Individually Adaptive VR Learning Applications

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ABSTRACT

This research-focused Bachelor of Business Administration thesis was commissioned by HAMK Smart research unit. The thesis aims to investigate the key design elements of individually adaptive virtual reality learning applications. The primary objective is to gain a comprehensive understanding of the key components of an adaptive VR learning application, including user modelling, machine learning, self-adaptive systems, adaptive core modular components of virtual reality systems, and learning models. The study involves a thorough literature review of existing research on VR learning and adaptive learning. The goal is to contribute to the existing body of knowledge on adaptive VR learning by collecting the existing design and implementation elements of such applications.

The thesis explores how individual user adaptiveness can improve learning outcomes and engagement by utilizing different learning methods, and it examines best practices and knowledge on how to design adaptive VR learning applications. The research methods used in this study include a thorough literature review. The findings of this research contribute to the growing body of knowledge on adaptive VR learning, and provide useful insights for those working in the education sector, and for software developers who are interested in creating individually adaptive VR learning applications. By collecting the existing design and implementation elements of adaptive VR learning applications, this thesis aims to enhance the quality of education and training through innovative technology.

Keywords	Individually Adaptive, Virtual Reality, Adaptive, Learning, Applications
Pages	40 pages and appendices 1 page

Glossary

2D	Two-dimensional
3D	Three-dimensional
AI	Artificial Intelligence
AVLE	Adaptive and Virtual Learning Environments
CAMIL	Context-Activated Multiple Item Learning model
CR	Conditioned Response
CS	Conditioned Stimulus
EDA	Electrodermal Activity
EEG	Electroencephalogram
FSLSM	Felder-Silverman Learning Style Model
HMD	Head-Mounted Display
HR	Heart Rate
IVR	Immersive Virtual Reality
ML	Machine Learning
R-W	Rescorla-Wagner model
UM	User Modeling
UR	Unconditioned Response
US	Unconditioned Stimulus
VLE	Virtual Learning Environments
VR	Virtual Reality

Contents

Figures and Tables

Annexes

Annex 1 Material Management Plan

1 Introduction

Virtual reality has gained a lot of attention in recent years due to its potential for immersive and engaging user experiences. As this field becomes more accessible, educators are increasingly exploring its potential. Especially, that is, as individually adaptive VR learning applications can personalize the learning experience to the particular requirements and preferences of the learners. As such, this can lead to better learning outcomes and experiences, as learners can consume information in their most meaningful way.

First, the thesis collects the essential background knowledge of Virtual Reality, which includes the components of virtual reality systems, and the different types of applicable data collection methods. This technical background will provide the necessary foundation for understanding the capabilities and limitations of VR as a tool for education.

Second, the thesis examines important learning theories based on their relevance to adaptive learning. This section will provide an overview of major learning theories, such as classical and operant conditioning, Rescorla-Wagner model, the model of Cognitive Apprenticeship Model for Immersive Learning, and learning style models. In addition, their respective potential integration into virtual reality-based learning environments is also discussed.

Third, adaptive virtual reality-based learning environment related definitions are discussed. This section collects the key features of user adaptive VR learning apps, such as user modelling, adaptive technologies, and customizable UI elements.

In the context of the VR strategy of the commissioner, HAMK Smart Research Unit, and its strategic partner, HAMK Edu Research Unit, this thesis aims to explore the best practices on how to create individually adaptive VR learning applications. With this aim in mind, the following research questions shall be addressed:

- What knowledge currently exists about individually adaptive VR learning applications?
- What learning models can be integrated into adaptive VR learning applications?

2 Theoretical framework of individually adaptive VR learning applications

The theoretical framework of this thesis explores the realm of individually adaptive virtual reality (VR) learning applications, encompassing three main domains: virtual reality technology, relevant learning theories, and adaptive learning. Firstly, the thesis delves into the relevant theories and models of learning, such as behaviourism, cognitivism, and VR-specific learning models examining how these theories have been, and can be adapted, within the context of VR learning.

Secondly, the VR technology domain encompasses the principles and advancements of immersive virtual environments, including its essential components, user interaction possibilities, and data collection capabilities. Lastly, the adaptive learning domain focuses on the integration of personalized and adaptive techniques within existing VR applications.

By exploring these interconnected domains, the theoretical framework aims to provide a comprehensive understanding of user adaptive VR learning applications, as well as lay the groundwork for empirical investigation and analysis.

2.1 Virtual reality technology

Biocca and Levy (1995, p. 63) define Virtual Reality (VR) as “the sum of the hardware and software systems that seek to perfect an all-inclusive, sensory illusion of being present in another environment.”

Technologically speaking, virtual reality can be defined as a computer-generated environment that is capable of providing a realistic experience to the user. The essence of this experience lies in the ability of the technology to create an immersive environment that mimics reality in such a way that the user perceives it as genuine. By wearing a headset, the user enters a virtual world where computer-generated environments and items can be viewed and engaged with. Gaming, education, training, healthcare, and numerous other industries make use of virtual reality. (Virtual Reality Society, n.d.)

2.1.1 Immersion

One of the most important key elements of VR is immersion. It can be defined as the subjective perception of feeling physically present within an artificial or computer-generated 3D environment by shutting out the outside world, resulting in a sensation of being present in the virtual space rather than in the surrounding physical environment. In other words, the user is submerged or otherwise absorbed in the virtual environment. The concept can also be referred to as Immersive Virtual Reality (IVR). Different media channels have different levels of immersion, and it is generally very low in most forms of media. Most of the media channels exhibit varying degrees of immersion, with many forms of media commonly showcasing low levels thereof, whereas VR can be associated with high level of immersion. (HTC Vive®, n.d.)

Table 1 - Immersion types (Linde, 2022)

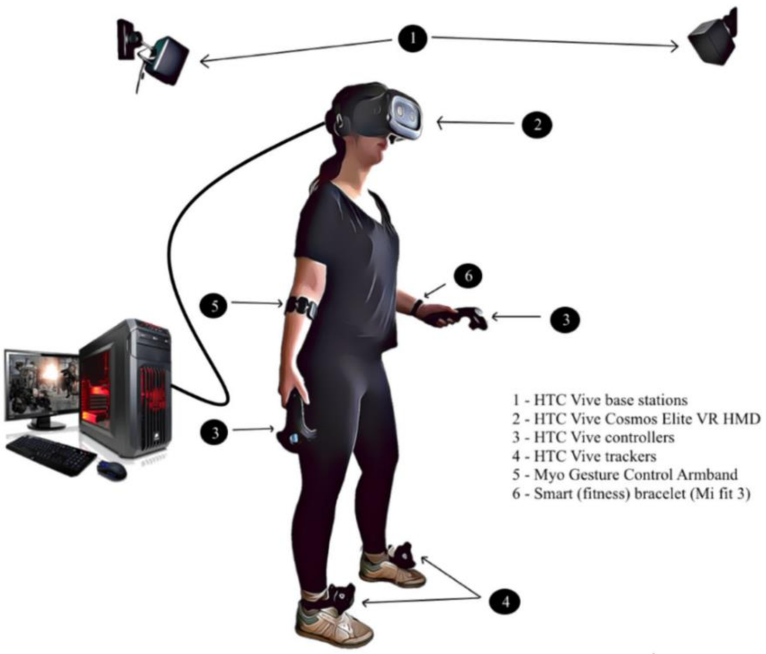
Immersion Type	Description	Example
Sensory immersion	Relates to realistic graphics, displays, multi-channel sound systems, seat movements and feedback controllers.	Augmented reality (AR).
Spatial immersion	Makes the user feel like the created synthetic world truly exists around them.	Performing activities similar to those in real life.
Tactical immersion	Based on tactile operations, important for VR training, repetition is key.	Making training sessions feel real.
Strategic immersion	Tackles mental skills such as planning, problem solving and decision making, often used in LVA.	Immersion based on interaction with tactical immersion.
Imaginative immersion	Develops a feeling of being closely connected to a character, via a deeply developed narrative and a virtual world.	A feeling is developed while reading a book or watching a movie.
Social immersion	Occurs when interacting with other users, working collaboratively with teammates to solve tasks and challenges.	Completing group tasks and challenges much faster and with better results, via collaboration.

VR offers unique immersion types, such as sensory, spatial, tactical, strategic, imaginative, and social. Each possess unique characteristics and benefits. Sensory immersion aims to create an enhanced experience using various senses, such as vision, hearing, and touch. Spatial immersion provides user engagement by providing a sense of real-world presence. Tactical immersion is based on tactile operations, whereby repetition and realism are required for effective learning. Strategic immersion requires cognitive skills such as planning, problem-solving, and decision-making. The sensation of imaginative immersion is comparable to that of reading a book or watching a movie, where the user becomes emotionally invested in either a character, or in the story itself. Social immersion is achieved when users interact with each other while completing group assignments and challenges, thus providing a fun and engaging experience for everyone involved. Table 1 illustrates the possible immersion types. (Linde, 2022)

2.1.2 Essential components of a virtual reality immersive application

VR technology can be described using the human-computer interaction loop, which breaks down the interactions between the user, input devices, computer, and output displays. The user is provided with output devices such as a head-mounted display (HMD) and an audio device, tracking sensors, and an input device such as a controller or data glove. These components work together to create a convincing and realistic virtual environment that fully engages the user's senses, and creates a sense of presence. As the user engages in actions such as walking, teleportation or changing their point of view by rotating their head, data describing their behaviour is transmitted from the input devices to the computer. The computer then processes this information in real-time, and generates suitable feedback that is transmitted back to the user via output displays. (Masaryk et al., 2020, pp. 14–15)

Figure 1 - Possible hardware components of a VR system (Stanica et al., 2020, fig. 5)



As is shown in Figure 1, a VR system usually consist of a VR headset, two base stations, two motion controllers, and two trackers. To set up the VR system, initial configuration involves placing the base stations in opposite corners, in order to ensure accurate tracking within a designated area. Typically, a minimum tracking area of 2m × 1.5m is required. For comprehensive limb tracking, the controllers are used to follow up arm movements, and the trackers to track leg movements. Both the controllers and trackers have the capability to play haptic feedback to enhance the user experience. Since VR is an immersive technology, a high-performance PC, including a powerful processor, a high-end graphics card, sufficient RAM memory, and a compatible motherboard, is required to ensure optimal performance and compatibility. (Stanica et al., 2020, p. 11)

2.1.3 User interface and interaction modes

In VR, the user interface (UI) refers to the visual and auditory elements that enable users to interact with the digital world and its objects, while the actions performed and behaviours displayed by users within the computer-generated environment, are referred to as user interactions. Such interactions, involve utilizing input devices, hand gestures or physical movements, which can be mapped to corresponding user interactions. The goal of user interaction in VR is to enable users to navigate, select and manipulate objects, and control system functions within the VR interface. This mode leverages consumer-grade motion capture devices like Kinect or Leap Motion to accurately track and interpret the user's gestures and movements, providing an immersive and intuitive user experience in the VR environment. (Kharoub et al., 2019, pp. 3–4)

Gesture-based interaction eliminates the need for external input devices by allowing users to interact with the virtual environment using different hand gestures. Hand tracking enables users to seamlessly manipulate objects and navigate through the virtual environment. Voice recognition enables users to handle objects, retrieve information, and perform various tasks in the VR environment using voice commands. Eye tracking technology detects the direction of the eyes, known as gaze, and facilitates effortless navigation, object interaction, and virtual environment manipulation. These forementioned user interaction modes in VR provide users with diverse and intuitive means to interact with the virtual environment, ultimately delivering a more immersive and engaging VR experience. (Kharoub et al., 2019, pp. 4–6)

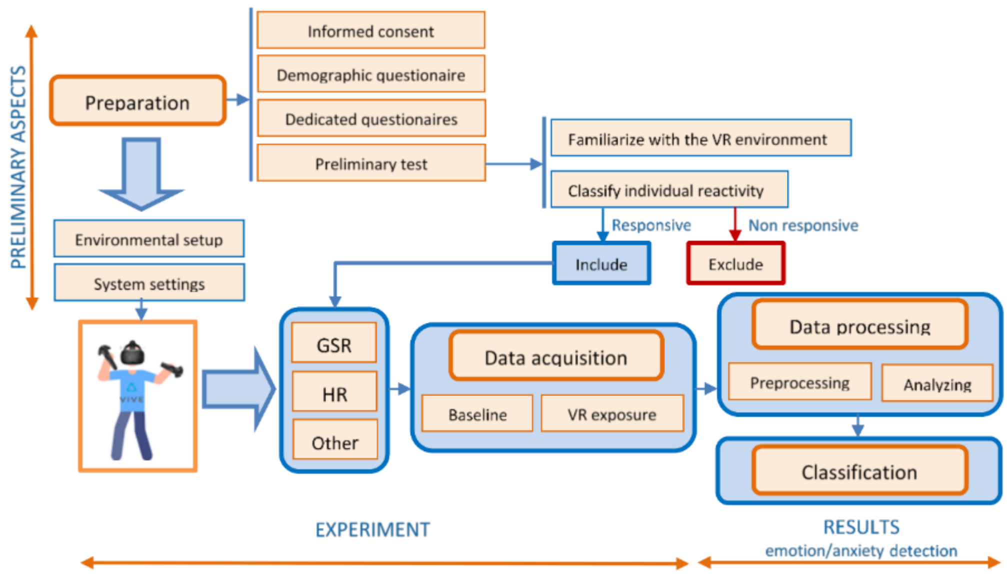
2.1.4 Data collection in VR

The collection of user information is an essential aspect of VR technologies, which rely on multiple data sources to deliver a satisfactory user experience and perform unique functions that traditional consumer devices cannot achieve. As shown in Table 2, a variety of sensors are used to track the motions and actions executed by the users, thus enabling natural interactions in the virtual environment. Moreover, the data collected by sensors during VR experiences can also be analysed to provide insights into user behaviour and performance, enabling developers to improve the technology and optimize its applications. (HP®, n.d.)

Table 2 - Commonly used sensors in VR (HP®, n.d.)

Sensor type	Description	Examples
Head tracking	Tracks the head movements and adjusts the virtual environment accordingly.	Gyroscopes, accelerometers, magnetometers.
Eye tracking	Tracks the eye movements and gaze direction.	Infrared scanners, eye-tracking cameras.
Motion-tracking	Collects data on the physical movements and orientation.	Inertial measurement units, optical tracking, magnetic tracking.
Haptic	Provides tactile feedback, allowing the users to feel sensations such as pressure.	Vibrotactile actuators, force sensors.
Audio	Captures and processes audio creating a realistic soundscape.	Microphones, speakers, spatial audio processing algorithms.

Figure 2 - An experimental design and protocol of data collection in VR (Petrescu et al., 2020, fig. 3)



As Figure 2 suggests, biophysical signals can also be collected via VR applications through electrodes attached to the skin of the subject. The quality of the collected physiological signals is greatly affected by their placement, and by the data acquisition and processing protocol executed during the interactive sessions. Depending on the use case, various physiological signals can be acquired. The most common of which, are electrodermal activity (EDA), heart rate (HR), and electroencephalography (EEG). Due to the lack of standardised protocol, as it is illustrated in Figure 2, an experimental protocol has been proposed with the aim to ensure the quality of the collected signals and their processing in an immersive setup. (Petrescu et al., 2020, pp. 7–9)

2.2 Relevant learning theories and models

Learning is a fundamental concept in psychology, and it has been defined in a variety of ways. According to Hilgard (1961) "Learning is a relatively permanent change in behaviour or knowledge that results from experience or practice." (p. 6) This operational definition emphasizes the importance of observable changes in behaviour as a result of experience or practice. (Hilgard, 1961, p. 6)

Another way to define learning is through a functional perspective, as Tarpy (1982) suggests. Tarpy defines learning as “the acquisition of expectancies, based upon patterns of stimulus inputs and response feedback, which allow an animal to behave in an adaptive fashion.” (p. 10) This functional definition emphasizes the adaptive benefits of learning and the importance of acquiring knowledge and skills that can help an organism successfully navigate its environment. (Tarpy, 1982, p. 10)

Levy (2012) offers an adaptive definition of learning, which describes it as “an adaptive process whereby individuals acquire the ability to predict and control the environment.” (p. 15) This definition emphasizes the ongoing, dynamic nature of the learning process, and highlights the importance of flexibility and adaptability in response to changing environmental demands. (Levy, 2012, p. 15)

2.2.1 The scientific framework of adaptive learning

Adaptive learning, as a sub-discipline of psychology, entails the methodical alteration of experiential factors to investigate their influence on individual behaviour. To identify cause-and-effect relationships that apply under naturalistic conditions, psychologists use experimentation by manipulating independent variables to determine their influence on dependent variables. In order to conduct such experiments, group and small-N experimental procedures have been devised. To maintain the veracity of research results, researchers often employ animals with a simple genetic makeup, in order to reduce the number of variables that could potentially influence the outcomes. Such an approach allows researchers to focus on specific research aspects and draw accurate conclusions. The subjects are placed in specialized equipment or devices, such as a Skinner Box or a T-maze, that facilitate the systematic manipulation of independent variables, and the precise measurement of dependent variables. (Levy, 2012, pp. 18–23)

However, external validity concerns arise when forming conclusions about human behaviour based on animal studies, due to the inherent differences between animal and human subjects. The replication of findings through human studies under naturalistic conditions, is thus required to ensure the generalizability and applicability of results to real-world scenarios. In order to maintain the credibility of research findings, one of two approaches can be adopted: simulating natural environments within the confines of a laboratory setting, or incorporating precision and control into the natural environment. Overall, the field of adaptive learning heavily relies on experimentation and the systematic manipulation of variables. (Levy, 2012, pp. 24–28)

2.2.2 Predictive learning

Predictive learning, also known as classical conditioning (also Pavlovian and respondent conditioning), is a fundamental learning mechanism where, during the so-called conditioning phase or acquisition stage, the subjects learn to associate a neutral conditioned stimulus (CS) with a biologically significant unconditioned stimulus (US). The US automatically induces or evokes an unconditioned response (UR), resulting in the CS evoking a conditioned response (CR) that is, in quality, similar to the UR. As time progresses, even when presented alone, the CS (neutral stimulus) eventually triggers the same response as the biologically significant stimulus. (Pavlov, 1927, pp. 25)

To put it more succinctly, during the process of the Pavlovian conditioning, the subjects are repeatedly being exposed to a strictly controlled previously neutral environmental stimulus being paired with a meaningful outcome or event resulting in the formation of an intended acquired reaction (neurological association between the two stimuli). Conclusively, the subjects acquire the capability to anticipate favourable or non-favourable events associated with the practical environmental stimuli (CS). (Pavlov, 1927, pp. 26)

Pavlov’s classical conditioning experiment was conducted on dogs (subject) involving a metronome (CS), food (US), and salivary gland secretion (UR and CR). The sound of the metronome was repeatedly paired with the presentation of food to the dogs. The mere presence of food induced an innate salivary response (UR). In the conditioning phase, the sound of the metronome, that served as the neutral stimulus, was repeatedly paired with the presentation of food, which can be considered as a biologically potent stimulus. As a result of this classical conditioning process, a new expected associative reflex was displayed. The dogs began to salivate at the sound of the bell, anticipating the arrival of food, even when the food was not immediately presented. (Pavlov, 1927, pp. 26–28)

2.2.3 Rescorla-Wagner model

The Rescorla-Wagner reinforcement-based learning model (R-W model) of classical conditioning, is a widely used psychological theory, which aims to comprehend the mechanisms underlying predictive learning. The model proposes that learning occurs through an empirical process of experimentation and feedback (trial-and-error). It is presumed that the main driving factor of learning is the element of surprise. Surprise forces the subjects to update their expectations; thus, knowledge is obtained. To be more concise, the gap between the expectations of the subject and the actual feedback, is what governs the learning process. (Levy, 2012, pp. 62–63)

The R-W model also explains the phenomenon of overshadowing. Overshadowing occurs when a prominent stimulus is present alongside a less prominent one. As such, the dominant stimulus is able to capture a significant portion of the attention and learning resources of the subject, at the cost of the less dominant stimulus. As a result, the inconspicuous stimulus provides less of a contribution towards predicting the outcome of an event. Blocking occurs when a cue that has already been learned prevents the acquisition of a new one that is presented alongside with it.

The new stimulus does not provide any additional surprise, as the subject has already learned to anticipate the outcome based on a previous one. (Levy, 2012, pp. 64–65)

2.2.4 Control learning

Control learning (or operant conditioning) is another crucial learning concept in psychology that was introduced by Edward Thorndike and B.F. Skinner. Contrary to predictive learning in control learning, as Skinner pointed out, the subjects are enabled to operate on their environment. During this learning process, the subjects, considering the environmental consequences of their actions, aim to assume control over their environment through continuously altering their behaviour. For example, the subject is provided with the opportunity to type on a computer as the environmental setting. As a result, the subject responds by typing on the keyboard (change in behaviour). If a typo is made, an aversive environmental consequence, such as an error message, may be produced that shapes the behaviour displayed by the user. Over time, the subject can develop typing skills and strategies. (O'Donohue & Ferguson, 2001, pp. 87–88)

The Beauvoir shaping environmental consequences can be grouped as reinforcements and punishments. In case of positive reinforcement, the behaviour of the subject is succeeded by a desirable consequence that can result in the long-term maintenance of the desired behaviour. Negative reinforcement occurs when the displayed behaviour leads to the removal of an unpleasant stimulus; thus, the likelihood of that behaviour being repeated over time, is increased. Positive punishment is when a behaviour results in an unpleasant outcome, which reduces the probability of behavioural repetition. If the behaviour causes the removal of a desirable stimulus, this negatively affects the reiteration of the exhibited behaviour. (McSweeney & Murphy, 2014, pp. 222–227)

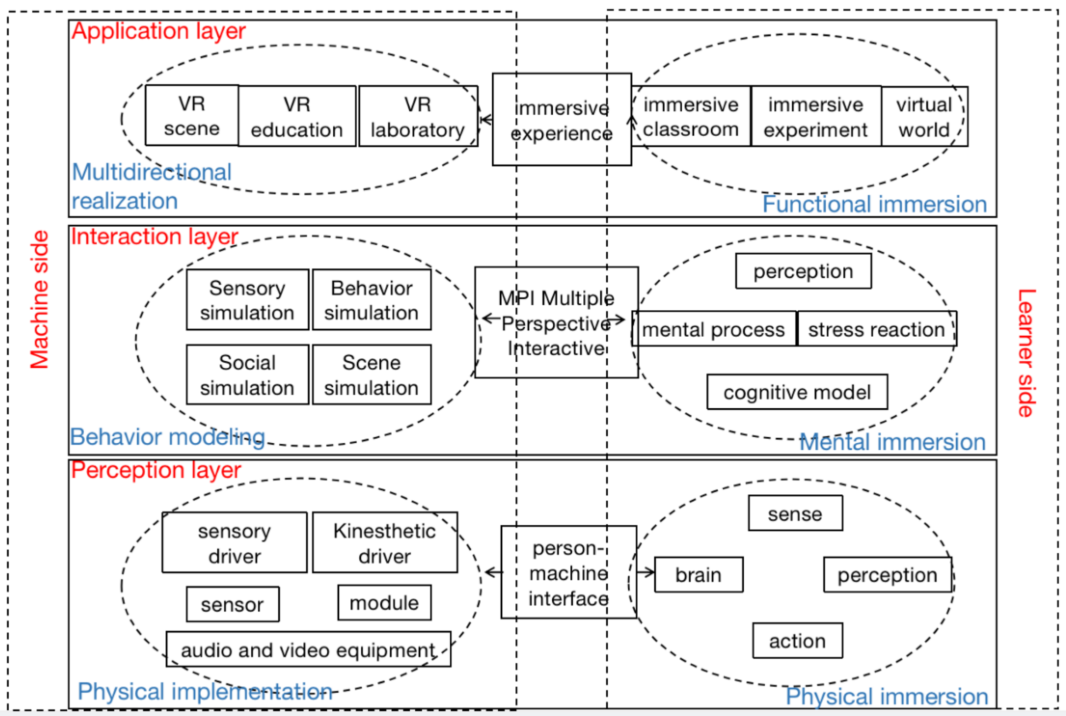
Sometimes, it is necessary to break down a complex set of actions or behaviours that are linked together in a particular order, into separate, more digestible subtasks. In this way, the learning experience of the subject can be better affected. In behaviourism, this scenario is referred to as a stimulus-response chain. If the links are taught in reverse order, then the procedure is called backward chaining. The learning experience starts with the completion of the final subtask and systemically builds the previous steps on top of the stack, signalling the impression that the whole task has been already accomplished. In this way, the targeted behaviour is already reinforced;

thus, the subject may experience an increased level of motivation and enthusiasm. This technique can be used to teach a wide variety of skills, in a well-structured and coordinated manner. (Levy, 2012, pp. 89–90)

2.2.5 Constructivism and cognitive learning

Cognitive constructivism is a cognitive theory that is deeply rooted in the cognitive development hypothesis of Jean Piaget. It asserts that while the world exists objectively and independently of the learner, the perception of things is subjective and shaped by their previous experiences. Knowledge is constructed through mental processes such as attention, perception, and memory. The role of the teacher or the learning environment is to provide tailored resources so that the learners can construct their individual, respective understanding. Constructivism aligns well with VR teaching, as both concepts rely on similar principles. For example, such principles include: the active role and autonomy of learners, the subjectivity of knowledge, an interactive and contextualised learning environment, and the permitting of learners to construct meaning based on their prior knowledge. (Aiello et al., 2012, pp. 319–320)

Figure 3 - VR-enhanced cognitive learning model (W. Li et al., 2023, fig. 1)

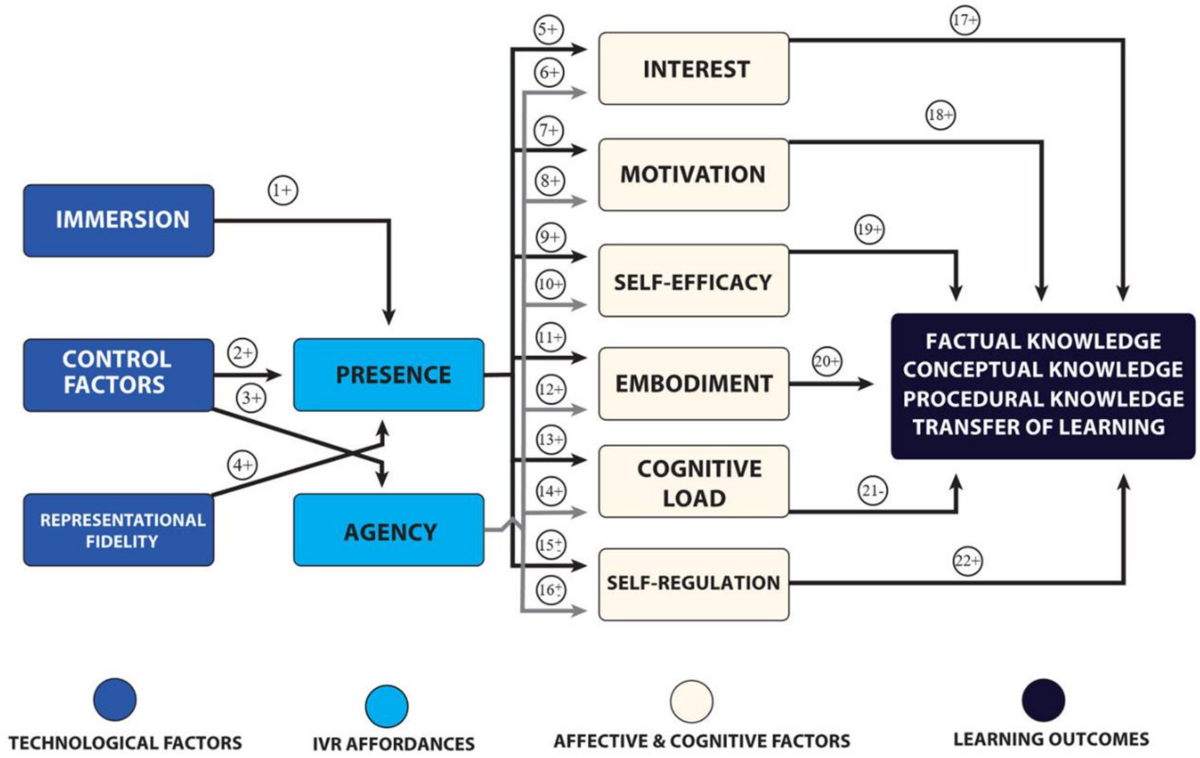


As shown in Figure 3, a learning model called the VR-enhanced cognitive learning model has been designed that combines the principles of cognitive constructivism with the immersive and interactive capabilities of VR technology, to enhance learning outcomes. The model consists of three separate layers: the application layer, the interaction layer, and the perception layer. The application layer handles the core logic of the software, including the VR scenes and educational content. The interaction layer engages with the cognitive processes of the learner and enables user interaction through various type of simulations. The perception layer represents the hardware of the VR environment. This is the layer where the actual human-computer interaction and integration (submersion) is facilitated, enabling the learners to engage with the VR environment. (W. Li et al., 2023, p. 6)

2.2.6 The CAMIL immersive learning model

The Cognitive Affective Model of Immersive Learning model (CAMIL) is a theoretical framework, that elucidates the process of learning in immersive settings, such as those found in VR applications. The model posits that the learning outcome is influenced by the interconnection between different learning variables. The technological factors include immersion, interaction (or control factors) and the representational fidelity (the way the learning content is presented to the subject). Some of these technological factors are IVR components, and they enable additional benefits, called IVR affordances. These affordances, namely the physical presence (presence) and agency, then influence the six available affective and cognitive factors resulting in different learning outcomes. The relation between the aforementioned factors, is presented in Figure 4. (Makransky & Petersen, 2021, pp. 939–943)

Figure 4 - A schematic of the CAMIL model (Makransky & Petersen, 2021, fig. 2)



According to the CAMIL model, learning can be defined as a positive change in long-term memory. Studies where the pre-and post-test declarative knowledge of individuals were benchmarked, showed that an IVR learning environment facilitates significantly greater results compared to other non-immersive approaches. Furthermore, as such studies suggest, the efficacy of IVR learning can be improved with the use of various instructional modalities. Most of the aforementioned affective and cognitive factors, except the extraneous cognitive load, had a positive impact on the learning outcomes. The IVR specific immersion and interactivity factors have a positive influence on all the other variables of interest, including the IVR affordances, the affective and cognitive factors, and the learning outcome. The relevant factors and their respective impact, have been summarized in Table 3. (Petersen et al., 2022, p. 5)

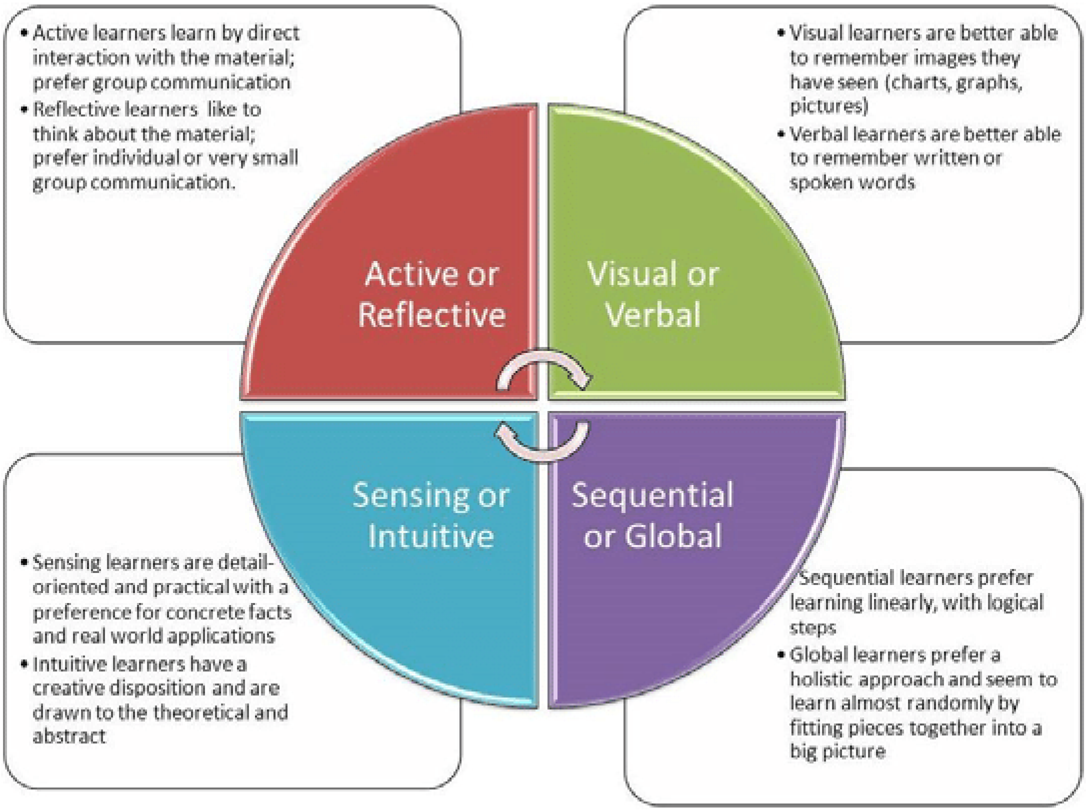
Table 3 - CAMIL variables and their impact on the learning outcome (Makransky & Petersen, 2021, pp. 944–948; Petersen et al., 2022, p. 5)

Variable	Description	Impact
Situational Interest	Focused attention and an affective reaction triggered by environmental stimuli.	+
Intrinsic Motivation	Engagement in an activity because of its inherent satisfaction, not for external reasons.	+
Self-Efficacy	Beliefs in one's capabilities to produce particular attainments.	+
Embodiment	Learning through experiencing the world as a "lived body" subject that senses and does the sensing in a meaningful way.	+
Extraneous Cognitive Load	Mental effort required to process non-relevant information.	-
Intrinsic Cognitive Load	No additional mental effort required to process information.	+
Self-Regulation	The ability to control one's thoughts, emotions, and behaviours to achieve goals.	+

2.2.7 Learner models and learning style models

To provide tailored experience and engagement in learning learner models, student models were introduced. By definition, a learner model is a system-generated representation of the individual characteristics of a student or learner. Personal information, cognitive traits, knowledge level, and learning styles and preferences are captured and stored within. The captured data can be divided into domain-specific information and domain-independent information. The former contains emotional and behavioural data and profile, while the latter includes the psychological model and the generic model of the learner. That is, aspects such as the interests, learning goals, motivations, experience, and preferences of the subject. (Labib et al., 2017, p. 434)

Figure 5 - Dimensions of Felder-Silverman's model (Cater, 2011)



Learning styles are unique characteristics that are displayed by the learners. The concept describes how a subject perceives, processes, and interacts with the learning materials provided during the training sessions. Two main behavioural patterns can be distinguished in respect of the learners. Divergent learners are emotionally driven and creative, whilst convergent learners prefer to apply existing logics and concepts. Generally speaking, more than one learning style can be displayed by the learners. There are several learning style models, the Felder and Silverman model (FSLSM) being one of the most frequently used. As Figure 5 illustrates, the model consists of four dimensions: Information Perception (Intuitive/Sensing poles), Information Processing (Active/Reflective poles), Input modality (Visual/Verbal poles), and Understanding (Sequential/Global poles). By combining these dimensions the model defines sixteen different learning styles. (Labib et al., 2017, pp. 434–436)

2.3 Adaptive learning in VR

Virtual reality has emerged as a powerful tool for personalized and adaptive learning in the 21st century. Through VR technology, educators can introduce choices, multiple modalities of information, authentic user interactions, adaptive feedback, and data-driven adjustments in the learning environment; thus, enhancing the learning experience. VR enhances the motivation and engagement of the learners. It heavily relies on action, problem-solving and fosters creativity. Through adaptive mechanisms, different learning styles can be accommodated according to the need of the learners. Educators can use VR across a variety of different subjects, such as language, science, math, history, art, and vocational education, in order to create immersive and impactful learning experiences. (LinkedIn, n.d.)

2.3.1 3D virtual learning environments

3D Virtual Learning Environments (VLEs) are 3D environments specially designed to teach people a specific subject or assist them in learning new skills. Such environments are realized using Virtual Reality technology. In such an environment, users can move their viewpoints freely in the space and can perform actions, like interacting with objects and invoking changes in the behaviour of the environment or in any of its components, which are defined in Table 4. In general, the objects in the virtual space are 3D objects, although 2D objects can also be displayed. As Table 4 suggests, multiple components and associated functionalities can be distinguished. (Ewais & De Troyer, 2014, p. 4)

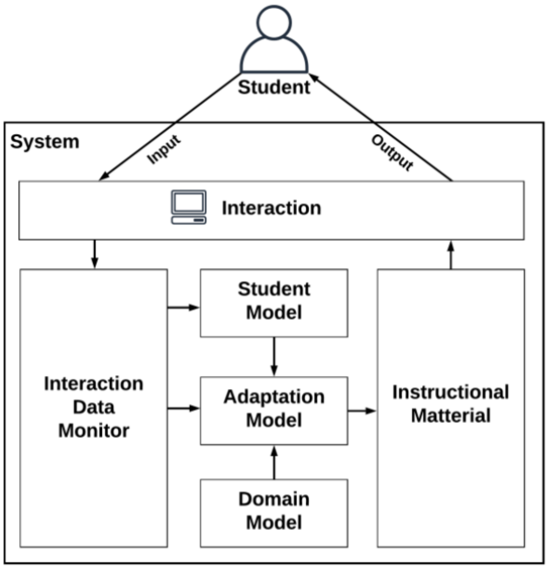
Table 4 - 3D VLE components and their functionality (Ewais & De Troyer, 2014, pp. 4–5)

Component	Definition
Virtual Scene	A 3D environment populated with virtual objects, visual elements such as lights, viewpoints, and cameras. These objects share certain properties across the environment.
Virtual Objects	Objects having a 3D or 2D visualisation and custom properties such as size, material, and orientation.
Object Behaviours	The virtual objects can have behaviours, such as rotation, velocity transform, and so on.
User Interaction	The user or player can interact with the environment and its elements. This can modify the behaviour of the object that has been interacted with.
User Navigation	The player-controlled avatar can freely navigate in the virtual space (walking, running, flying) or it can navigate through a predefined path (teleportation).
Communication	A collaborative aspect through which remote players can interact with each other in a multiplayer setting.
Sound	An organic part of the environment often used in conjunction with other elements, in order to enhance the feeling of reality or to provide instructions to the user player.

2.3.2 Adaptive virtual learning environment

The primary goal of Adaptive and Virtual Learning Environments (AVLEs) is to tailor the instructional materials and their delivery to meet individual needs, resulting in an enriched learning experience. Various research directions are known related to AVLEs. One prominent focus area is the theme of adaptive models and frameworks. Another focus area is the user or student modelling, which involves representing, storing, and maintaining the individual characteristics of the subjects such as performance, learning style, knowledge level, and motivation. The theme of adaptive methods and techniques is also an essential research direction. The concept incorporates the utilization of adaptive link annotations as well as the customization of the learning material based on individual preferences of the students. (Alshammari, 2020, p. 41)

Figure 6 - Adaptive framework (Alshammari, 2020, fig. 1)

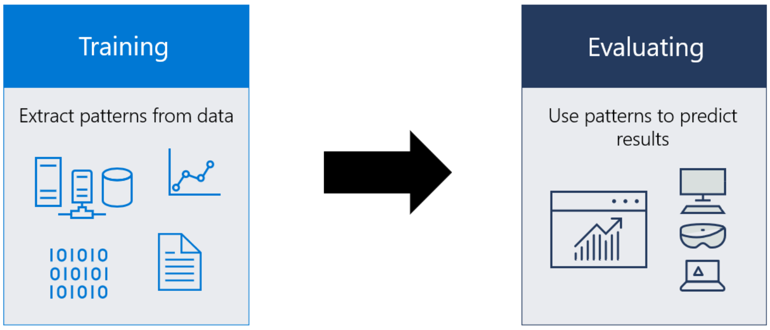


As Figure 6 illustrates, an adaptable framework has been proposed for developing Adaptive Virtual Learning Environments (AVLEs). The framework consists of three main modules: the content domain model, the student or user model, and the adaptation model, which allows for adaptability, based on the characteristics of the learner. The framework also includes auxiliary modules such as the interaction data monitor module (records student activities), and the interaction module (a graphical interface). The content domain model organized the learning materials for adaptability. The student model incorporated two student features, including the learning style and knowledge level. The adaptive virtual learning environment was capable of generating different sets of learning paths, tailored to the learning style and knowledge level of the students. (Alshammari, 2020, pp. 42–46)

2.3.3 Machine learning and user modelling

As a subfield of artificial intelligence (AI), machine learning (ML) uses statistical algorithms and mathematical models to allow computers to learn from data and improve their performance on specific tasks, without the use of declarative or explicit programming. The key strength of machine learning is that ML models do not rely on pre-defined rules, instead they are trained to recognize patterns in the data. To effectively use ML, a scenario involving repeated decision-making or evaluation is imperative, as well as labelled data or examples that can be utilized to describe and map the scenario. As is illustrated in Figure 7, ML models can be used to make informed decisions and predictions about data that has not been previously fed into the model. (Burkov, 2019, pp. 3–8)

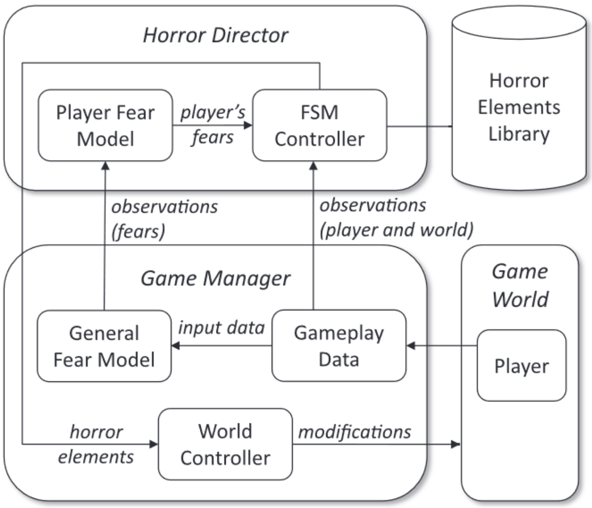
Figure 7 - The model flow of machine learning (QuinnRadich, 2021)



User modelling (UM) aims to create a representation of different characteristics and traits of the users, such as behaviours, preferences, and cognitive processes, through machine learning. Early applications, focused on developing models based on the cognitive processes, however the focus has been shifted towards behaviour-based user models. Standard machine learning techniques are ideal for modelling situations in which the user has to perform repeated task such as selecting an item from predefined options. The user-provided information regarding the problem and their decision-making process, can be used as training data for a machine learning algorithm. This algorithm can enhance the user experience by then delivering tailored content based on the individual interests or needs of the user. It is worth mentioning, that user modelling requires large data sets, labelled data, concept drift, and computational complexity. (Webb et al., 2001)

By leveraging the power of player modelling (user modelling) and in-app data analysis, more engaging and tailored experiences can be created for the users. Player modelling (or user modelling) involves the creation of detailed user profiles of each player based on their playing style, preferences, and skill level. Such information can be gathered through a variety of methods, such as tracking user behaviour and collecting feedback from the players themselves. To deliver tailored experiences, the data was analysed to detect trends and patterns in player behaviour, such as popular features, frequency of games, and time spent on different activities. Figure 8 illustrates the possible architecture of such an application. (de Lima et al., 2022)

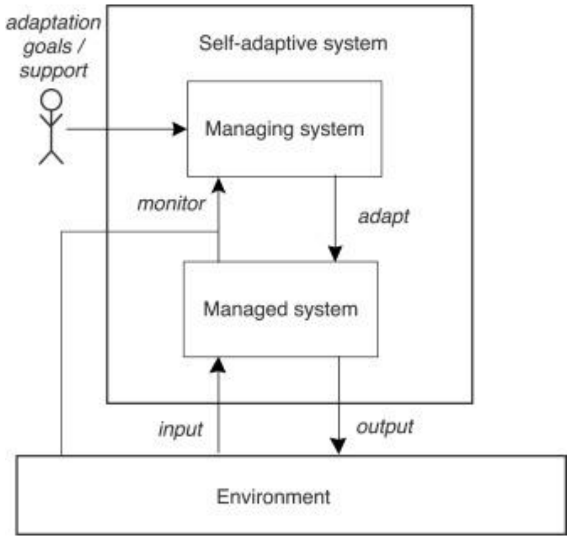
Figure 8 - The architecture of an Adaptive VR horror game (de Lima et al., 2022, fig. 7)



2.3.4 Self-adaptive systems and autonomous VR training

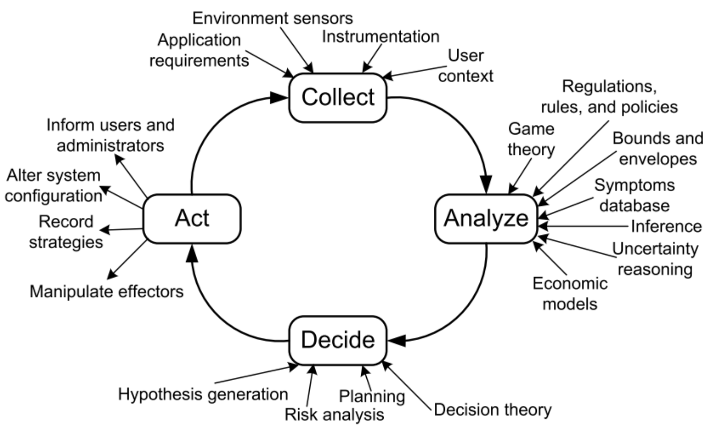
Self-adaptive systems (or auto-tuned systems), shown in Figure 9, are programmed to be able to reason about their own state and dynamically control their behaviour and structure at runtime, in response to changes in their environment or requirements. A self-adaptive system consists of two sub-systems, namely a managed system (domain) and a managing system (adaptation). The managed system is the software being altered based on the environmental input, whereas the managing system monitors the aforementioned system and/or its environment; and responsible for setting and carrying out the necessary adaption goals. (Quin et al., 2022, p. 4)

Figure 9 - A model of a self-adaptive system (Quin et al., 2022, fig. 1)



Feedback loops play a critical role in self-adaptive systems. They provide the generic mechanism for self-regulation and control. A feedback loop, as is presented in Figure 10, typically involves four key activities: collect, analyse, decide, and act. First, data is collected from the executing system and its context, then the gathered data will be analysed in order to infer trends, which can serve as a basis for predicting future behaviours and for decision making. Finally, the system acts to drive itself towards the desired direction. Feedback loops can be categorised as positive (amplifying response), negative (counteracting response) and complex loops. (Brun et al., 2009, pp. 51–53)

Figure 10 - Data flow of a feedback loop (Brun et al., 2009, fig. 1)



Autonomous VR training systems utilize feedback loops to connect different components. Such a system presents a task to the learner, evaluates their performance on various aspects, such as accuracy, time taken, and expertise, then selects the next task based on their previous performance. The collected data provides intelligent intervention to increase training effectiveness. The system uses data from past training outcomes for each user, in order to make informed decisions about which training modules are most beneficial at the time. Automating VR training involves adaptive learning mechanisms, reactive capabilities, simulation-based autonomous training, intelligent progress monitoring, and adaptive material. (Vaughan et al., 2016, p. 68)

2.3.5 Adaptiveness through gesture-based UI

In the field of VR, the term gesture refers to any conscious or unconscious movements of the upper limbs that are being utilized by the users to express their intent, and convey interactive information. The goal of gesture interaction is to govern an interaction by tracking and capturing user gestures, which is critical for facilitating natural and immersive interactions in VR settings. Gesture-based interactions are often enabled and performed through the usage of wearable devices, including data gloves and touch devices. Data gloves, illustrated in figure 11, hold a significant role, since these types of wearable devices allow for the real-time tracking and capture of user gestures. Gesture interaction technology is a progressing field, and incorporating such technology into VR applications may foster immersive and more genuine human-like user interactions. (Y. Li et al., 2019)

Figure 11 - Data gloves (Y. Li et al., 2019, fig. 1)

The integration of gesture-based user interfaces provides users with an intuitive and immersive interaction experience and can be used to personalize the user experience of any VR application.

Recently an attempt has been made to introduce a gesture-based user interface in VR. Users were asked to compare a gesture-based setting with that of a controller-based one. Their experiences were collected and analysed using a questionnaire, which aimed to grade various aspects, including the ease of use and reliability. From the conducted user tests, it was discovered that gesture-based interactions are easy to learn, yet they fail when it comes to the reliability of the functionality, as it was easy to trigger unintentional interactions through hand movements. Despite such minor setbacks, gesture-based interactions offer a natural and easy to learn way to implement user interactions. Furthermore, it enables the virtualisation and spatialization of UI elements. (Nyyssönen et al., 2022, pp. 1776–1780)

Figure 12 - Possible gesture and UI elements in the VR environment (Nyyssönen et al., 2022, figs 1–2)

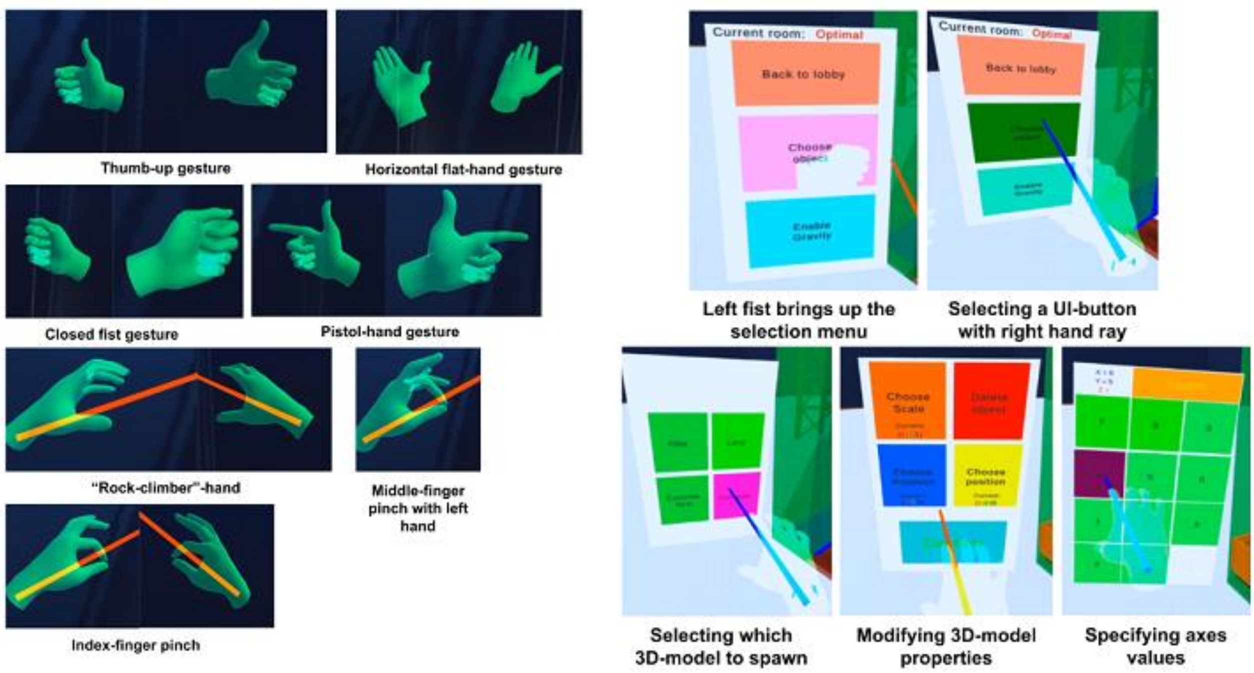
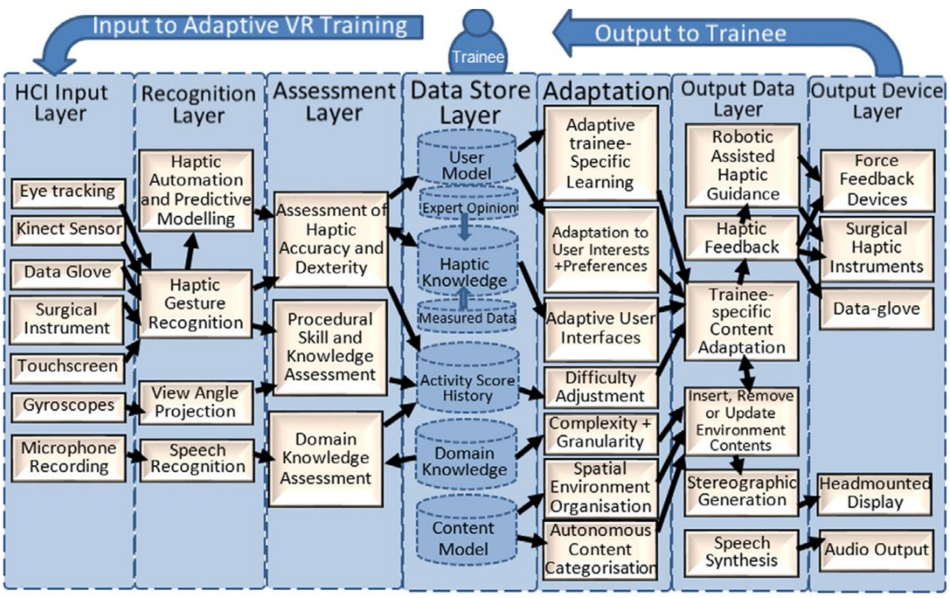


Figure 12 shows the gesture library used by Nyyssönen et al. Forward movement could be initiated with a thumbs-up gesture, and the direction was set based on the head position of the user. The flat-hand gesture was used to regulate the continuous up and downward movement of the user. The pistol gesture was recognized as a continuous right or left turning, based respectively on the hand performing the aforementioned gesture. The rock-climber hand gesture, performed with either the right or left hand, brought up a visible ray beam that could be used to select a teleportation feature. Continuous pinching of the left middle finger repeated the teleportation in fixed intervals. A closed fist gesture with the left hand brought up a selection menu, while a closed fist gesture with the right hand closed the selection menu. The pinch gestures were utilized for hover over and select menu items, and to request information about any interactable 3D objects in the scene. (Nyyssönen et al., 2022, pp. 1772–1774)

2.3.6 The adaptive core technologies of VR learning

Figure 13 - Multimodal components within VR-based adaptive learning (Vaughan et al., 2016, fig. 1)



Adaptive technologies are a type of technology that modifies its behaviour or output in order to meet the different requirements of learners (students). Adaptation, as Figure 13 illustrates, links different technologies together in the VR training environment, and can occur in a variety of ways, including changes to the scene, objects, behaviours, navigation, interactions, and sound. In such cases where the user interacts with an autonomous agent or a haptic device, the adaptation can respond by adapting the display output. In virtual reality training, adaptive technologies can be used to adjust the difficulty or complexity of training exercises based on the progress and/or preferences displayed by the subject. (Vaughan et al., 2016, p. 69)

Table 5 contains relevant adaptive technologies, such as haptic devices, head-mounted displays, evaluation and scoring feedback, and autonomous agents. These are the core technologies that serve as the foundation for VR-based training simulations. In addition, these technologies work together to create a seamless and effective training experience for the users. The application of these five fundamental technologies has revolutionized VR-based training simulations, making them more effective, engaging, and tailored. Users may utilize these technologies to study and enhance their abilities in a secure and controlled digital environment, preparing them for real-world circumstances and problems. (Vaughan et al., 2016, pp. 68–69)

Table 5 - The core technologies in VR-based training simulations (Vaughan et al., 2016, pp. 68–74)

Technology	Function	Example
User interfaces	Generate user-centred VR-based training material. Personalize feedback and adjust difficulty based on the needs of the users.	User experience can be enhanced through adaptive user interfaces and autonomous content categorisation that enables spatial re-arrangement of the environmental elements.
Haptic devices	Aims to improve psychomotor-dependent skills for precision tasks, such as surgery through creating a sense of touch and feel in the virtual environment.	By incorporating adaptive haptic guidance, the VR training system can effectively teach users how to accurately position their hands in precision tasks.
Head-mounted displays	Provides a visual and auditory immersive experience to enhance realism and memorability.	Head motion tracking and eye tracking provides context rich motion data that can be analysed; thus personalized / adaptive content can be generated.
Assessment and scoring feedback	Evaluates a user's performance and provides feedback on areas for improvement.	The system can track the user's performance and can provide tailored feedback and assistance on specific areas that need improvement.
Autonomous agents	Computer rendered animated characters or virtual avatars. Enables interaction with the trainee and provides realistic scenarios and challenges.	Intelligent Tutoring System (ITS): A virtual avatar can interact with the user to demonstrate how to perform a certain task.

3 Research methodology: exploring the research approach

In this chapter, the research methodology employed in the present literature review conducted for HAMK Smart is described. This chapter provides a detailed account of the methods and procedures used to search, select, and analyse the literature sources, ensuring the validity and reliability of the research findings. The chapter begins with an overview of the research design, followed by a discussion on the research approach, literature search methods, and data analysis techniques.

3.1 Research questions

The aim of this study is to investigate the existing knowledge about individually adaptive VR learning applications. Specifically, the thesis seeks to identify the key components and their theoretical background, that are vital in the design and development of individually adaptive VR learning applications. This shall be achieved by studying the current state of research in this area.

3.2 Literature review

The author of this thesis conducted a comprehensive review of the existing literature on individually adaptive VR learning applications and its relevant theoretical background. To achieve this, the author utilized academic scholar databases such as Science Direct, Google Scholar, HAMK Finna, and Finna, as well as relevant and trusted web pages and articles. The literature review put focus on research articles, books, and reports published in the last ten years. In the case of definitions, historically relevant scientific works, well established domains, the criteria that have been published within the past decade have been disregarded, as fundamental definitions and scientific models remain unaltered. Keywords such as **individually adaptive**, **virtual reality**, **learning**, **adaptive**, and **applications** have been used to identify relevant literature.

3.3 Research design

A qualitative research design was used during the literature review in order to thoroughly analyze the acquired literature on individually adaptive VR learning applications. The selected design method was appropriate as it provided a flexible and adaptable framework for an in-depth exploration and analysis of the existing and scarce literature. Given the lack of well-established design and development practices of the topic at hand, as part of the qualitative assessment, the author aimed to recognize the key and distinctive design elements of individually adaptive VR learning applications. Where necessary, a brief theoretical foundation has been provided to support the comprehension of the technical aspects of the identified key component.

3.4 Material collection and analysis

The data for this study have been collected through a comprehensive review of the existing literature on individually adaptive VR learning applications. The author of this thesis academic work collected relevant books, e-books, scientific articles, and trusted web pages from the fields of psychology, biophysics, and computer science. The author used a qualitative content analysis approach to process the acquired publications and scholarly works. Such an approach involved recognizing and classifying key elements and patterns in the existing literature of individually adaptive VR learning applications.

3.5 Implementation plan

The researcher will first identify and screen the search results based on the inclusion and exclusion criteria. The inclusion criteria will be: (1) literature published in the last ten years, (2) literature written in English, (3) literature that focuses on individually adaptive VR learning applications or the theoretical background of an identified key theme. The exclusion criteria have been: (1) literature that did not focus on the research question, (2) studies that were not available in full text, (3) studies that were not accessible through the academic institution of Häme University of Applied Sciences. Then, the author read the full text of the successfully screened studies extracting the relevant theories and key findings, which were coherently structured and presented.

3.6 Results and discussion

The results of the qualitative evaluation were presented in a narrative form, with an emphasis on the presentation and interpretation of the key themes and patterns that emerged from the thorough literature review. Whenever the narrative presentation was not satisfactory, the results and / or interpretations were conveyed using visual illustrations. The discussion put focus on the implications of the findings for the research question, as well as on any limitations and gaps in the existing literature. In this section the author also provided suggestions and recommendations for future research in this area.

4 Results and discussion

As the aim of the thesis work was to collect the essential key elements of individually adaptive VR applications, this chapter explores the best practices for developing user-adaptive virtual reality learning applications. The phrase “individually adaptive” refers to tailoring the learning experience to meet the individual needs, preferences, and abilities of the users. By incorporating user adaptivity into VR learning applications, enhancements can be made to the effectiveness and engagement of the learning process. This chapter provides a comprehensive overview of the best practices and applicable learning models, which can be utilized to guide the development of user-adaptive VR learning applications.

4.1 Best practices

Virtual reality learning applications have witnessed remarkable progress in achieving adaptiveness through the integration of various adaptive technologies and approaches. During the research work, the author has identified various key components, such as: the adaptive learning environment, machine learning, user modelling, and self-adaptive systems (feedback loops). In this section, these components will be discussed, including the ways in which adaptiveness can be achieved through the possible manipulation of different adaptive, core VR components, and ultimately the first research question will be addressed here:

- Research Question 1: What knowledge currently exists about individually adaptive virtual reality learning applications?

The adaptive learning environment (ALE) is a key element of any user adaptive VR application. ALE means that the learning content must be tailored according to the needs of the learners. Such an environment can be achieved by introducing machine learning (ML), user modelling (UM), and self-adaptive systems into the application. Machine learning techniques enable adaptive VR learning applications to analyse learner data, identify patterns, and make predictions. By leveraging machine learning algorithms, such applications can personalize the learning experience by adapting the content, difficulty level, and instructional approaches to meet individual learners' needs. For example, recommendation systems can suggest relevant learning materials based on the preferences and prior knowledge of the learners.

Adaptiveness can also be implemented through self-adaptive systems. Such systems use feedback loops, which continuously monitor the actions, performance, and progress of the learners within the VR environment. Through feedback loops, the learning experience can be dynamically and proactively adapted to user needs in real-time, based on the feedback received. For instance, if a learner is struggling with a particular concept, the system can provide additional explanations, or offer alternative learning resources to facilitate comprehension and mastery.

Machine learning and self-adaptive systems are tools that can be used to create individually adaptive learning solutions. Such solutions can be utilized in a variety of adaptive technologies in VR. Many aspects of a VR application can be altered or adjusted based on individual needs. For instance, some learners may prefer visual content, whilst others may ask for audio content. Such preferences can be configured via the user interface. Haptic feedback (vibration in the controller) is another adaptive technology that can be adjusted and configured according to individual preferences. Furthermore, autonomous agents (virtual non-player characters) can also be introduced to assist the learning process by aiding and guiding the user. When adaptive technologies are selected for development purposes, the goal and nature of the learning content must also be taken into account, as these may have an impact on design decisions.

While both machine learning and feedback loops contribute to achieving adaptiveness in VR learning applications, they have distinctive characteristics and functionalities. Machine learning places emphasis on the analysis of learner data and making data-driven predictions to personalize the learning experience. It relies on statistical algorithms to identify patterns and adapt the learning content accordingly. Feedback loop driven self-adaptive systems, on the other hand, operate by continuously gathering and analyzing data from learners and adjusting the system configurations and learning experience accordingly. Such systems establish a dynamic feedback mechanism that allows for real-time adaptations based on the actions and progress displayed by the learners.

One potential example of machine learning in the context of VR learning, is an adaptive recommendation system that analyzes the past interactions and preferences of the learners, in order to suggest personalized learning materials, such as relevant interactive simulations. This personalization enhances engagement and facilitates effective knowledge acquisition. In the case of feedback loops, consider a VR language learning application that provides immediate pronunciation feedback. The system continuously evaluates the pronunciation accuracy of the speech patterns recorded by the learners and offers real-time feedback on pronunciation accuracy. Based on this data, the system dynamically modifies the degree of difficulty of the pronunciation exercises to ensure appropriate challenges for each learner.

Adaptive VR technologies, as it has been presented in section 2.3.6, play a crucial role in creating immersive and personalized learning experiences. For instance, user interface (UI) design ensures intuitive and user-friendly interactions within the VR environment. It automatically adapts to the choices of the learners, enabling a smooth and tailored learning experience. Haptic devices provide realistic tactile feedback, enhancing the sense of presence and engagement in VR learning. Through the use of these tools, learners may engage with virtual objects and situations by simulating touch and physical feelings. User feedback and assessment mechanisms collect real-time data on learners' actions, performance, and preferences. The learning content and instructional tactics may be adjusted adaptively thanks to their individualized feedback, evaluation, and progress tracking capabilities. Autonomous agents, acting as virtual instructors or guides, adjust their behaviour based on the activities and performance of their students to offer individualized help, direction, and feedback.

In conclusion, adaptive VR technologies, including UI, haptic devices, HMDs, user feedback and assessment mechanisms, and autonomous agents, contribute to creating immersive and personalized learning experiences. Machine learning and feedback loops, while different in nature, both play essential roles in achieving adaptiveness within VR learning applications. By harnessing these technologies and approaches, individually adaptive VR learning applications can provide personalized, immersive, and effective learning experiences.

4.2 Applicable learning models

The design of individually adaptive VR applications must also cover learning aspects. This section is addressing the following research question:

- Research Question 2: What learning models can be integrated into adaptive VR learning applications?

The machine learning and user modelling approach strongly requires the understanding and deployment of VR compatible learning models. Integrating various learning models into adaptive VR learning applications is vital for personalized and effective learning experiences. These applications can improve learning outcomes by taking into account individual learner characteristics.

One deployable learning model is the so-called CAMIL model. It has been designed to describe the prominent factors of immersive VR learning environments. The model introduces and measures the process of learning via learning variables. These learning variables impact each other and can be categorised as technical factors, immersive factors, and cognitive affordances. For example, poor technical factors (bad HMD or unrecognisable graphical elements) will have a negative impact on the immersive factors, meaning that the learner will not be able to fully submerge into the virtual world. This affects the motivational cognitive variable, leading to bad learning outcomes.

Cognitive constructivism can be considered as another prominent learning model. This learning model enables the learners to form their own subjective perception of the objective aspects of the physical reality. The role of the adaptive learning environment is to provide individually applicable resources; thus, the learners can construct knowledge and meaning through an iterative and autonomous process where the user is free to discover the learning environment. This model shares many conceptual similarities with immersive VR environments. It promotes active learning, allowing learners to explore and interact with the virtual environment, thereby facilitating knowledge construction and conceptual understanding.

Learning styles refer to the idea that individuals have different preferences and approaches to learning, and that instruction tailored to these preferences can enhance learning outcomes. They capture individual learner characteristics and preferences. Learning style models encompass cognitive, affective, and sensory preferences, allowing adaptive VR learning applications to tailor instructional strategies, presentation of learning materials, and assessment methods to suit individual learners. It must be noted that there is an ongoing debate within the scientific community regarding the existence and applicability of learning style models.

The Rescorla-Wagner model of Behaviourism can be employed to predict and respond to performance and motivation metrics in real-time. The user data can be analysed to identify relevant stimuli in the VR environment for learning and adaptation. For example, through machine learning mechanisms, the application can individually associate stimuli with positive outcomes. Furthermore, user behaviour can be continuously monitored; thus, feedback and user reward adjustments can be made through feedback loops, increasing parameters such as user motivation.

By integrating these learning models into adaptive VR learning applications, personalized and immersive learning experiences can be created.

4.3 Ethical considerations

User adaptive applications often require the acquisition of user data, in order to analyze different user related factors such as performance and engagement. The collected data may include various psychological and / or behavioral metrics. The collection of such data raises important ethical considerations that must be addressed to ensure the protection of user privacy and well-being. Based on the General Data Protection Regulation (GDPR) and its Finish implementation: Data Protection Act (1050/2018) the following key considerations can be associated with user data acquisition and handling: informed consent, privacy and anonymity, data minimization and purpose limitation, transparency and openness, data security and confidentiality, and benefit-risk assessment.

4.3.1 Informed consent

To collect user data in compliance with the regulations, it is essential to establish a lawful basis for collecting and processing personal data. This legal basis is frequently obtained through user consent. The consent should be freely given, it is imperative to provide clear and transparent information to users about the purpose of the data collection, the type of data being collected, any potential data sharing possibilities (involvement of third parties such as service providers), user rights (how the collected data can be accessed), duration of data retainment, the right to withdraw the consent at any time, and contact information.

4.3.2 Data minimization and essential user rights

By adhering to the concept of data minimization, only essential data should be acquired for the intended purpose. Excessive and / or unnecessary data acquisition should be avoided. Furthermore, the retention time of the obtained data must be kept to a minimum. Under the GDPR, individuals have several rights, including the right to access their own personal data acquired via the application. In some cases, data erasure can be requested. It must be ensured that these rights can be exercised at any time by the user.

4.3.3 Data security and confidentiality

To ensure data security, appropriate technical and organizational safeguards should be implemented. These safeguards should aim to prevent accidental loss, destruction, unauthorized access, or the manipulation of the collected data. If there is an intention to transfer the acquired data beyond the borders of the European Economic Area (EEA), a valid legal basis should be established, such as an adequacy decision issued by the European Commission.

5 Conclusion and summary

Virtual reality technology has opened up new possibilities for individually adaptive learning applications. Adaptive VR learning apps may offer tailored and immersive learning experiences through the integration of learning models, user modelling, machine learning, and self-adaptive systems. In this thesis, the existing research on the topic, including learning models that may be incorporated into adaptive VR learning applications, was reviewed and examined.

This thesis aimed to address two key research questions:

- Research Question 1: What knowledge currently exists about individually adaptive virtual reality learning applications?

The knowledge currently available highlights the importance of designing VR immersive applications with carefully considered modular components, such as user interfaces, interaction modes, and data collection mechanisms. Such applications can improve the learning experience by fostering a sense of presence and engagement.

The individual behavioural characteristics of the learners can be captured by using user models. This enables the system to tailor instructional strategies and adapt content based on parameters, namely prior knowledge, progress, and performance history. Learning style models consider cognitive, affective, and sensory preferences to personalize the presentation of learning materials and assessment methods. User models can be developed using machine learning algorithms by collecting and analysing user data.

- Research Question 2: What learning models can be integrated into adaptive VR learning applications?

Learning theories, such as cognitive constructivism, provide a foundation for designing adaptive VR learning experiences. These theories complement the immersive aspect of VR technology by placing an emphasis on active involvement and knowledge construction. Additionally, the CAMIL immersive learning model offers a scientific framework for designing adaptive VR learning experiences that promote meaningful interactions with the virtual environment.

Adaptive learning models, such as the Rescorla-Wagner model and predictive learning models, enable systems to track and predict the behaviour and performance displayed by the users. Adaptive systems can optimize learning progress and enhance learner engagement by dynamically and proactively adjusting learning content, and difficulty levels, according to user needs.

In summary, individually adaptive VR learning applications hold great potential for tailored and immersive learning experiences. By integrating learning models, self-adaptive systems, machine learning and user modelling techniques, these applications can optimize learning outcomes and cater to the diverse needs of individual learners. As the effectiveness and applicability of available adaptive technologies heavily rely on the specific context of the learning environment, further research is needed to explore more specific implementation strategies, and to uncover new insights in this rapidly evolving field.

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Annex 1: Material Management Plan

This thesis work did not involve any interviews or surveys; thus, none have been recorded or stored in any format.

A thesis agreement has been signed between HAMK Smart (represented by Joni Kukkamäki), Elina Vartiainen (supervisor) and Daniel Kovacs (author) for the thesis project, stipulating that the thesis will not include any confidential material, and will be publicly available. The agreement also permits the publication of the commissioning party's name. As a result, no obligation to anonymize the thesis material has been made."

The thesis and the signed thesis agreement is stored and backed up at *C:/HAMK/Thesis/* on the author's computer (Dell Inspiron 15). The forementioned documents will be kept there for at least one year after publishing the thesis work.

Throughout the thesis work the General Data Protection (EU) 2016/679 and the Finnish Data Protection Act (2016, Data Protection Act 5.12.2018/1050, 2018) were followed and applied.