A Review of Research Discussing Analysis of EEG Data During Training and Skill Transfer for Skills Learned in Virtual Reality

Maj Shawn C. Adams
Air University
Maxwell AFB, AL
Adams.shawn.c@gmail.com

Dr. Andrew Clayton
Air University
Maxwell AFB, AL
Claytonasc0928@gmail.com

ABSTRACT

Muscle memory can be defined as the ability to reproduce a physical movement without conscious thought and is acquired from repetitions of that movement. Many skills can be learned by applying training routines in the physical world to build muscle memory so that the skill becomes second nature. However, at times the skills may involve material requirements that may restrict the ability to perform the training in a real-world environment. At the same time, Virtual Reality (VR) provides an environment where the required material can be simulated and potentially remove restrictions that exist in a real-world environment. Previous studies have shown that VR can be used to successfully train users in skills consisting of repetitive tasks. Other research has shown how electroencephalograph (EEG) techniques can be used to analyze brain activity during learning. This paper expands on previous work from both areas to correlate findings between using VR for skill training/transfer learning and analysis of EEG recordings taken during training sessions to highlight potential similarities in learning in both environments.

ABOUT THE AUTHORS

Major Shawn C. Adams is a Cyber Operations Officer in the United States Air Force Reserve performing cyber security operations as the Director of Operations of the 426th Network Warfare Squadron at Lackland Air Force Base, TX. Prior to his current assignment, he attended Air Command and Staff College (ACSC) in-residence program and participated in the Immersive Technology Research Task Force. In addition to his duties as a Cyber Operations Officer, he works as a software consultant for CGI in Birmingham AL developing advanced software solutions for numerous clients in the region. He currently is also pursuing his Ph.D. in Computer Science from the University of Alabama at Birmingham.

Dr. Andrew Clayton serves as an Assistant Professor at Air University. Dr. Clayton teaches and researches topics related to leadership and experiential learning. Dr. Clayton also provides guidance and research for Air University's Innovation and Technology Research Task Force on current topics related to augmented, virtual, and mixed reality immersive learning environments. Dr. Clayton is a 1999 graduate of Purdue University and has served in the United States Air Force on active duty and in the Air Force Reserves as a Lieutenant Colonel. While on active duty, Dr. Clayton served as a Maintenance Officer for five years within Air Combat Command and Air Force Special Operations Command. Dr. Clayton then joined the Air Force Reserves as an Academic Instructor and Academic Affairs Officer for Air University. Dr. Clayton has served as a master instructor, course director, program manager, and academic advisor for 12 years with more than 8,000 hours of classroom instruction time at Air University. Dr. Clayton holds a Masters in Adult Education and Training, is certified as a Master Instructor and Distance Learning Instructor. Lieutenant Colonel Clayton also holds a Doctorate degree in Organizational Leadership with an emphasis in Higher Education.

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INTRODUCTION

Understanding how people learn and how to improve retention is a field that has long been researched across multiple fields of study. New technologies often allow us to incorporate new methods that can be applied to learning activities that challenge conventional approaches. One such emerging technology, which can potentially shift how people learn, is Virtual Reality. Virtual Reality provides an opportunity for users to be trained to work on complex pieces of equipment without having the equipment on hand or even operating from the same location. Virtual Reality (VR) also allows users to have an interactive experience with other people separated by thousands of miles, creating an artificial feeling of presence and locality with the members they interact with. However, for a new technology to be used for learning activities, it must be effective in providing a similar level of learning as the methods the technology aims to enhance or replace. The question regarding the effectiveness of virtual reality when applied to learning activities has been the topic of many research papers. In this paper we will review some papers which show VR has the potential to enable users to learn new skills, which can be transferred to real-world applications. We will also review research that has examined how the brain reacts to VR environments compared to real-world ones when attempting to learn new skills. As the research in these areas is vast, this paper attempts to consolidate and review the findings for recent papers on the two topics to evaluate VRs effectiveness as a learning tool. Learning incorporates a neurobiological process as information that is observed is processed and stored within the brain. However, what is observed when using virtual reality is distinct between what is observed in the real world which begs the question if what is learned in one environment is treated the same by the brain, or if there are identifiable differences that can be observed. With the help of Electroencephalograph (EEG) technology, a comparison of learning in both environment is possible.

This paper will start with a review of some of the most used Learning Theories to provide context to some of the ways in which humans are believed to learn and acquire new skills. Next, this paper will explore existing studies that incorporate the feasibility of effectively transferring these skills learned in a VR environment into the real world. Next, this paper will examine research papers which utilized Electroencephalograph (EEG) technology to conduct an analysis of brain patterns while learning. Following that, this paper examines areas where the fields of learning theory, VR and EEG brain activity during learning intersect. Finally, we end by acknowledging gaps in knowledge that still exist and potential future work that can be conducted.

GENERAL LEARNING THEORY CONCEPTS

From the earliest days of human civilization where people attempted to formalize the education process, various approaches have been taken to pass knowledge on from one person to another. Two of the oldest approaches are Rationalism and Empiricism which date back to Plato and Socrates respectively (Edgar, 2012). Rationalism postulates that humans can learn by applying reason and logic to their environment and that application is what leads to gains in knowledge. Conversely, Empiricism holds a belief that humans learn through their experiences and from actively performing what they want to learn. Evidence indicates that both appear to be true despite vastly different approaches to learning. More recently, these concepts have been expanded upon by modern learning theorists to bridge the gap between the two approaches. While there are numerous models and theories available, the ones highlighted here are those that are most applicable to skill acquisition.

One of the most popular attempts to create an updated learning model was proposed by Kolb in 1984 as the Experiential Learning Model (Kolb, 1984). In the experiential learning model, learning can take multiple forms across an ongoing process consisting of four cyclical phases. Each of the phases are made up of distinct actions, however, just as a circle has no defined beginning or end point, neither of the four phases are designated as the starting or ending point. Learning can begin at any of the four phases, but generally transitions from one to the next sequentially in a continuous and cyclical process. Kolb argues that learning following the four phases maximizes learning capacity. The four phases can be summarized as Feeling, Watching Thinking and Doing and can be visualized in Figure 1. Feeling involves experiencing something yourself to enable learning to occur and is followed by a step to watch and reflect on what is occurring to reinforce the learning. The next step is to perform thinking in such a way that you transform what you learned into abstract concepts and compare the abstractions to knowledge or skills that were previously acquired, creating cognitive connections. Finally, the Doing phase involves active experimentation by taking what you learned and applying it to various situations while making assumptions about what will occur and comparing with results. By actively participating in the experiments, you gain experience and as such re-enter the Feeling phase and continue the process in perpetuity. A part of experiential learning highlights that something that is learned can potentially be unlearned and relearned based on experiences. In addition, using reflection, a person will mentally adjust what they believe is known during learning based on variations between expectations and actual experiences related to a subject that is learned. Reflecting allows the individual to create and test a new hypothesis and compare expected and actual results to reinforce or adjust that individual's perception of what they have learned.

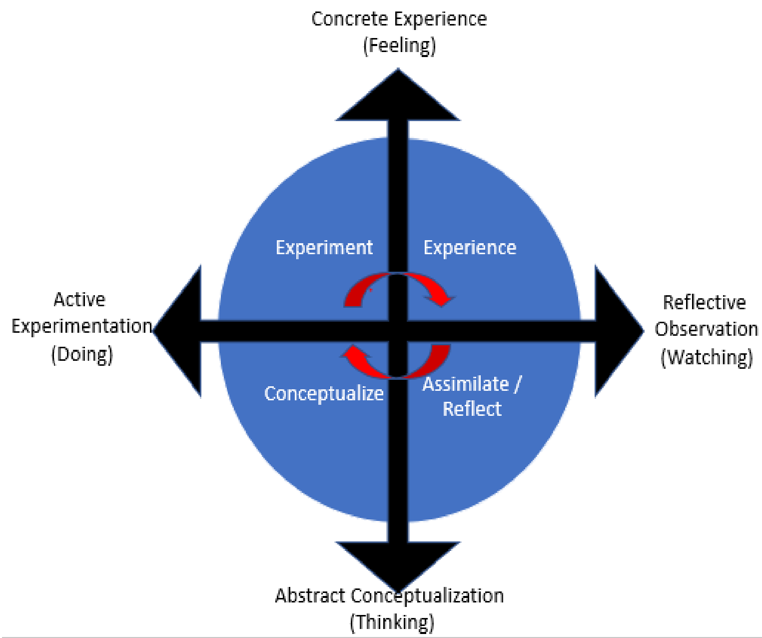

Figure 1. Experiential Learning Model

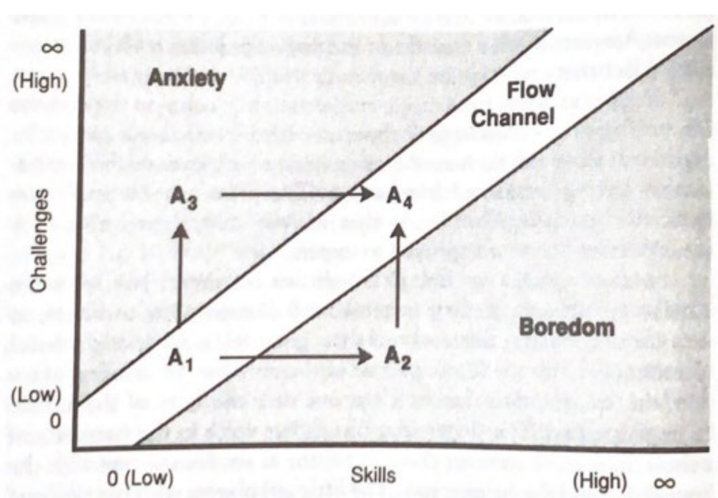

Figure 2. Flow Theory Flow Channels

Another popular learning theory was proposed by Mihaly Csikszentmihalyi in 2008 when he coined the term "Flow" to describe a state of optimal performance that can be achieved in learning as well as general skill performance (Csikszentmihalyi, 2008). Flow is often referred to in less scientific terms as operating "in the zone" when there is such a high level of focus that time appears to slow down relative to the individual. Flow is believed to be a biological state that can be triggered if a specific set of conditions are met. In general, these conditions can be met in a learning environment when there is an appropriate balance of challenge to the participant relative to their skills (Csikszentmihalyi, 2008). Figure 2 illustrates a zone of equal challenges and skills to create a "flow channel" that exists between having high challenges with low skill (anxiety) and high skills with low challenges (boredom). Flow theory has been used to tailor education experiences to the levels of the participants to minimize risk of boredom and anxiety.

VIRTUAL REALITY KNOWLEDGE TRANSFER STUDIES

Many studies have been conducted to show that VR can be used to train skills that are translatable to the real world. In this section, the paper examines a few of the studies across a range of different motor skills and focuses on what elements of VR help and hinder knowledge transfer. One study conducted in 2021 examined the ability to train users to play ping pong in a virtual environment (Wu et al., 2021). The authors implemented a multi-phased approach to experiments ranging from building a prototype of a robot simulating serves in the real world before making modifications producing a training system that existed completely in a VR environment. The paper addressed three concepts related to using VR for ping pong training. The first concept the paper examined was whether VR training can benefit real world performance. The next concept explored if haptic feedback for the paddle impacted learning. The final concept examined if the introduction of visual cues in VR could aid training (Wu et al., 2021). Using the virtual reality setup, the researchers were able to overlay information about the spin and estimated trajectory of the ball in the environment as well as allow users to adjust the flow of time, allowing them more time to determine the best approach to returning the ball. The overlay visual feedback included indicator arrows for the spin of the ball and an animated guidance trail of the ball showing the path traveled. Figure 3 illustrates the 4 scenarios used for the visual feedback during table tennis training. To determine the longer-term retention of skill acquisition, participants returned 3 weeks later and were evaluated against a serving robot. The results showed that in terms of both immediate and long-term retention, scenarios that used the guidance visual cues and spin arrows saw the highest success rate and lowest failure rates indicating that the addition of visual data while using VR played a significant role in the skill learning process (Wu et al., 2021).

Interestingly, training in VR alone performed slightly worse than when using the serving robot in the real world. The limited impact of VR training alone appears to be consistent with other research conducted on skill transfer for VR training. Another study used a modified version of the Sequential Visual Isometric Pinch Task (SVIPT) (Reis et al, 2009) in a real-world environment and compared it to a simulated environment using VR (Clements et al., 2018). Participants were trained to apply specific amounts of pressure to a sensor that would move a cursor to various targets on the screen. The research showed that there were no significant differences between the time it took to acquire the skill in VR and the real world. However, the research showed that the participants that were trained in the real world were able to more easily transfer the skills learned to the VR environment than those trained in the VR environment were able to transfer to the real-world environment (Clements et al., 2018). While some research seems to show that additional visual cues may be helpful in learning, other research appears to counter the claim. In a study conducted by Adolf et.al, a comparison of the ability of participants to learn how to juggle in a real-world environment and a virtual environment was examined (Adolf et al., 2019). The study used an application developed to work on Oculus Quest and Oculus Rift VR headsets which allowed users to practice juggling in an environment that enabled users to adjust the speed at which the simulation moved as well as adjust the impact of gravity while juggling (Adolf et al., 2019). Participants were divided into two groups, one which practiced juggling in a real-world environment and the other which used the VR application. Both groups also watched an introductory video explaining how to juggle step

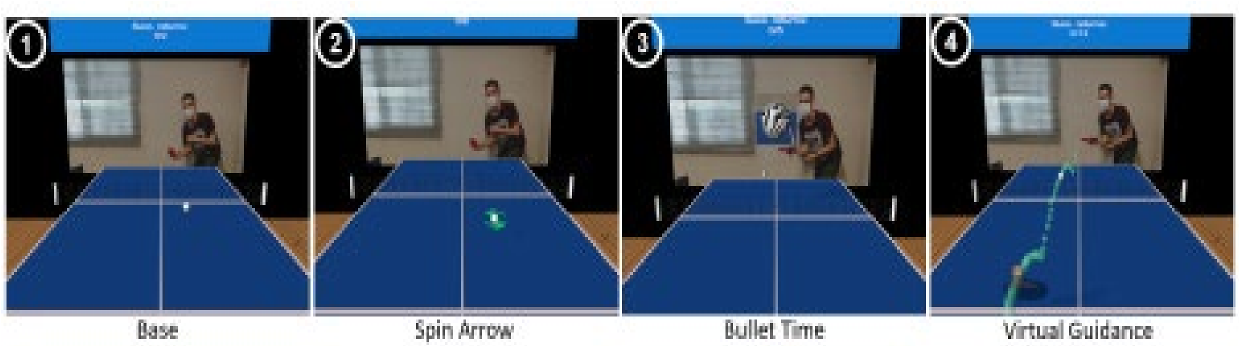

Figure 3. Optional Modes for Ping Pong Training in Virtual Reality

by step. The real-world group was given the opportunity to watch the video as many times as needed and practice juggling during a 1-hour period. The VR group watched the video once and for the remainder of the hour used the application to practice juggling. The results showed that the real-world group had a better success rate during an evaluation period, which evaluated the participants based on their ability to juggle in a real-world environment (Adolf et al., 2019). Watching a video prior to performing may have allowed the participants to navigate through the cycle of experiential learning theory, leading to higher success rates. In addition to quantitatively measuring accuracy during the testing phase, qualitative measurements were also taken. A survey was used to gather qualitative data that was not clearly discernible from raw data collected during the experiments. The survey focused on mental perception of the training by asking each participant to rate their level of enjoyment during the training, and their desire to continue the training exercise. The qualitative measurements were used to determine each participant's level of fun and willingness to continue during the training. In both qualitative measurements, the VR group had higher scores than the real-world group. The higher qualitative scores could indicate that VR training could lead to an increase in motivation to continue learning activities which may offset a decrease in training efficiency (Adolf et al., 2019). The higher qualitative scores may also have resulted from a more immersive environment that shifted the participants away from boredom toward a state of flow, and higher engagements. Figure 4 shows participants from the study juggling in a VR headset and the corresponding images shown in the headset.

Figure 4. Participants juggling in VR and the view from the VR headset

ELECTROENCEPHALOGRAPH (EEG) STUDIES

Everything that we do, whether consciously or unconsciously, and everything we know is a result of activity and interactions within our brains. Cells within the brain use electrical impulses between each other activate different parts of the brain. The pules may be triggered by external stimuli or other biological processes and are used to trigger nearly all conscious and unconscious functions of the body. The interactions between cells occur at different intervals and produce signals that can be interpreted as brainwaves that are broken into five main categories based on their respective frequencies. The five categories, from lowest frequency to highest, are Delta, Theta, Alpha, Beta and Gama. Higher frequencies are associated with a higher level of thought, and each is though to play a role in the biological process of leaning. Due to the relationship between how our brains operate at a biological level and how memories and skills are learned and recalled, it is no wonder that an area of research which has seen some growth in recent years is related to trying to define what learning looks like on a neurological and biological level. The interaction been individual neurons within the brain is possible through electrical impulses between the cells. It is possible to use sensors to record those impulses to measure a level of activity of regions of the brain. The human brain is divided into three main parts with specific functions. The Brainstem is responsible for many of the automatic actions that keep us alive such as breathing and keeping a regular heart rate. The Cerebellum is located at the back of the brain, connecting to the brainstem and is responsible for managing our motor skills. Finally, the cerebrum makes up most of the brain's mass and is broken into a left and right hemisphere, with each hemisphere consisting of four lobes (Johns Hopkins Medicine, 2022). The lobes are responsible for perception, and a significant portion of memory storage for learned activities. Figure 5 highlights the four lobes found on each hemisphere of the brain. The four lobes are the frontal lobe, responsible for thinking, memory and movement, the Parietal lobe, which is responsible for processing of language and touch, the Temporal lobe which manages hearing and learning and the Occipital lobe which is related to sight processing (Johns Hopkins Medicine, 2022). Research utilizing EEGs to study brain activity during learning focuses on measuring the levels of activities in each of the respective lobes during and after learning activities are conducted.

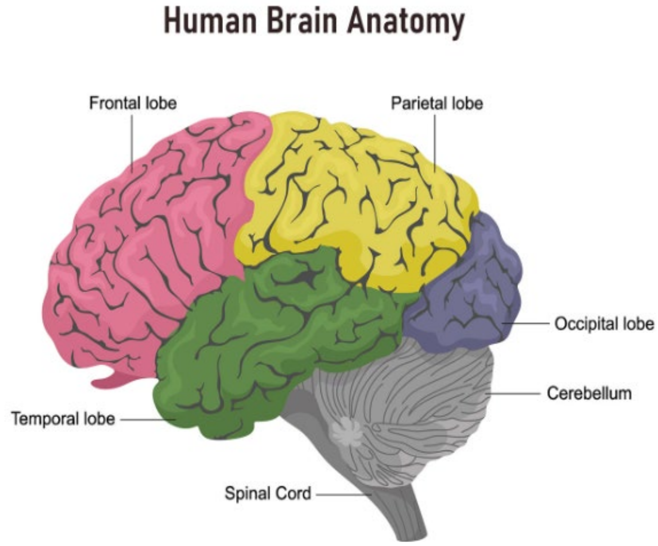

Figure 5. The four lobes of the human brain

EEGs have been used to measure and analyze changes in brain activity before, during and after the execution of controlled motor skill activities. In the previous section, we reviewed papers that seemed to indicate that motor skills learned in VR could be transferred to a non-VR environment, however, the transfer of skill does not necessarily indicate that the brain treats both environments the same. To determine if skills learned in VR and the real world have the same impact on the brain, we first must examine some research that examined what happens to the brain during learning in a real-world environment to establish a baseline. A sample configuration of EEG electrode placement and sample data results can be seen in Figure 6. In this section, we begin by looking at studies which utilized EEG for analysis of motor skills in the real world before transitioning to studies that combine EEGs and VR motor skill training and transfer.

Motor skills and voluntary movement are handled in a large part by the frontal lobe of the brain (Johns Hopkins Medicine, 2022). One such study conducted an experiment that analyzed brain behavior in the frontal cortex while performing multiple iterations of a motor skill task involving tracing a shape on a computer with a mouse when the controls were left-right inverted (Mak Chan & Wong, 2013). The results of their study showed that a positive correlation existed between the accuracy of completing the task over multiple iterations and a decrease in delta and gamma frequency bands recorded by the EEG (Mak Chan & Wong, 2013). The findings indicate that one indicator of motor skill learning, from a neurological perspective, appears to be the intensity of delta and gamma frequencies in the frontal cortex. However, one limitation of the paper was that it did not examine the results against a baseline of a known skill to see if the levels observed after proficiency was reached was consistent with the levels observed for a task the participants were already proficient in.

In a step closer to VR-based learning EEG analysis, one study was conducted that measured brain activity during mental practice and visualization of a motor skill task by utilizing a video of a task and asking participants to visualize themselves performing the task (Erfani & Erfanian, 2004). The multi-stage approach to testing is similar to the experiential learning theory concepts by performing a watching component in conjunction with conceptualization component and feeling component (Kolb 1984). It is possible that the ability of participants to learn and perform the motor skill test were impacted by including multiple learning methods, however a direct connection with the experiential learning theory was not examined in the paper. The research also looked at mechanisms for removing noise activities related to natural biological processes, such as blinking or breathing, using Independent Component Analysis (ICA) (Erfani & Erfanian, 2004). The results showed that participants had an increase in both the levels of delta and

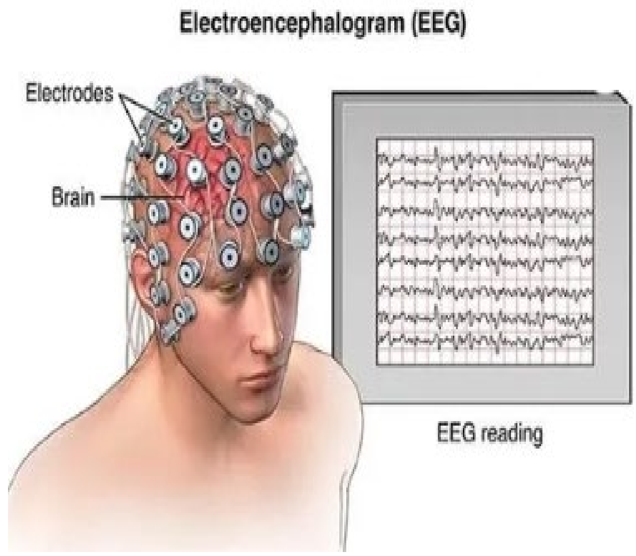

Figure 6. Sample EEG electrode placement and data output

gamma frequencies recorded by the EEG (Erfani & Erfanian, 2004). However, the increase in delta levels appeared to be short lived and only after the start of the video, so it could be related to the recognition of audio-visual cues, while gamma levels remained higher for the entire time the motor skill was imagined (Erfani & Erfanian, 2004). The increase in gamma signal levels after training would appear to be counter to the findings by Mak et al. which showed the levels should decrease after the skill was learned. However, it is possible that mental rehearsal of the skill involves the activation of gamma frequencies while actual execution does not. Like the previous paper, the authors did not provide a baseline to compare what the imagination process looks like prior to training being conducted, which could be a potential area for improvement for future research.

COMBINED STUDIES

With academic research interest for both VR knowledge transfer and neurological analysis to describe what learning looks like biologically, the fact that there has also been some research conducted which overlaps both research areas Is not surprising. The question of potential interference from VR headsets with signals recorded by EEG systems is one that has also been looked at, as such interference could potentially lead to anomalous data. However, while some interference does in fact occur, the range of frequencies where the interference is present does not overlap with pertinent frequencies used in measuring brain activity with an EEG. Generally, most interference related spikes recorded by the EEG occurred around 50Hz and above 90Hz (Hertweck, 2019) while Beta frequencies occur between 15Hz and 30Hz and gamma frequencies occur between 30Hz and 80Hz (Moffett et al., 2017). One such study used a 2D virtual scenario with haptic feedback to simulate the putting of a ball into a hole at various distances and angles from the participant (Pitto, et al., 2011) While the paper also examined kinematic responses, the inclusion in this work is based on its use of EEG technology to study the alpha, low beta, high beta, and gamma frequencies during the learning process. Training involved members participating in 10 rounds, each consisting of 5 instances each of 6 possible directions to putt the ball (Pitto, et al., 2011). Of note, the authors found that there was no significant change throughout the training process regarding the alpha band, which is typically associated with idle mental processes. However, high beta frequency seemed to be correlated with successful attempts and theta frequency activity seemed to decrease as training continued (Pitto, et al., 2011). The last point seems to follow what was found in the study by Mak et al. that showed a decrease in Theta frequencies in real world training as the skill was acquired. The decrease in activity is highlighted in Figure 7.

An alternative approach to combining VR and EEG technologies into a single research topic was conducted where the participants played VR and 3D games, while measuring levels of brain activity using an EEG (Wan et al., 2021). In the study, the authors attempted to analyze the ability to recall actions from memory and the level of attention, rather than focus on muscle memory aspects, skill acquisition and skill transferability (Wan et al., 2021). Participants played two games, one focusing on memory and one on attention. Participants first played a 3D computer game version of the games and then played the same games in a VR environment. The memory game required participants to repeat a pattern that would display on screen and increase in length after each turn. The attention game involved throwing digital snowballs at characters as they would pop up on screen. A representation of the game and environment setup can be seen in figure 8. An EEG was used to measure general levels of brain activity during the sessions and did not focus on extracting data from any specific frequency bands. Instead, the overall level of activity measured by the EEG system was used to calculate an EEG score. In addition, participants received a score based on how well they performed in the games, which was also used to determine the level of success the participants had in each version of the respective games. The results showed that the VR memory game resulted in higher scores and with completion times faster than the 3D game in both cases (Wan et al., 2021). Additionally, the VR version resulted in higher EEG scores as compared to the 3D game (Wan et al., 2021). A graph depicting the results can be seen in Figure 9. The immersive

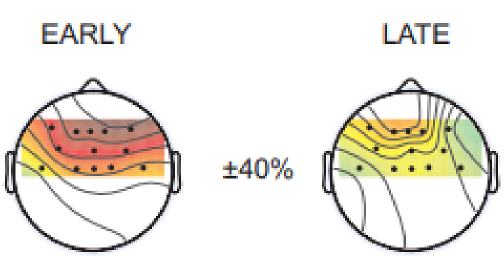

Figure 7. Theta Frequency Activity Decreases as Participants Practice More

environment of VR game versions may have provided enough player engagement to induce a flow state resulting in better performance, however this correlation was not explored as part of the research paper. One additional limitation of the study is that the data recorded using an EEG system does not provide fine-grained details in terms of specific frequencies and intensity of signals at those frequencies, or how intensity changed during training. As a result, the possibility exists that higher levels of activity were due to signal frequencies that are not necessarily related to learning. Nonetheless, the experiments still show that the brain appears to be more active in a more immersive environment.

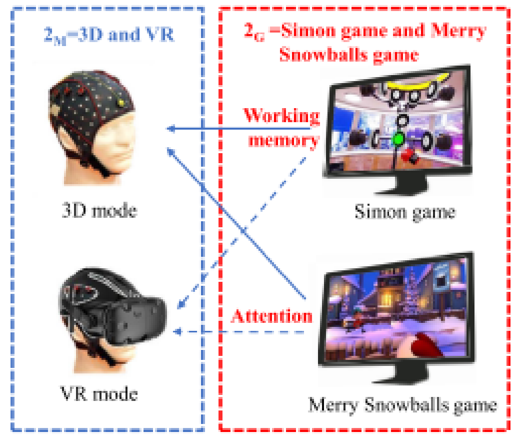

Figure 8. Cross Testing of VR and 3D Games

The relationship between brainwave activity and flow state is a research topic that has also been explored (Wang, 2014). A state of Flow was attempted to be achieved by 20 participants using computer-based training consisting of tasks categorized as easy, medium, and high difficulty. The computer-based training involved training videos for easy, medium and hard tasks for Microsoft Excel, and after completion of the videos, the participants completed an exercise based on the video topics (Wang, 2014). In each of the three cases, participants had 30 minutes to complete the videos and the tasks. The study evaluated the participants' ability to reach a state of flow using both a written survey and EEG technology to measure the participants level of attention based on the intensity of brain activity. During the EEG portion of the study, the level of attention was measured using EEG equipment, as well as the levels of performance for completing the computer-based training task. High levels of activity recorded by the EEG was seen to be correlated with entering a state of flow (Wang, 2014). Additionally, the most significant indicators of entering a state of flow appeared to be correlated largely with completing high difficult tasks more so than the easy and medium difficulty tasks as is predicted by the flow theory model. Finally, the experiments also compared the level of attention with learning outcomes from the computer-based training. Surprisingly the researchers found that there was little correlation between entering a state of flow, as measured by the EEG and the learning outcomes for the easy, medium, or hard tasks (Wang, 2014). The authors conclude that brainwave attention is related to a flow experience, but the converse is not always true (Wang, 2014). One potential limitation of this study was that the EEG portion used a small sample size which was further divided into groups which had a balance between skill levels and challenge levels, and a group which had an imbalance between the two. The small sample sizes may indicate the results may not be representative of a larger population, but it is worth exploring with a larger group. Additionally, the data measured using the EEG only measured general level of intensity and did not provide in-depth analysis of the specific bands of brain wave frequencies active during collection.

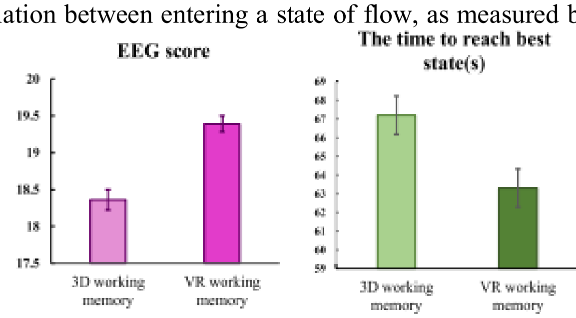

Figure 9. Showing EEG Higher Intensity in VR and Reaching Best State Faster than 3D Case for Memory Game

FUTURE WORK

While there has been some research related to recording EEG behavior during learning, skill transfer using VR and some research that ties both together, there is still a significant gap that is worth exploring further. To our knowledge, there currently is no research that objectively sets a scenario that incorporates the use of an EEG to record brain data while performing an activity in the real world and comparing to the same activity conducted in VR. Correlations between brain activity and learning within real-world and VR environments were attempted to be established in this paper, however, the nature of each of the experiment were significantly different and any similarities in findings cannot be verified by a review alone. For instance, an experiment which incorporates a training system using VR and real-world actions to learn a new motor skill could be conducted while recording EEG data. The experiment could further be expanded to include a demonstration of the ability to transfer the skills learned between the VR and real-world environments to determine if one way is more effective than the other. Finally, future research experiments could be enhanced by incorporating a group of participants which also use haptic feedback tools in the VR environment to determine if the feedback has any significant feedback for learning.

CONCLUSION

In this paper, we reviewed existing research across three categories and examined their relationship to the ability to transfer skills learned in VR to a physical environment. Across the broad scope of papers reviewed, their appears to be some level of relationship between the ability to transfer skills learned in a VR environment to the real-world, but how the brain reacts appears to be different in real-world and VR environments. Research inconsistently suggested the efficiency for skill transfer between the two environments, with some showing that skills learned in VR easily transferred to better results in the real world, such as when data overlay were used in the ping-pong example by Wu et al. However, at the same time, skill acquisition in the real world appeared to produce better results long-term compared to a training scenario using VR for juggling conducted by Adolf et al. Additionally, the use of EEGs to record what learning looks like by analyzing brain activity appears to be a promising method. However, research conducted is inconsistent in terms of what data is collected and by the capabilities of the EEG equipment used. In general, common patterns seem to be present to indicate that the level of learning achieved by the participant can be qualitatively evaluated. Further, research conducted by Wang showed that achievement of a state of flow may be able to be measured by examining the overall level of brain activity recorded during the learning process. The higher level of brain activity was also seen by Wan et al. when training was conducted in a VR environment versus traditional computer-based training approaches which appears to indicate that the higher level of immersion in a VR environment may contribute to better learning or retention. Significant gaps still exist though to determine the true value of using VR environments for learning as no study covered fine-grained EEG results in both VR and real-world environments and objectively compared the results.

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