Connecting the Puzzle Pieces:

Adapting Virtual Reality Environments with Biometric Data to Support Learners with Autism Spectrum Disorder

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AUTHORIZATION TO SUBMIT THESIS

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ABSTRACT

Educators face many challenges when promoting engagement and retaining attention in neuro-diverse learners, such as those with autism. Recent advancements in virtual reality technology, biometric scanning, and education epistemology are opening new opportunities for these educators to connect with their students through adaptive real-time education simulations. This paper reviews the viability of several elements to propose a new, innovative framework for educating neuro-diverse individuals. First, virtual reality provides an immersive, controlled, high-fidelity presentation platform. Second, biometric data from cardiovascular responses, electrodermal activity, electroencephalograph, and eye tracking provide the data to determine mental state and adapt the environment. Finally, exploratory based learning grounds the learning experience helping engage learners and presenting knowledge in context. Together, these disparate elements have the potential to form a cohesive system, empowering neuro-diverse educators while promoting student success.

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CHAPTER 1: CONNECTING THE PUZZLE PIECES

Educators are faced with many challenges when designing lessons that spark interest, engage, and educate the many different types of students found in the classroom. These challenges take on a new light when teaching learners with Autism. People with autism have difficulty with communication and social interactions that limit abilities to form relationships, register social cues and interactions, and can also lead to unusual restricted and repetitive behaviors (*Autism spectrum disorder*, 2020). These behaviors can include increased sensitivity to environmental factors such as lights, colors, and sounds as well as a strong need for structure and routines in the environment. In addition to these core symptoms of ASD, many co-morbidities related to cognitive and mental health further complicate interaction with autistic people. One example of a common cognitive problem is difficulty with attention and concentration (Travers et al., 2011). This is an especially crucial piece of the puzzle for educators working with individuals on the autism spectrum as it leads to more difficulty engaging with the student.

Educators and parents are constantly looking for new ways to improve student engagement and environmental control for ASD learners. Technology is continuously being applied in new and creative ways to solve this problem. Recent refinements and reemergence of previously explored technologies opens the door for innovative new applications of these already explored technologies. Consider the resurgence of virtual reality over the last decade and its widespread availability in the consumer market. Another technology rapidly expanding in the consumer market are wearable fitness trackers which give users the ability to track basic biometric data such as heart rate, perspiration, and blood pressure. Solutions such as Fitbits and Apple watches provide users with a comprehensive look at health data via an unobtrusive and inexpensive platform. Researchers are taking advantage of these improvements and applying the technologies to new fields, including education (Franzen-Castle et al., 2017; Mooses et al., 2018). Finally, recent explorations in low-level real-time brain-scanning have allowed researchers to get a glimpse at cognitive state without the difficulties and intrusiveness associated with traditional electroencephalogram (EEG) methods.

These current research trends show the potential virtual reality and virtual environments could have on education in both neuro-typical and neuro-diverse students, such as those with autism. Reviewing recent studies however, educational environments taking advantage of these technological improvements are not as prevalent as expected given the potential benefits. The framework proposed within this paper attempts to connect the pieces between education, virtual reality, biometric tracking, and neurodiversity with three key elements. First, advancements in VR technology immerse the user, giving them a sense of presence in the virtual world. Second, biometric tracking and cognitive monitoring provide real-time data for adapting the virtual environment. Finally, exploratory based learning provides an engaging framework for presenting the learner with new information while grounding it in real world experiences.

CHAPTER 2: VIRTUAL REALITY AND VIRTUAL ENVIRONMENTS

OVERCOMING TECHNICAL BARRIERS

Virtual reality (VR) immerses a user in a virtual world by replacing at least their visual and auditory senses with virtual simulations. This is facilitated using a head-mounted display (HMD) and high-fidelity headphones that the user wears. Technology is also being developed to simulate other senses as well. For example, several companies are developing solutions for replicating touch and the physicality of objects (Haptx, Manus VR, Ultraleap). This is generally done via haptics, small, localized vibration motors that can be vibrated at different intensities and frequencies to give the illusion of touch. Using an HMD provides a high level of visual fidelity with stereoscopic 3D by using two high-resolution screens, precisely crafted lenses, and accurate 3D spatial tracking. In VR's infancy, screen technologies struggled to provide lightweight solutions that could replace human vision while computing power limited the quality of real-time vision and positional tracking. Modern VR headsets benefit from the major advancements in screen and computing technology removing many of these limitations. The cost-of-entry has also dropped considerably, with consumer headsets featuring all of these improvements available now for less than $400. For comparison, lesser quality headsets cost

$800 dollars or more as recently as 2016 when Vive and Oculus released their initial consumer headsets (Table 1.1. Comparison of pricing for VR technologies.

In addition to screen and computing power, modern headsets now offer six-degrees of freedom (6DOF) motion tracking, where many earlier headsets were limited to three degrees of freedom (3DOF). A 3DOF headset only tracks the players head rotation in space, while 6DOF tracking includes rotation and translation. This helps reduce motion sickness by more closely matching the user's movements. Even a slight tilting of the head results in 3D translation in addition to rotation, and the disconnect in a 3DOF headset can disorient users, especially those new to virtual reality. An accurately tracked 6DOF headset precisely matches the user's movements, limiting this disconnect from reality and the side effects.

Table 1.1. Comparison of pricing for VR technologies.

	1996	**2016**	**2019**
Headset	ProVision 100	HTC Vive	Oculus Quest/Rift S
GPU	Integrated	GTX 1080	RTX 2080 TI
Compute Power	35,000 Triangles per Second	16 Billion Triangles per Second	20 Billion Triangles per Second
Availability	Limited, Professional Market	Widely, Consumer Market	Widely, Consumer Market
Cost	$115,000 adjusted for Inflation	$800	$400

Historically, the technical limits of VR have pushed researchers towards other options for representing virtual environments. Strickland et al's (1996) case studies placed two ASD children in VR simulations and analyzed their ability to track and identify objects as well as their immersion in the world (Strickland et al., 1996). She had difficulties maintaining the children's suspension of disbelief however, causing the children to continually remove the headset to figure out "where the image was coming from." The image provided with Strickland's case studies (Figure 1) showing the virtual world used illustrates how far rendering technology has come when compared to modern computer-generated images (Figure 1.2). Based on the quality of rendering available to Strickland, the difficulties in maintaining immersion may be related to graphical quality, although further research is needed to confirm if this is the case. Table 1 shows a comparison between the Provision 100, the headset used in Strickland's study, and consumer headsets and hardware from 2016 and 2019.

Figure 1.1. Screen capture from Strickland's virtual environment

Figure 1.2. Screenshot of modern graphics inside Unreal Engine 4 with Quixel Megascans assets

Recent studies using VR in education show this issue resolving as the higher fidelity technology removes many of the sensory disconnects for the user (Alhalabi, 2016; Jensen & Konradsen, 2018; Merchant et al., 2014). These improvements open new opportunities for applying VR technology in support of education.

VR IN SUPPORT OF EDUCATION

In education, engagement plays a key role in learning outcomes. Engagement contributes to student satisfaction, retention, and overall experience (Carini et al., 2006; Martin & Bolliger, 2018; Portelli & McMahon, 2004). Traditional education experiences generally place students in a generic classroom and utilize content memorization and repetition for learning. These methods have little real-world similarities to the content being discussed. New learning epistemologies, such as experience-based-learning (discussed in depth later in this paper) place users in realistic scenarios for learning, which allow them to relate learning experiences to the real-world more effectively (Kolb, 1984). This is difficult to achieve in a school environment, however the immersive nature of VR and removal of previous barriers faced in VR education studies makes VR a potential solution to bringing more engaging and effective learning strategies into the classroom.

The River City Multi-User Virtual Environment (MUVE) studied in 2005 by Dede et al. is one example showcasing the effectiveness of immersion in virtual environments on student engagement. (Dede Clarke, J., Jass-Ketelhut, D., Nelson, B., & Bowman, C., 2005). At the time of the River City study, VR technology was still primitive, therefore River City was a traditional flatscreen experience. The inquiry-based learning system implemented in the project (discussed later in this paper) helps add immersion as students are solving realistic problems, in realistic scenarios. Study results showed participants in River City had more improvement than a control group in several areas. In results measured via more traditional results such as testing, participants showed significant improvements over a control group. A second type of assessment focusing on writing a 'Letter to the Mayor' returned far more interesting results, however. Students in the MUVE curriculum more than doubled the score of the control group peers with their letters showing a higher level of engagement with the content. Post-test interviews with students and teachers as well as attendance records supported this suggestion of increased engagement.

Based on this research, it seems virtual reality and virtual environments can positively impact education by increasing student engagement, knowledge retention, and application of skills. Currently, this is demonstrated in a variety of

VR TO SUPPORT AUTISTIC LEARNERS

In the context of autism, the control that VR brings to learning experiences, or other types of simulation could be invaluable in keeping autistic students engaged with the content, as well as promoting social interaction. Because virtual reality replaces the visual and auditory senses of the user with a simulation, the educators and developers can easily remove and control potential triggers. This level of control allows environments to quickly be adapted to an individual both before and during the experience. Research with virtual reality experiences has already shown that virtual experiences warrant the same response between neuro-typical and autistic individuals, as well as promote engagement and social interaction (Wallace et al., 2010). Combine this ability to realistically represent the physical world with the control provided by virtual environments and a compelling solution is revealed for avoiding meltdown triggers while promoting student learning.

Sensory Control

Many times, when an autistic individual is overwhelmed, or presented with environmental triggers they breakdown, or fall into disruptive behaviors. These 'meltdowns' as they are referred to in the autistic community can be varied and unpredictable (Ryan, 2010). Lights, sounds, textures, and shapes can all overwhelm an autistic individual, triggering a meltdown and disconnecting them from the experience. This causes difficulties with education environments as the loss of engagement from the learner damages the education experience.

Educators also have difficulty maintaining attention from many autistic learners (Travers et al., 2011). Sensory control gives educators and developers more control over attention through the adjustment of focal points in the environment, which is easily done with lighting, color, or audio tweaks. For example, research has shown that warmer colors draw stronger attention than cool colors (Pal et al., 2012). In a scenario where the user's visual attention is directed away from the focal point, environment light intensity could be lowered, and temperature shifted to a cooler tone. Focal point lighting would be inversely adjusted, raising intensity, and shifting color temperature to a warmer tone. This should naturally draw the user's focus towards the focal area.

There are many other cases for sensory control involving light, sound, and touch to redirect user attention as well as limit stimulus that can trigger meltdowns. Replacing the senses of the user in real-time based upon their responses and interactions within the environment has great potential for encouraging deeper learner engagement for longer periods of time, while preventing damaging behaviors such as meltdowns.

Social Interactions

Autistic individuals also struggle with social cues and interactions. In real-world environments social interactions are highly unpredictable and the actions of passerby's on the street can easily trigger autistic meltdown's disruptive behavior (Ryan, 2010). In virtual reality, real-world settings can have a variety of different virtual avatars. All aspects of these avatars can be altered by the educator such as visual appearance or complexity, occurrence, and speech. For example, some autistic individuals connect more effectively with stylized characters from cartoons or movies. In virtual reality, avatars could easily have different types of stylization to connect with a variety of different learners. Speech can also be controlled, whether via pre-scripted dialogue sets, or live speech from an educator outside of the virtual experience.

In addition to adaptive control of avatars and speech interactions, virtual environments allow realistic simulation of scenarios without unpredictable events than could upset the user. Various studies have shown virtual environments can help autistic learners in social and cognitive applications. VR simulations have shown potential for increasing emotion recognition and general social cognition in several advanced autism cases (Didehbani et al., 2016). VR travel simulations also have shown improvements for enabling autistic individuals to use public transport without being overwhelmed by social and sensory stimulus (Simões et al., 2018). In the context of adult professional development, early research has shown increased confidence and preparedness after autistic adults participated in virtual reality job interview trainings (Smith et al., 2014).

With all of this control available to the educator, each environment can be adjusted before and during the experience by the educator. This allows the avoidance of triggers that can lead to disruptive behaviors and loss of student engagement. Virtual reality therefore allows the simulation of the real-world while removing many potentials triggers and distractors that could easily disconnect the learner. So far, this paper has mainly focused on adjusting the environment beforehand. Technological advancements in areas outside of VR can potentially break this restriction however and allow the environment to be adjusted in real-time based on the response of the user, allowing learning experience to push the boundaries of the individual.

CHAPTER 3: BIOMETRIC DATA: PROVIDING THE DATA FOR ADAPTATION

While pre-scripted experiences have the potential to be effective in communicating ideas, there is still a level of uncertainty about how an autistic user may respond to the generated environment. Biometric data can remove some of this uncertainty by providing a real-time glimpse at the mental and physical state of the user and adapting the environment in real-time when red flags are noticed. With the recent explosion of lightweight, inexpensive, and easy-to-use personal health sensors being adopted by the consumer market it is easier than ever to track biometrics, which can then be used to gain the necessary picture of mental state.

Smart watches such as the Apple Watch or Samsung Galaxy Watch are prime examples, providing real-time heartrate, SP02, and even ECG monitoring. In addition to that, other recently developed instruments allow the measurement of sweat rate and low-level EEG without an in-depth setup process. Psychophysiology, defined in the handbook of Psychophysiology as “the scientific study of social, psychological, and behavioral phenomena as related and revealed through physiological principles and events in functional organisms” defines relationships between physiological measurement and psychological factors (Cacioppo et al., 2017). This data interpreted using psychophysiology can provide the basis of a biometric feedback loop that drives the virtual environment.

BIOMETRIC INDICATORS

In the context of education for learners with ASD, a measure of mental distress can give educators and researchers the ability to predict the onset of an aggressive or self-injuring ASD meltdown. When attempting to measure any mental state, close attention must be paid to the autonomic nervous system. The autonomic nervous system (ANS) works to maintain homeostasis within the body by regulating major body systems such as cardiovascular, gastrointestinal, and endocrine (Bergström, 1964). It is composed of two branches; sympathetic (SNS) and parasympathetic (PNS). The sympathetic branch reacts to threats or other triggers and adjusts the body's systems for necessary action, while the parasympathetic works inversely, returning the body to homeostasis (Cacioppo et al., 2017). Activation of ANS can be observed across the entire body through events such as increased sweat production, heart rate elevation and variability, and intestinal discomfort. As noted in Sylvia Kreibig's *Autonomic nervous system activity in emotion: A review*, ANS as a predictor of emotion or mental state is still debated within the fields of psychology and physiology (Kreibig, 2010). Kreibig's review however discovered many empirical research studies connecting physiological responses with emotions. Therefore, measures of the various systems activated by ANS responses could potentially provide a picture of the mental state of ASD individuals.

One thing illuminated in Kreibig's review is that a single biometric measurement struggles to accurately predict specific emotions or shifts in mental state. Multiple measures considered together however increase the predictive ability. For a framework such as the one proposed in this paper accuracy is paramount, therefore several different measurements from multiple systems would be used and cross-related to develop as accurate a prediction as possible. The two primary systems would look at cardiovascular indicators, and electrodermal activity to measure ANS responses. Biometric data from these two systems can be easily acquired with various consumer devices, such as smartwatches, or professional devices such as the Empatica E4. In addition to cardiovascular and electrodermal measurements, advancing technology for low-level EEG measurement and eye-tracking being applied to VR headsets are beginning to open these metrics up to researchers, although more research is required to fully validate them.

Cardiovascular System

Possibly the most commonly used physiological organ to measure mental distress is the heart (Kreibig, 2010). Simple wearable sensors can measure a variety of different metrics within the heart. These measurements serve as a peripheral metric for activation of the ANS. SNS and PNS activations directly affect the sinoatrial node or 'pacemaker' of the heart (Cacioppo et al., 2017). These activations cause changes in heart rate and heart rate variability. For example, anger, anxiety, fear, and happiness have all been found to cause an elevation in heart rate, and a decrease in heart rate variability (Kreibig, 2010). While this range of emotions is broad and contains both positive and negative emotions, when coupled with measurements in other physiological systems specific emotional response can be determined with relative accuracy. Adding an analysis of cardiac T-Waves allows the emotion to be narrowed down to anger, as T-Waves decrease during anger while staying the same in the other emotions characterized by elevated heart rate and decreased variability. Electrodermal SCR (discussed further in the next section) is elevated under all negative emotions (anger, anxiety, and fear) without significant change for positive emotions. Kreigbig's table coding physiological measurements with emotional states based on her extensive review of empirical research illustrates how these systems are connected.

An example of this in practice is a study conducted in 2018 by Matthew Goodwin et al. Goodwin's study looked into using physiological signs to predict the onset of aggressive response in youth with ASD (Goodwin et al., 2018). In the study, an Empatica E4 Biosensor was used to measure physiological response. The E4 can measure blood pulse volume (BPV), electrodermal activity (EDA), physical motion, and peripheral skin temperature (Empatica Product Page). In the study, heart rate and heart rate variability were recorded using the BPV measurement, while skin electrodermal activity was measured with the EDA sensor. Naturalistic observations were used to record aggressive events providing time between events and times for the beginning of an event. The study found that the E4 biosensor, which is a lightweight, un-invasive wristband could reliably predict aggressive outbursts in the sampled population via physiological markers around one minute before they occurred. While the participants in this study were from a subset of ASD (minimally verbal in an inpatient setting) it seems plausible that similar methods could be applied in other settings with ASD individuals from many locations on the spectrum to help predict outbursts. With emerging technologies, more sources of data can be added to a scenario such as this one to further solidify and expand predictions of outbursts.

Electrodermal Activity

As mentioned, Goodwin's study also used the E4 Biosensor to track electrodermal activity (EDA). Previously known as Galvanic Skin Response, EDA is a measure of the conductivity or resistance of skin. EDA can be measured via two methods; Exosomatic which is the application and measurement of a small external electrical current across the skin, and Endosomatic which measures the bodies internally generated electrical signals without applying a current (Cacioppo et al., 2017). Exosomatic has proven more reliable as it has less external and internal interference caused by electronic devices or physical movement when compared to Endosomatic. EDA measurement has been connected to the body's fight or flight response and can provide fast indicators for mental distress (Öhman & Soares, 1998).

There are two response measures obtained from both exo and endo-somatic EDA devices. First is skin conductance response (SCR), or the momentary increase in skin conductivity caused by an unexpected stimulus. Similar to the cardiac measurements discussed before, SCR can be linked to a variety of different psychological states such as anxiety and anger. However, SCR by itself cannot distinguish between positive and negative responses, it can only determine when a response has been triggered.

The second response type, skin conductance level (SCL) is a measurement of conductance over time. SCL can be related to the expectation of performing a test. SCL increases when a participant is told they must perform a task, whether that task is information processing and calculations such as math, or external sensory stimulus (Lacey et al., 1963).

In 1957, James Dittes conducted a study titled *Galvanic skin response as a measure of patient's reaction to therapist's permissiveness,* analyzing SCL response in the social context of psychotherapy (Dittes, 1957). Dittes found that EDA measurements were related to "the anxiety of the patient, or his 'mobilization' against any cue threatening punishment by the therapist." (p. 303, Dittes, 1957). This aligns with Kreigbig's review which shows

SCL elevating during anxiety, as well as anger, disgust, and fear. SCL is also elevated under several positive emotions, once again illustrating the importance of combining many different measures of physiological state.

Research has also shown SCL as an indicator for arousal and engagement in virtual world experiences. Increased visual and auditory fidelity for example cause elevations in SCL measurements (Ivory & Kalyanaraman, 2007). This suggests that higher fidelity experiences engage the user more effectively, although further research tying SCL measures to virtual engagement is needed to confirm this relationship. SCL measurements were also linked to virtual avatars. When players could customize and see their avatars such as in a third-person experience significant SCL measurements were recorded. While character customization does not apply in an education environment this response to virtual avatars could play a role in the development of how avatars are dynamically represented in virtual environments and could help tailor experiences towards specific outcomes.

Electroencephalograph (EEG)

Both cardiovascular and EDA measurements use simple, unobtrusive sensors to collect data, however the picture they provide of a participants mental state is based on responses and results in the body rather than what is taking place in the brain. Electroencephalograph (EEG) on the other hand measures electrical activity across the brain using a series of electrodes placed on the scalp. Traditionally, EEG measurements have required a high number of wet electrodes on the scalp to successfully measure brain activity making them highly intrusive and time-consuming, and difficult to setup. Participant comfort is also an issue as many participants report them as uncomfortable and distracting. Because of these limitations, the medical sensing industry has been dedicating research and development towards dry-electrode technology. Dry electrodes require no conductive gel, and less precise positioning on the scalp which allows them to be applied faster and with less discomfort for the participant. Historically, dry-electrode EEG measurements have failed to be as accurate as wet-electrode applications due to the higher electrical impedance and additional sources of interference. Due to the recent investments by medical technology companies however, dry-electrode EEG is rapidly becoming valid within the psychophysiology community. Research from 2017 and 2019 shows a gradual improvement in dry-electrode measurement accuracy and significance while maintaining ease of use and participant comfort (Di Flumeri et al., 2019; Mathewson et al., 2017).

These advancements in dry-electrode technology are now making their way into the consumer market with the advent of all-in-one EEG solutions that require little knowledge and experience but provide real-time usable results to developers. A leading example of this is Neurable, a dry-electrode based EEG head strap designed to be connected to existing Virtual Reality headsets and allow EEG data to control events within the virtual environment (Pereira et al., 2018). While it does not offer the level of detail provided by research-grade equipment, Neurable provides an insight into actions taking place in the brain for many different people, with a simple and unobtrusive setup. As technology continues to advance, systems like Neurable could incorporate new advancements in dry-electrode technology to approach the level of detail required for more scientific applications, such as emotional measurement and mental state. Even today however, when coupled with the other sensing technologies discussed dry electrodes have the potential to provide enough detail about brain activity to increase the accuracy of mental state predictions based on emotions measured from the EEG electrodes.

EEG as a measure of emotion has been studied extensively since it's conception (Lin et al., 2010; Niemic et al., 2002; Petrantonakis & Hadjileontiadis, 2010; Takahashi, 2004). Research conducted in 1987 by Paul Ekman established six universal emotions based on facial expressions which are commonly used in research today to establish links between physiological markers and emotions (Ekman et al., 1987). These six emotions are happiness, surprise, anger, disgust, sadness, and fear. In addition to these six emotions, emotions are commonly represented on a 2-D scale consisting of valence and arousal (Petrantonakis & Hadjileontiadis, 2010). Valence indicates whether the emotion was positive or negative, while arousal is a measure of the level of energy the emotion exhibits in the participant. EEG measurements are able to predict both the valence and arousal dimensions of emotions with significant accuracy across a variety of different stimuli.

An Institute of Electrical and Electronic Engineers (IEEE) study conducted in 2010 measured emotion from participants presented with different musical tracks (Lin et al., 2010). Based upon earlier conducted research that identified six resting state networks

(RSNs) across the different lobes of the brain (Mantini et al., 2007), the IEEE study was able to classify joy, anger, sadness, and pleasure with a maximum accuracy of 82% (Lin et al., 2010). This study developed several models which can be applied to future research to help identify these emotional states using EEG.

Another study conducted at Doshisha University in Japan used EEG, pulse, and EDA measurements to determine emotional responses to audio-visual stimulus via support vector machines (SVMs) (Takahashi, 2004). Takahashi's use of machine learning through SVM learning algorithms was able to identify emotions with approximately 50% accuracy. While low, the advancements in machine learning, artificial intelligence, and simulated neural networks since 2004 would likely improve the machine learning side of the study, increasing accuracy. This can be seen in several of the other studies mentioned, such as the IEEE music study mentioned above (Lin et al., 2010; Petrantonakis & Hadjileontiadis, 2010), where similar techniques were used but greater accuracy was achieved.

To summarize, EEG analysis of delta, theta, alpha, beta, and gamma wave amplitude across multiple lobes categorized by RSN's can provide an accurate measure of emotion from auditory and visual stimulus. Psychophysiological research in this area, coupled with the recent advancements in dry-electrode EEG technologies provide researchers, educators, and developers with an easy to use, comfortable emotion measuring system that can be applied to many different individuals. This type of solution could be ideal in developing education systems for ASD learners when combined with other psychophysiological system measures such as cardiac and electrodermal activity to verify the accuracy of the data.

Eye Tracking

Eye tracking is another technology with recent advances and widescale adoption. Commonly added to virtual reality headsets, modern eye trackers are small, lightweight, and unobtrusive and provide accurate gaze analysis. This data can be used in a variety of ways. Developers can use eye tracking to increase the detail and performance of virtual environments (VE's) through the process of foveated rendering. Foveated rendering lowers the render resolution within a real-time engine based on where the user's gaze is focused. In VR environments, rendering demands are high due to the necessity of rendering two images, one for each eye. Any performance gains give developers more resources to allocate to visual and auditory fidelity, providing a more realistic and immersive experience.

Eye tracking can also be monitored and recorded throughout sessions to analyze where users are devoting attention. This can be used both during the experience as well as after the experience. During the experience, if users are distracted by an area of the VE that is unimportant, developers can redirect attention using animation, lighting, or audio to help keep users on track. Post experience, this recorded data could be analyzed to determine where attention is undesirably drawn. Layout and visual adjustments to the VE could then prevent users from losing focus on the task at hand in the future.

Eye tracking has also been used in research covering both Autism and education for various reasons (Conati & Merten, 2007; Guillon et al., 2014; Risko & Kingstone, 2011). Studies have used eye tracking to identify differences between typically and atypically developing children and adults when viewing complex images with faces (Guillon et al., 2014). This suggests eye tracking can be used as a measure of attention towards a virtual avatar. Eye tracking further adds to the easily obtainable datasets for individuals experiencing VE's and can be applied to improve VE's in a multitude of different ways.

COMBINING THE RESULTS

Cardiovascular measurement, electrodermal response, EEG, and eye tracking measurements are all more accessible than ever due to recent advances in technology. Data from these various measurements can be recorded and passed into coding software which draws upon psychophysiological research to provide a real-time image of the user's mental state and reactions to the presented learning environment. In the past, achieving this level of data tracking and analysis was uncomfortable, obtrusive, and expensive, discouraging their use in many fields of research such as autism where individuals are sensitive to over stimulation. Today, these technologies no longer suffer from many of these obstacles however, providing an opportunity to draw them together into one cohesive system.

CHAPTER 4: EXPERIENCE/EXPLORATORY BASED LEARNING

While studies show that virtual environments can provide effective learning scenarios for a wide variety of students, the educational potential of the VE is only as effective as the framework used for learning. Typically, in traditional education situations a highly structured didactic teaching method is commonly used where the educator provides strict framework for the content, and students are expected to assimilate the content before repeating it back in a testing scenario. This theory of learning is not adaptable to the needs of different individuals and can result in students only temporarily memorizing content before a test, while long-term knowledge retention is inhibited. A more student-driven, adaptable model of learning is emerging in the form experience or exploratory based learning (EBL).

WHAT IS EXPERIENCE/EXPLORATORY BASED LEARNING

EBL places the student or students in a scenario based problem-solving environment where they work with real-world elements to discover solutions. David Kolb explored the three major models of EBL in a chapter for the book *Leadership Perspectives* (Kolb, 1984). One of Kolb's section headings was titled "Learning is a Continuous Process Grounded in Experience," which aptly describes the goals of EBL. The focus of EBL is not the outcomes as seen in testing with traditional education, but in the process of reaching a goal. Executing a process in order to solve a given problem allows the student to develop ideas, implement and observe the effects of these ideas, and analyze and repeat in order to develop a suitable action plan. In many ways, EBL is similar to the design process commonly used in creative and business industries for idea generation and problem-solving. Going through these processes also gives the student a level of experience in the topic which they can draw upon in future situations, creating innovative relationships between seemingly unrelated problems. As the student's experience builds, they can solve problems with more effectiveness and efficiency, while also developing a better understanding of the subjects involved. At the same time, the goal-driven basis of EBL provides students with extrinsic motivation in the form of a successfully solved problem. Research shows extrinsic motivation helps engage neuro-diverse learners with interest in the subject (Schunk et al., 2008). In short, EBL facilitates adaptive learning that is grounded in personal experience, giving students a high relatability to the problems at hand.

EBL IN CURRENT RESEARCH

Recent studies have mostly proven the points developed by Dewey, Lewin, and Piaget that are summarized in Kolb's 1984 book. Several studies conducted by Sara De Freitas have explored and shown the positive effects EBL and virtual environments can have in a variety of educational scenarios while also proposing new ways to take advantage of the EBL framework (De Freitas et al., 2010; De Freitas & Liorakapis, 2011; Freitas & Neumann, 2009). Other research has shown promising improvements in knowledge retention in EBL frameworks when compared to didactic frameworks (Chittaro & Buttussi, 2015).

An example of EBL epistemology applied in virtual environments is the River City virtual environment discussed earlier in this paper. River City presents participants with problems that they must solve by exploring a variety of different fields and applying acquired knowledge to the given scenario. This multi-disciplinary, inquiry-based approach helps connect students with the content they have learned and allows them to apply it with realistic scenarios. The knowledge is then grounded in experience as Kolb described in his book covering EBL. River City found greatly increased levels of engagement from both students and teachers, as well as better knowledge retention over time (Dede Clarke, J., Jass-Ketelhut, D., Nelson, B., & Bowman, C., 2005).

EBL IN SUPPORT OF AUTISTIC LEARNERS

Currently, there seems to be little research exploring experiential learning in the context of Autism, possibly due to the common social elements of EBL, however in a virtual environment where social interaction can be controlled EBL may provide a new method of engaging neuro-diverse effectively, while improving their social abilities.

Student engagement is a major challenge faced by educators working with autistic learners (Lindsay et al., 2013; Van Hees et al., 2015). The more engaging nature of EBL demonstrated in existing research seems promising if effectively applied to autistic students.

EBL accentuates several of the other challenges faced by autistic educators however, mainly in the areas of social and environmental interactions. An EBL experience such as River City thrives on collaboration and interaction with avatars within the environment to learn and experience the given scenario. This is something autistic learners struggle with, however further research into the effects of stylized and abstracted virtual avatars is needed to determine if this obstacle can be surmounted using the adaptive abilities of the virtual world. If so, a secondary benefit in improvements in social interaction could also be seen as autistic learners spend more time interacting and engaging with virtual avatars in a setting they can relate back to the real world.

In summary, experience/exploratory based learning (EBL) provides an education pedagogy that improves knowledge retention and student engagement while grounding experiences in reality. Currently, little research has explored the effects of EBL epistemology in autistic learners, however many of the benefits of EBL experiences seem applicable to autistic learners, such as increased student engagement. At the same time, the challenges presented by EBL could plausibly be overcome by utilizing virtual worlds to simplify and abstract social interactions based on each individual leaner. This combination of new teaching methods and emerging technologies provides the basis for the framework proposed in the next section of this paper.

CHAPTER 5: CONNECTING THE PIECES

Every year, the technology makes huge strides forward in quality, ease of access, usability, and affordability. As discussed earlier, ten years ago lower fidelity virtual reality setups costs tens of thousands of dollars. Today, high fidelity virtual reality headsets are available for less than $400, with many sub $1000 computer setups available to power them. The side effect of this rapid development of technology is a tendency towards slow adoption of emerging technologies resulting in research opportunities being lost in the cascade of new options. With the affordability and quality of the current virtual reality hardware, the leaps in easily achievable visual fidelity for virtual environments, the miniaturization of complex biometric scanning devices, and the ability to easily connect all of these elements together the potential for a new paradigm in educational techniques that support neurodiversity seems strong. Looking at current research, virtual reality, virtual environments, biometric measurement, and experience-based learning have been studied separately, but seem to have not been combined into one cohesive unit working towards a goal. Now however, these disparate elements are at a prime time to be combined into a single system and studied for their effectiveness in a variety of contexts, such as supporting autistic learners.

Educators who support autistic learners face many environmental challenges that can lead to a degradation of the learning experience. Loud sounds, bright lights, and unexpected social interactions can easily trigger meltdowns in these learners, disconnecting them from the learning experience. Virtual reality and virtual environments provide complete control to the educator, while modern hardware and software maintains the required level of visual fidelity for effective learning. At the same time, these VE's can be dynamic; any element can be adjusted at any time. This is where the Biometric data can be used.

Biometric data for cardiovascular activity, electrodermal activity, EEG, and eye tracking can be used to develop a strong idea of mental state in the participant. While accuracy for any one of these technologies is low, cross-relating them as discussed earlier greatly increases the ability to predict mental state. This mental state can then be fed into the simulation engine to adjust variables. Lighting, sound, object complexity, avatars, and many other pieces of the simulation can be dynamically adjusted based on mental state to help achieve the desired learning state. This then creates a closed feedback loop where the simulations reaction to the participants mental state continuously drives itself. The feedback loop should consist of several data sources, and several engines working together to dynamically adjust the environment.

HARDWARE

Several pieces of hardware are necessary for gathering real-time data from the user, and effectively presenting the desire environment. First, a Virtual Reality system must be worn by the user to replace the real-world with the digital. Second, a high-end PC provides the required processing power for rendering the image, interpreting the data, and driving the learning narrative. Finally, biometric scanners are worn by the user to track psychosomatic responses to stimuli in the environment. Combined, this hardware forms an integrated system that connects the learner with the learning experience, while allowing the experience to adapt intelligently.

Virtual Reality

More affordable than ever, high quality virtual reality headsets are readily available at $400 per headset or less (Table 1). For the best possible virtual education experience, a headset with high-resolution, high-refresh rate, and accurate positional tracking is optimal. Examples include Varjo's enterprise headsets, or Valve's Index consumer headset. Both of these headsets come at a cost however, and the experience can be adjusted and downscaled to work with any headset that offers six-degrees of freedom. While three-degrees of freedoms headsets can provide interesting experiences, the lack of translation when moving or tilting the head breaks user immersion and increases motion sickness. Even small translational disconnects between the virtual worlds and the user's physical sense of space can cause intense discomfort. In addition to the headset, users should have either hand-held controllers, or headset mounted hand trackers that provide precise six-degrees of freedom tracking for each hand. Without semi-natural hand interaction inside the virtual world, level of immersion and ability to familiarize with the virtual world is decreased. Accurate hand controllers also allow users to interact with the virtual world as they would interact with the physical world, translating virtual experiences into physical practice more effectively.

Computer System

To render high-quality virtual images while simultaneously interpreting biometric datasets, a high-end PC is necessary. VR experiences are most effective when rendered at the highest possible resolution and framerate. In VR, rendering involves a significant increase in system overhead as the scene must be rendered twice, once for each eye. Higher resolutions and framerates also help decrease motion sickness for participants allowing them to stay comfortable and immersed for longer periods of time. Powerful graphics processing units (GPU's) help push rendering potential. Another point to consideration is the target application of a GPU, either consumer or enterprise. Enterprise GPU's such as Nvidia Quadro's are targeted towards complex data processing and visualization workflows. Consumer GPU's such as Nvidia's GTX and RTX series are more effective for rendering games and virtual environments, such as this type of educational experiences, therefore a consumer GPU is more effective. Consumer GPU's are also far less expensive which brings down the cost of a complete educational environment setup.

At the same time, the PC must ingest and interpret biometric data from the user in real-time with minimal latency. This involves considerable time on the systems central processing unit (CPU), therefore a powerful CPU also helps support the experience. As with the GPU, a consumer targeted CPU is also most effective for rendering virtual environments. The extra data overhead taken by the biometric processing and motion tracking systems benefit from a high-end consumer CPU however, such as Intel's Core i7 /i9 processors, or AMD's Ryzen 7/9 processors.

Biometric Scanners

In order to drive adaptation in the virtual environment various different somatic response must be tracked from the user. To help encourage adoption of a framework such as this, biometric measurements should be as unobtrusive as possible with easy setup and tear down times. For cardiovascular and electrodermal activity, a system such as the Empactica E4 Biosensor used in Goodwin's 2018 study provides a comprehensive dataset with minimal comfort and hygiene issues (Goodwin et al., 2018). Electroencephalograph (EEG) data is historically difficult to measure requiring obtrusive hardware that is uncomfortable and time-consuming to setup. Recent advancements in compact dry-electrode systems have removed many of these obstacles and are an excellent fit for this framework. Currently, Boston based Neurable is developing an all-in-one dry-electrode unit that attaches to existing VR headsets. While accuracy suffers in dry-electrode systems data from the other systems proposed in this framework can increase the significance and accuracy of EEG data.

SOFTWARE

Assimilation and application of the collected data and desired learning strategies takes place at the software level in this framework. There are two crucial systems or engines necessary for supporting an adaptive world based on biometric data. First, an engine that determines mental state and second, a simulation engine that takes all the collected data, information, graphics, and narrative and presents it to the user.

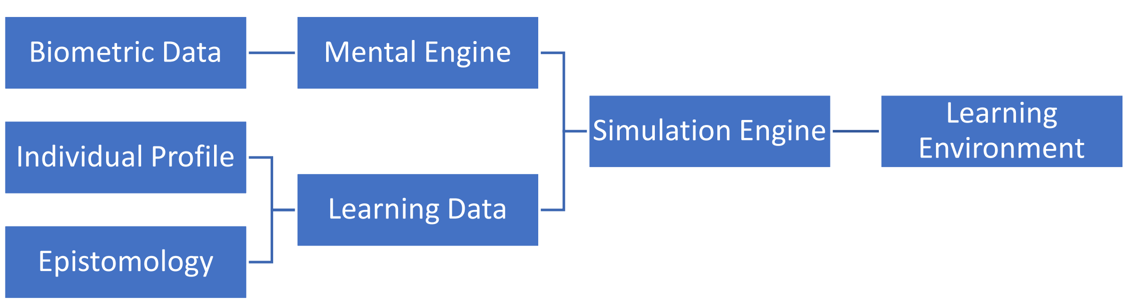
Mental State Engine

The mental state engine ingests biometric scanner data from devices such as the Empatica E4 or Neurable, and codes it into an approximate real-time picture of the user's mental state. Mental state includes positive or negative arousal, discomfort, concentration, engagement, fear, and many other cognitive states which can be inferred from biometric data using psychosomatic research as a code. Using multiple biometric measurements provides a system of checks and balances that improves coding accuracy through cross-checking relationships between various psychosomatic indicators. A custom application would be created with an easy-to-use, adaptive application programming interface (API) to allow input of data and communication with other parts of the framework.

Simulation Engine

Images are created and presented to the user through a simulation engine that renders a 3D environment created by artists or artificial intelligence. The simulation engine is also where all collected data is manifested. Mental state data from the mental state engine, epistemology data determined by the educators, and individual profiles based on user history feed into the simulation engine and drive variables that change the lighting, audio, and visual elements of the virtual environment dynamically to keep users focused on the desired task. The simulation engine is constantly working towards the goal of creating the most effective learning environment possible. For rendering virtual environments such as this, a mainstream game engine such as Unreal Engine 4, or Unity 5 provides all of the necessary tools and expandability while also benefitting from ease-of-use and responsive support teams.

Figure 4.1: Engine and Data Framework



Multi-User Support

Another key piece of the simulation engine is multi-user support, or allowing multiple people to enter the environment as virtual avatars. Both Unreal Engine 4 and Unity provide networking subsystems that allow users from across the world to connect with each other in a shared virtual space. Educators, peers, parents, and extras can populate the simulated virtual space, providing touchstones for knowledge acquisition, comfort, and observation as well as a sense of life within the world. For autistic learners who struggle with social interaction, the abstracted avatars applied to previously mentioned simulated characters could also apply to these other connected users, helping to mitigate meltdowns. This can help the autistic learner adapt and learn social interaction skills and cues, and further connect the simulated space with the real-world. The environment also does not have to be presented to every user in the same way. Each user can see a different visual representation or 'skin' of the environment tailored to their needs, and the responses of the biometric trackers.

The end result is a series of systems that communicate with each other to provide real-time adaptation. These connections are illustrated in Figure 3, with data input from biometrics, individual profiles, and learning goals being passed through various analysis engines and eventually into a simulation which is presented to the user, complete with high quality visuals and audio, and a diversely populated world of simulated, and human avatars.

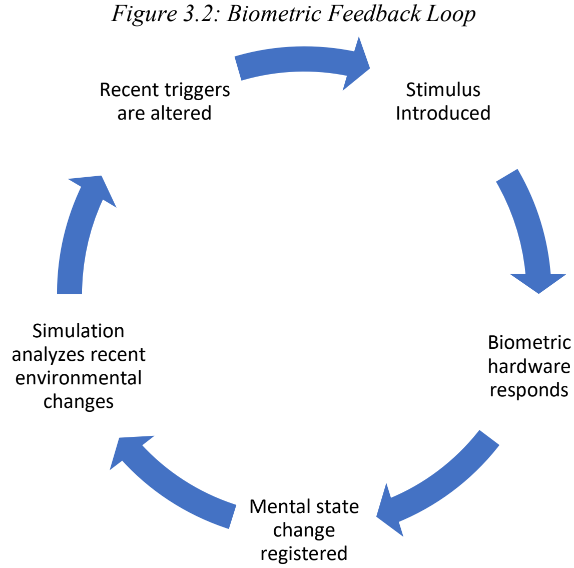
EXAMPLE SCENARIO

Given the ability to implement such a system, we can explore the conceptual possibility of dynamically adapting a VR learning environment to an ASD leaner's mental state, targeting specific learning goals. In example of this in action could be a scenario designed to help autistic learners interested in the medical field step through the problem-solving process of diagnosing a patient's symptoms. Diagnosis starts with taking patient history and symptoms via an in-person interview. This requires levels of social interaction and cognition that are commonly difficult for autistic learners. To help the learner connect with the experience, the virtual avatar is adjusted to match the individual profile of the learner before they begin the experience. Before and during the experience, environmental factors such as form, sound, and light are adjusted to minimize distraction and stimulus from sources outside of the virtual patient. Social cues from the virtual patient can also be exaggerated or annotated if needed to help learners pick up on cues. Overtime, the intensity of these aids can be decreased as the learner becomes more comfortable in the space and scenario.

Further steps in the diagnosis process also benefit from an adaptable environment. After interviewing patients, various lab tests are generally run to measure body statistics and search for easily identifiable diseases. Medical lab facilities commonly have complex equipment, harsh lighting, and many unfamiliar sounds, all of which are potential triggers than can overwhelm an autistic learner. Neutralizing lighting and removing sounds not related to the task directly at hand can help the learner feel more comfortable in the environment. Many of these background sounds can also be replaced with sounds that are soothing to the learner to further remove distraction.

While the learner is interacting with the patient, or processing lab results biometric data is constantly being monitored and interpreted into the patients perceived mental state. Based on the strength of the various biometric results, the system can develop a level of confidence in any given state. If for example lab machinery such as a blood analyzer finishes processing and begins emitting a sound, the sound could quickly agitate the learner. This would then register in the mental state engine, which would analyze recent events to find potential trigger sources.

Figure 3.2: Biometric Feedback Loop



When the recent addition of the blood analyzer completion sound is noted, the mental state engine passes the collected data to the simulation engine which either removes or adjusts the sound (based on the individuals profile) to decrease mental agitation. In a real-time virtual environment these calculations and adjustments take places hundreds of times a second, and the results can quickly be seen based on new data from the biometric sensors. This creates a biometric feedback loop, visualized in figure 4. Overtime, the biometric feedback loop would tell the simulation engine whether its action has lowered agitation in the learner, and further adjustments could be made in real-time.

With these constant adjustments, potential meltdowns could be avoided, allowing the autistic learner to stay immersed in the education environment without interruption. The learner is not only responsive to the environment, the environment is also responsive to the learner. The environments response helps keep the learner immersed and focused on the task at hand while the problem-solving processes presented by experience-based learning keeps the user engaged, while promoting personal exploration and knowledge retention.

CHAPTER 6: CONCLUSION

Altogether a dynamic immersive learning environment using virtual reality and biometric data tracking has the potential to shift the paradigm of education for a wide range of neurodiversity. Research suggests that the rapid advancement of biometric systems can give educators and simulators a picture into the mental state of the user, driving an adaptive world. Screen and tracking advancements in virtual reality hardware allow the real-world to be replaced with an accurate, fully immersive virtual environment. Application of innovative experience-based learning techniques gives this virtual environment a purpose that promotes self-exploration and experiential relationships for idea generation, problem-solving, and knowledge retention. The educator now can now immerse the learner in an environment of their choosing while removing potential distractions and triggers that could degrade the learning experience.

IMPLEMENTATION

In order to implement this system, several levels of research and development must first take place. First is additional research with psychologists and autistic learners, applying these various technologies. While virtual reality has been explored in the context of autistic education, the body of work is still limited, especially with newer hardware. It is crucial that developers understand differences in reactions between the physical and virtual world in order to create systems that help limit triggers for a variety of users. Biometric data is similar, with limited research exploring whether neuro-diverse and neuro-typical learners have similar responses in cardiovascular, EDA, and EEG measurements. Further research in these areas will also help discover the best possible hardware for accuracy and comfort.

Once these various areas have been explored and a general understanding of how neurodiverse learners will react within virtual spaces is established, software developers will then work with the psychologists and researchers to begin developing the mental state engine. Each stage of development would optimally be evaluated against real learners, starting with neurotypical learners to establish a baseline of triggers to reactions, and including neurodiverse learners later in the development process to ensure reactions are consistent and as predictable as possible. From there educators will be added to the team to begin outlining necessary systems and interactions for learning environments for the development of the simulation engine. These educators should be from many different disciplines to help develop an application that is highly adaptable to different learning scenarios.

While psychologists, software developers, and educators can provide technical information and data, another valuable source of information are the parents of neurodiverse learners. Parents can provide key insights into how their child reacts to various triggers and environments. Including parents in the design discussions throughout the development process can bring these insights to light and further refine the experience. These observations could also be helpful in defining the data points for the individual profile provided to the mental state engine.

Once a working prototype of this system is developed and tested with neurotypical learners, the entire framework can be applied to neurodiverse learners with a gradient of complexity over time. Initial testing would focus on a limited number of individuals learning within their own private spaces. These first spaces would have less extreme environmental tweaks, and be based on the individual profile to develop baseline measurements for mental state, as well as allow machine learning systems to begin processing data. As the system is refined, learners can began connecting from the safety of their home instead of traveling to controlled lab spaces. This removes the challenges of travel from parents and guardians and keeps the learner in a familiar space. Eventually, the multi-user aspect can be fully utilized, placing multiple learners into the same space with each other, each given a visual representation suited to their personal profile. Educators can also enter the environment to help guide learners, and present content in context. During the experience, data about each user can be recorded to further fine-tune the learning environment. This data would track different triggers occurring within the space and the user's responses, allowing educators to review the entire experience afterwards. Based on the review, adjustments to the environment would be made, preferably by multiple educators to help prevent purely subjective changes. Over time triggers for each user would be identified further developing the base individual profile. Once this profile has stabilized and tailored environmental changes become unnecessary, reliance on biometric data could be removed, allowing the learner to work in environments with less development time.

Overall, developing a system such as this requires continuous design and open collaboration between many different people. For the most effective solution to be developed, psychologists, software developers, educators, learners with autism, and parents must all communicate and work together to properly research, test, and apply these technologies and techniques to the neurodiverse learners, such as those with autism.

CHALLENGES

Developing a system of this magnitude comes with many challenges. The amount of data being ingested, combined with the variability of the individual learner in terms of co-morbidities, sensitivities, and position on the autism spectrum make it difficult to develop a solution offering enough adaptability to meet these many needs. These challenges will be present throughout development.

One example is discovering the optimal hardware as many options with varying levels of accuracy and cost exist. For a system such as this to succeed a balance must be struck between accuracy and cost, allowing educators to place it in as many hands as possible while maintaining a high level of quality. Once hardware options are established, developing data processing solutions can also present several difficulties. First and foremost is noise reduction for the various biometric sensors. Biometric measurements naturally have some level of noise in the data, and software would have to take this noise into account, establishing a balance between being able recognizing changes in the user's mental state while trying to account for false positives due to signal noise.

As with any highly collaborative design project, balancing inputs and priorities from various teams and maintaining objectivity can also prove difficult. It is crucial to develop a set of strongly defined design goals at the beginning of the project which can later be referred to when in doubt about the correct direction to take. Throughout development, the focus must be on creating the best possible experience for the learner based upon testing, iteration, and feedback.

Finally, promoting the adoption of a framework such as this can be challenging. The complexity and reliance on technology can easily discourage potential users, both educators and learners, from taking advantage of potentially beneficial tools. One small error or issue can easily write off this type of project. Extensive testing and analysis are crucial for avoiding these errors and maintaining a positive view of the framework. Ease-of-use also plays an important role when connecting with new participants, meaning any implemented version should be user-friendly for a variety of audiences.

If these challenges are met, and a framework such as this is created, a highly adaptable tool is potentially added to educator's toolbox for working with neurodiverse learners. And this is only the beginning for the application of these technologies. As technology continues to advance at a rapid pace, the viability of the elements that make up this proposed framework only increases opening new possibilities and applications. Exploration of these disparate elements connected into one cohesive system is a valuable addition to research that helps keep education practices up to date in an ever-changing world.

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