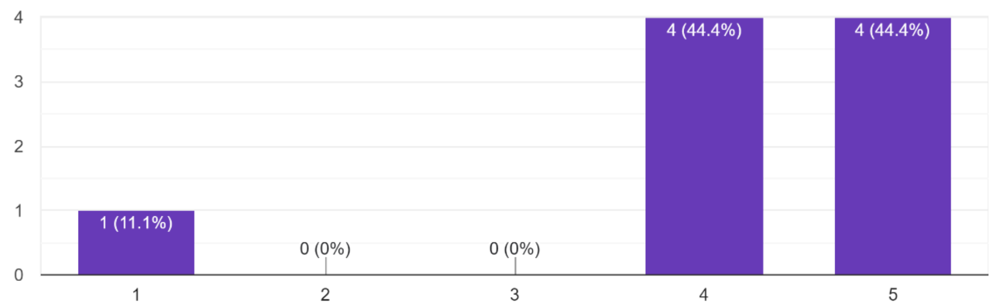
There was something interesting at the beginning of the using the VRLE that captured my attention
9 responses



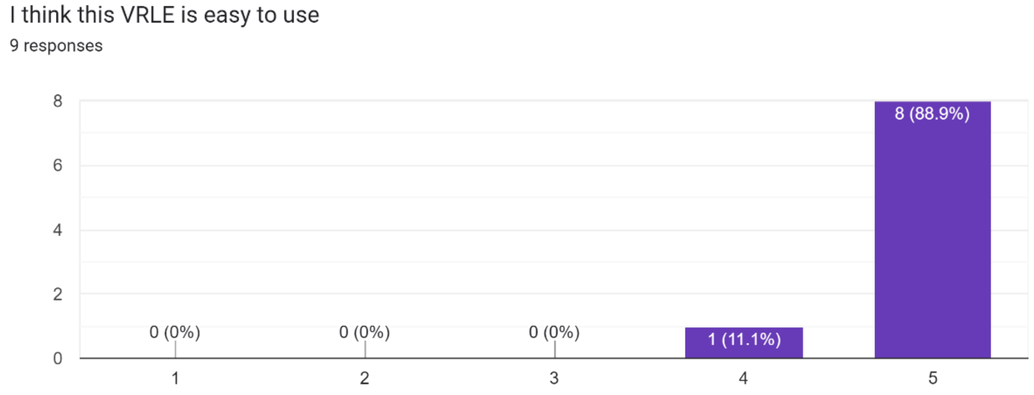
I was so involved in using the VRLE that I lost track of time
9 responses

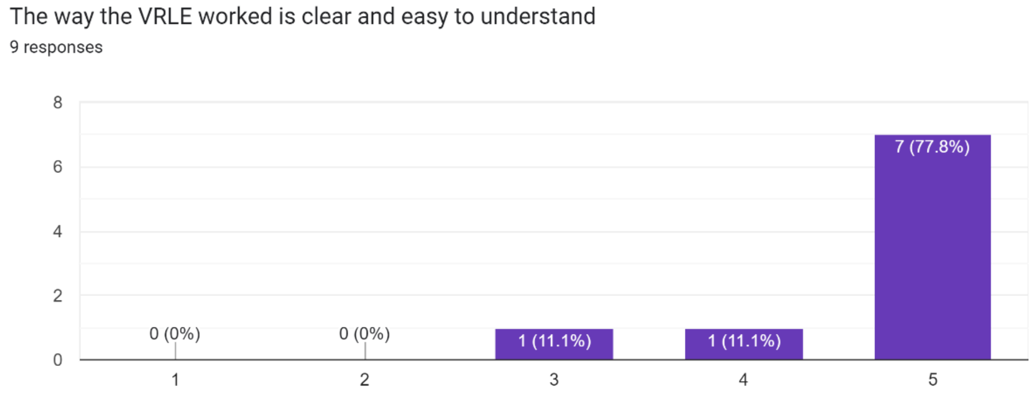


I forgot about my immediate surroundings while using this VRLE
9 responses



Operability Questions and Scores:





I. Focus Group Session Prompts

The contents of this appendix show the prompts used by the main researcher during the focus group session. These prompts were to be used to guide the focus group session rather than be strict guidelines to follow, since the session was intended to follow a free-form nature to allow participants to drive the conversation.

Any Feedback on the experience?

- Advantages of such a system
- Disadvantages of such a system

How do you think this type of technology could be improved?

How would you contrast and compare your experience in the standard vs AI designed VRLE?

Were there any specific features of the AI-designed VR classroom that enhanced or detracted from the experience?

Did you find the AI's customising of the VR classroom in real time based on your feedback effective?

What type of follow up research do you think should be done in in relation to AI customised VRLEs?

Any final thoughts or comments about this dissertation’s VRLE experience or the concept of AI environment customisation in education?