THE IMPACT OF VISUALIZATION STYLES ON MOVEMENT IMITATION ACCURACY IN VIRTUAL REALITY

by

GABRIELA ROSARIO SHAMBLIN
B.S. Computer Science, University of Central Florida, 2023

A thesis submitted in partial fulfilment of the requirements
for the degree of Master of Science
in the Department of Computer Science
in the College of Engineering and Computer Science
at the University of Central Florida

Spring Term
2025

Major Professor: Joseph J. LaViola Jr.

ABSTRACT

Virtual reality has become a powerful tool for motor learning and skill acquisition, offering immersive environments for users to practice and refine movements. This thesis investigates how different visualization styles in VR affect movement imitation accuracy, specifically focusing on hand movements. While prior research has explored precise alignment and visualization individually, few studies have examined their combined impact. This study addresses that gap by evaluating the effectiveness of various visualization methods in relation to offset, animation, and manual type.

We developed an application to ensure all participants experienced each visualization factor as 12 combinations in varied sequences. The user study conducted with 30 participants combined performance data with responses from the qualification, between trial, and end of experiment questionnaires. Movement data assessed performance accuracy, and questionnaire data captured user perception.

The results indicate that manual type significantly affects user satisfaction and accuracy ($p < 0.001$), with the unimanual condition yielding the highest accuracy. Animation style also had a significant effect ($p < 0.001$), with discrete animations improving accuracy compared to continuous animations. Offset had no significant effect on accuracy, but users did prefer closer visualizations.

These findings provide valuable insights into VR-based motor learning applications. By using discrete animation and close-up visuals, developers can enhance the effectiveness of movement learning tools. This could have a direct impact on careers where muscle memory is a necessity. Future research could explore applications in rehabilitation, training, and remote teleoperation to optimize VR-guided motor tasks. Research could also evaluate the impact of visualization design in VR on real-world applications.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to Dr. Joseph LaViola II for his guidance and support throughout the development of this thesis. I am also sincerely thankful to Dr. Ryan McMahan, whose mentorship has had a lasting impact on both my undergraduate and graduate studies. His influence on my academic and professional growth has been immeasurable, and I am grateful for his continued support. I would also like to thank Dr. Mary Amon for her insightful feedback and perspective that helped strengthen this work.

Special thanks to Jake Belga for his help through the IRB approval process, and Pierce Powell for his knowledge on data analysis. I would also like to thank the participants, whose time and contributions made this research possible.

Lastly, I am grateful to my friends and family for their constant support, patience, and motivation throughout this journey. Their belief in me has been a continual source of strength and encouragement.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 Background

Virtual reality (VR) has emerged as a powerful tool for motor learning and skill acquisition, offering immersive and interactive environments for users to refine and practice movements. Over the years, VR has been integrated into various fields, from education and training to healthcare and industrial applications, providing realistic simulations that enhance skill development. One promising area of VR application is teleoperation, where users control robotic systems remotely, often in hazardous or inaccessible environments.

1.2 Motivation

Teleoperation enables humans to remotely operate robotic systems, improving safety and efficiency in domains such as space exploration, underwater robotics, surgery, and heavy machinery operation. A crucial aspect of teleoperation is the ability to perceive and interpret visual information accurately to ensure precise movement execution. However, stable, high-speed transmission of visual data remains a challenge, especially in environments with latency, limited bandwidth, or communication delays.

Virtual reality can enhance situational awareness in teleoperation by providing immersive visual feedback and intuitive control mechanisms, allowing operators to execute complex tasks more effectively. However, the way visual information is presented—including factors such as animation style, movement offset, and handedness—may significantly impact movement accuracy and efficiency. This study explores the impact of different visualization styles on movement imitation accuracy in VR-based teleoperation.

1.2.1 Robotic-Assisted Surgery

In minimally invasive surgery, robotic systems like the Da Vinci Surgical System enable precise and minimally invasive procedures. However, learning to operate these systems is challenging due to limited access to surgical consoles and the high costs associated with training. VR-based training solutions could offer an affordable, scalable, and accessible alternative, allowing surgical residents and medical professionals to gain practical experience before operating real robotic systems. Currently, Intuitive Surgical, the developer of the Da Vinci system, offers various training tools, including on-site training and courses, the Intuitive Learning online platform, the SimNow simulation platform, and remote case observation and telemonitoring [1]. Despite these resources, access to physical surgical consoles remains a barrier to frequent practice. VR-based teleoperation could bridge this gap, enabling more immersive and hands-on training experiences.

1.2.2 Space Operations

Teleoperation is a fundamental component of modern space exploration, enabling astronauts and ground operators to remotely control robotic systems in hazardous or otherwise inaccessible environments. Currently, teleoperated robots are employed in a range of critical tasks, including satellite servicing, planetary exploration, and space station maintenance. A notable example is the Canadarm2, a sophisticated robotic arm on the International Space Station (ISS), which is operated both by astronauts aboard the station and by mission control on Earth to facilitate spacecraft docking and perform essential repairs [2]. Furthermore, space agencies such as NASA and the European Space Agency (ESA) are advancing force-feedback teleoperation technology, allowing astronauts in orbit to remotely manipulate robotic rovers on planetary surfaces [3, 4]. The Analog-

1 experiment exemplifies this innovation, demonstrating the feasibility of controlling a rover on Earth from the ISS. These advancements significantly enhance the efficiency and safety of space operations by enabling complex tasks to be executed remotely, thereby mitigating risks to human personnel and broadening the scope of future deep-space missions, including those targeting the Moon and Mars.

1.2.3 Underwater Robotics

Underwater teleoperation is widely used in deep-sea exploration, marine research, and industrial applications where direct human intervention is impractical or dangerous. Remotely Operated Vehicles (ROVs) are one of the most common teleoperated systems used for deep-sea missions. For example, the ROV Jason, developed by Woods Hole Oceanographic Institution, has been used to explore hydrothermal vents and shipwrecks at depths exceeding 6,500 meters [5]. In industrial settings, teleoperated ROVs like the Saab Seaeye Falcon assist in offshore oil and gas inspections, pipeline maintenance, and subsea infrastructure repairs [6]. Additionally, teleoperated underwater robots are used in search and rescue missions, such as locating aircraft wreckage or recovering lost equipment from the ocean floor. Advances in haptic feedback and autonomous assistance are improving underwater teleoperation, allowing operators to perform delicate tasks like sampling marine life or assembling underwater structures with greater precision.

1.2.4 Heavy Machine Operation

Teleoperation is increasingly used in heavy machinery to enhance safety, efficiency, and precision in hazardous or remote environments. In mining, teleoperated haul trucks, bulldozers, and drilling rigs, such as Caterpillar's Command series and Komatsu's Autonomous Haulage System (AHS), allow operators to control machinery from safe locations, reducing exposure to dangerous conditions like cave-ins or toxic gases. In construction, companies like Built Robotics and Bobcat have developed teleoperated and autonomous excavators, enabling remote operation of digging and grading tasks, particularly in high-risk areas such as disaster zones or unstable terrain. Teleoperation is also widely used in nuclear decommissioning, where robotic arms and teleoperated cranes help dismantle reactors and handle radioactive materials without endangering human workers. These advancements in heavy machinery teleoperation not only improve safety but also increase productivity in industries where manual operation poses significant risks.

1.3 Research Questions

This study aims to answer the following key research questions:

1. What role does movement offset play in user performance and perception?
2. What role does movement animation play in user performance and perception?
3. What role does movement handedness play in user performance and perception?
4. Are there significant interactions between offset, animation style, and handedness that impact accuracy?

1.4 Problem Statement

While previous research has explored alignment, visualization techniques, and teleoperation strategies, few studies have examined their combined impact on movement accuracy in VR-based teleoperation. This study seeks to bridge that gap by evaluating how animation style, offset, and handedness influence movement imitation accuracy. We hypothesize that:

- Offset movement will result in higher accuracy than in-place movement.
- Discrete animation will result in higher accuracy than continuous animation.
- Unimanual handedness will result in higher accuracy than mirrored bimanual or asynchronous bimanual.

1.5 Overview

This thesis includes five chapters and two appendices. Chapter 2 reviews related works. Chapter 3 details the application and methodology design. Chapter 4 reviews the user results from the application and surveys. Chapter 5 offers a conclusion based on the findings. Appendix A outlines the three questionnaires given to the participants, while Appendix B provides the Institutional Review Board (IRB) approval.

CHAPTER 2: LITERATURE REVIEW

While numerous studies have explored the applications of virtual reality (VR) in education, visualization, and movement-based learning, research on object alignment in VR remains relatively limited. This chapter reviews key literature related to visualization techniques, movement imitation, and educational applications of VR, highlighting the existing findings and identifying gaps in the research.

2.1 Visualization

In their systematic review, Korkut and Surer (2023) examine the current landscape of visualization techniques within virtual reality environments. The authors categorize existing literature into three dimensions: background and theory, evaluation and design considerations, and empirical studies assessing the effectiveness and usability of visualization methods. A significant number of implementations utilize game engines due to their accessibility and flexibility. However, the authors note that these platforms may not be optimal for rigorous scientific applications. The review reveals a lack of visualization guidelines for VR visualization, with most studies developing individual frameworks or adapting existing 2D visualization principles. While this paper focuses mostly on visualizations of scientific data rather than movement data, they do highlight that as VR technology changes and the number of new interaction techniques increases, it is important to keep the target user in mind to design visualizations around [7].

Visualization techniques play a crucial role in user interaction and performance in virtual environments. A study by Martin-Gomez, Eck, and Navab (2019) investigates different approaches to assist users in aligning objects within a virtual space. Four shading techniques were evaluated: semi-transparent, wireframe, Fresnel-derivative, and silhouette. Results indicated that the silhouette shader, which highlights significant geometric features of an object, performed best in orientation tasks under "no time constraints" (NTC). However, semi-transparent shading was most effective for "translation" tasks, which measured the accuracy of moving an object from its initial orientation to a target position [8].

Visualization techniques have also been explored in medical augmented reality (AR). Fischer et al.'s (2020) research extends the work of Martin-Gomez et al. [8] by applying similar shaders—outline, semi-transparent, wireframe, and high-contrast replicate—to medical AR applications. The study involved aligning a virtual model of abdominal tissue with a physical 3D-printed counterpart using a HoloLens. Results indicated that the outline shader received the highest orientation accuracy and user preference ratings, whereas semi-transparent shading achieved the fastest alignment times. The authors suggest that less visually complex shading techniques, which emphasize key anatomical features such as veins, may be more effective for medical applications. However, the absence of a time constraint may have influenced the results, as no significant differences in task completion speed were observed [9].

In the context of motion data representation, shader selection is not the sole factor influencing user comprehension. The 2012 study by Coffey et al. examines various methods of displaying object motion both spatially and temporally. Three approaches were analyzed for each aspect: interactive, animated, and static. Interactive allows the user control time (move forward or backward) and the scene, rotating and repositioning to access multiple view points. Animated plays time normally with a loop and the scene is rotated automatically. Static time is shown as multiple still snapshots, while space is also static with additional widgets to enhance depth cues. There were a total of nine combinations consisting of every pair of time or static and interactive, animated, and static. Findings suggested that animated time yielded the fastest results, whereas users exhibited the highest confidence levels when interacting with both space and time interactively [10].

Kloiber et al. (2020) introduce an innovative framework for analyzing user motion within virtual reality. This approach emphasizes the importance of conducting motion analysis with the same immersive context in which the data was captured, thereby enhancing the understanding of user behaviors and interactions. User movements are represented as trajectories and highlights key motion frames, which facilitates intuitive exploration and analysis of complex motion patterns. This aid sin uncovering insight into user behaviors, task performance, and integration strategies within VR. The utility of this framework can be useful for evaluating design choices and training progress. By analyzing motion data, developers and researchers can make more informed decisions to improve user experience and training efficacy [11].

2.2 Movement

One domain where VR-based movement training has been explored is dance instruction. Chan et al. (2010) investigates a system that captures whole-body movement using motion capture. The system provides two types of feedback: immediate and delayed. Immediate feedback involves a stick-figure avatar that mirrors the user's movement in real-time, with segments highlighted in yellow for correct alignment and red for incorrect positioning based on joint angles. The delayed feedback includes a score report after each performance, where users receive a detailed score based on the Euclidean distance between their postures and the instructor's movements. A comparison between a control group that learned via video instruction and an experimental group using the VR system demonstrated that the VR-trained participants achieved a significantly higher rate of improvement [12].

Similarly, a 2011 study by Charbonneau, Miller, and LaViola examines the effectiveness of three feedback modes—video-only, game-only, and training mode (video + game)—using an Optrima Optricam depth camera for motion tracking. The game mode visualized the user's movement as particles, with discrepancies in motion indicated by red points. The instructor was represented in a similar fashion, with different colors. Additionally, the instructor's silhouette was either overlaid on the player (game mode) or placed above the player (training mode). Results from both game scores and an expert panel suggested that video-only mode led to better performance, indicating that the visualization method in game mode may have been insufficient for effective learning [13].

Another approach to dance training in VR is explored in Sun et al.'s research (2014). This study utilizes a Microsoft Kinect for motion tracking and a gesture recognition database for ballet pose analysis. Unlike previous studies that rely on head-mounted displays (HMDs), this system employs a CAVE (Cave Automatic Virtual Environment), which uses three projectors to create an immersive virtual space. Three feedback mechanisms are implemented: side-by-side comparison, overlay visualization, and score graphs. By analyzing postures, the system is able to provide immediate feedback to students, which was shown to increase performance scores [14].

Beyond dance, VR has been investigated for improving fine motor skills. Martirosov et al. (2021) examines how VR training affects users' ability to follow precise movement patterns using either a one-handed tool (glue gun) or a two-handed tool (caulking gun). Participants were required to trace straight lines, sine waves, and circular paths as quickly and accurately as possible. After seven VR training sessions, real-world tests were conducted before and after the VR exposure. Findings indicated that accuracy increased and task completion time decreased in real-world tests, though performance improvements plateaued after the fourth VR session [15].

There have also been several studies focusing on hand movement rather than full-body. The research by Nomoto et al. in 2016 explores a novel approach to assist users in performing precise manual tasks through the integration of visual and haptic feedback in a mixed reality (MR) environment. The system overlays a virtual hand onto the user's real hand, which is designed to guide and correct the user's hand movements during manual tasks. The experiment utilized viso-haptic feedback, which allows for virtual drawing while the user feels a sensation similar to an ink brush. The results of using this system showed improved accuracy and consistacy in task performance compared to those with such feedback [16].

Bertrand et al. (2015) examines specifically bimanual motion and the acquisition of bimanual motor skills. The study explores whether symmetrical or asymmetrical tasks influence learning outcomes and user performance in VR-based training. They found that tasks that had dimensional symmetry were learned faster and improved coordination compared to asymmetrical tasks, which suggests that symmetry plays a crucial role in enhancing motor skill acquisition. The study highlights the importance of incorporating symmetrical task structures in the design of training modules aimed at fields requiring precise hand coordination [17].

2.3 Education

The study conducted by Jensen and Konradsen in 2017 examines the effectiveness of VR HMDs in educational settings. With cognitive skills, five studies compared HMDs to less immersive technologies, such as CAVEs and desktops, and discovered that led to better learning outcomes, especially with spatial awareness. For psychomotor skills, the experiments did improve skills in certain tasks that translated to the real world, but in some cases only made the user better at playing the game. Simulator fidelity was also discussed, but there is conflicting information about higher fidelity leading to better learning outcomes. Some have argued that if environmental elements are too complex, it can confuse the user and cause worse outcomes [18]. A downside to using HMDs as a learning tool is cybersickness and physical discomfort. It has been shown to negatively influence learning, and has made some participants drop out of experiments due to the discomfort. These effects are very rare however, and is able to be lessened with repeated 3D gaming experiences. Despite these challenges, participants report positive attitudes. Ultimately, the findings indicate that HMDs are merely a medium for learning, no different from a classroom or other games, emphasizing that the effectiveness of a simulation depends on application design rather than immersion alone [18].

In a similar vein, Rourke (2020) conducted a systematic review to evaluate the comparative effectiveness of virtual reality simulation versus traditional simulated practice in facilitating the development of clinical psychomotor skills among pre-registration nursing students. The review included nine quasi-experimental studies of varying methodological quality. Despite the limitation of missing data and heterogeneity in methods, the majority of studies reported that participants in VR simulation groups showed greater improvements in post-test knowledge scores, cognitive processing, and psychomotor performance compared to those undergoing conventional simulated practice. Some evidence also suggested faster task completion times in the VR groups, though this finding was not consistent across all studies. The authors conclude that VR simulation is at least as effective, and in many cases more effective, than traditional simulated practice for teaching clinical psychomotor skills. However, they emphasize the need for further research employing standardized outcome measures and robust study designs to strengthen the evidence base and inform curriculum development [19].

A study that focuses on robot-assisted surgical training by Caccianiga et al. (2020) compares the effectiveness of physical (inanimate) models and virtual reality simulators in training psychomotor skills. Eighteen participants followed a custom needle driving task, where both formats had improvements on their respective platforms. However, the inanimate group performed better than the VR group during the cross-platform evaluation (inanimate on VR, and VR on inanimate). These results were true for the slow and moderate task speeds, but the fast task had no significant improvement in either simulator. Other studies with similar tasks received similar results, showing that the skill transfer from VR to inanimate is not significant, which might be caused by the difficulty of the task for the VR groups [21]. This hypothesis is supported by the previously discussed studies by Rourke and Jensen and Konradsen, that shows that skill transfer is possible across multiple applications and disciplines.

Pastel et al. (2022) studied whether virtual reality enables learning of complex karate techniques, specifically the Soto Uke movement in the Zenkutsu Dachi stance. Thirty-three participants were split into four groups of visualizations: whole-body (VR-WB), forearm (VR-FA), video-based (VB), and control. The researchers assessed improvements in the upper body, lower body, and fist posture in the pre-test, post-test, and retention phases across four training sessions. Results indicated that all training groups showed significant improvements, while the control group did not exhibit notable changes. The study also found no significant difference in the effectiveness of whole-body versus forearm-only representation. This suggests that simplified VR representations can be as effective as full-body models or traditional video instruction for teaching complex motor skills These findings support the viability of VR as a tool for motor skill acquisition, offering flexibility in visualization styles without compromising training efficacy [20].

CHAPTER 3: METHODOLOGY

This chapter outlines the experimental design, application development, and data collection methods used to evaluate how different visualization styles impact movement imitation accuracy. The study was designed to systematically test the effects of offset, animation, and manual types in a virtual environment. We created an application in Unity 2022.3.7f1 for the Meta Quest 2 headset (1832 x 1920 resolution per eye, 120Hz refresh rate, 97° field of view) using the Meta XR SDK package. Users participated in 12 randomized trials, each incorporating a different visualization combination, with 3 movements each. Video of the movements can be viewed at `https://youtu.be/ieZxalfBxis?si=Pho64lnhll4ZyjHq&t=66` and the data used to create the paths are available at `https://github.com/GabyShamblin/movement-visualization-data`. Both performance and perception were collected through the application data and surveys respectively.

3.1 Application Design

Upon startup, a virtual table appears in a white room where the gray controllers are displayed. Participants are given time to prepare and adjust their position in front of the virtual table before the recorded session begins. To enhance visibility, the table, back wall, and side walls are black, while the animation icons follow a rainbow gradient (red, orange, yellow, green, blue, and purple). This gradient transitions from fully opaque to mostly transparent, aiding participants in understanding their movement sequence, synchronizing both hands in bimanual tasks, and differentiating positions within the continuous animation (detailed later).

During movement execution, a predefined tolerance is applied to determine correctness. Position and rotation are considered correct within 0.05 meters (5 cm) and 40°, respectively. A time restric-

Figure 3.1: The experiment room

tion is also enforced: if one hand lags more than 120 frames (approximately 2 seconds) behind the other, the user must restart, and previously saved data is overwritten. Successful completion of the movement advances the program to the next sequence or visualization type. To prevent order effects and artificial score inflation, the presentation order of visualizations is randomized.

3.1.1 Visualization

The appearance of the hands plays a critical role in user interaction. The study examines three visualization categories, offset, animation, and handedness, which results in 12 unique combinations.

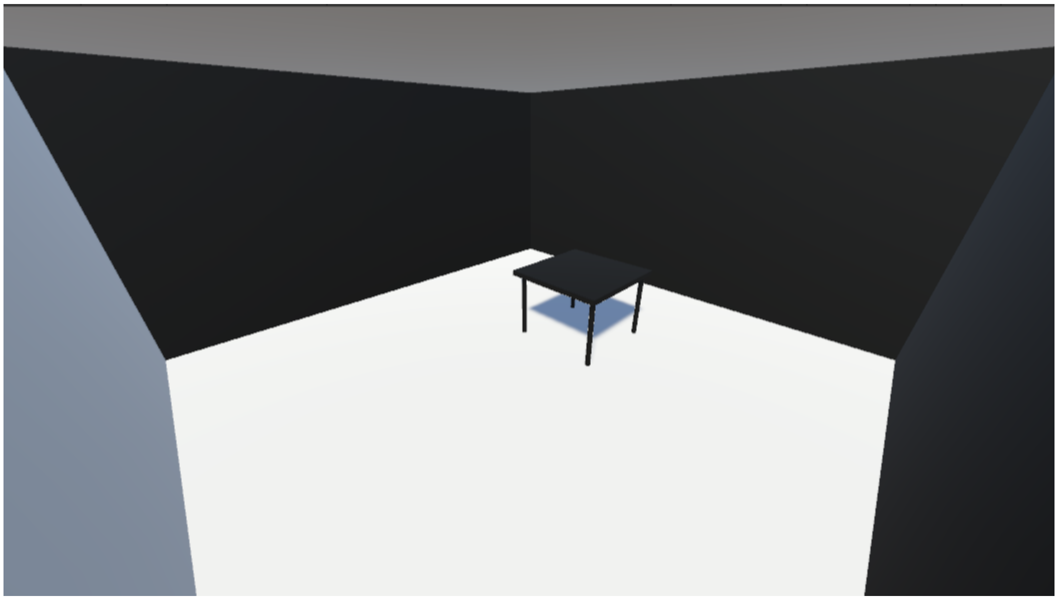
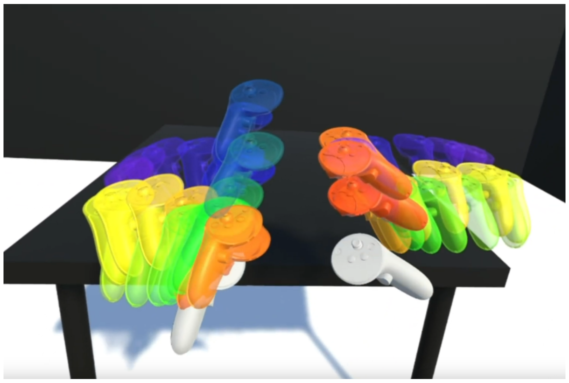


Figure 3.2: The virtual room

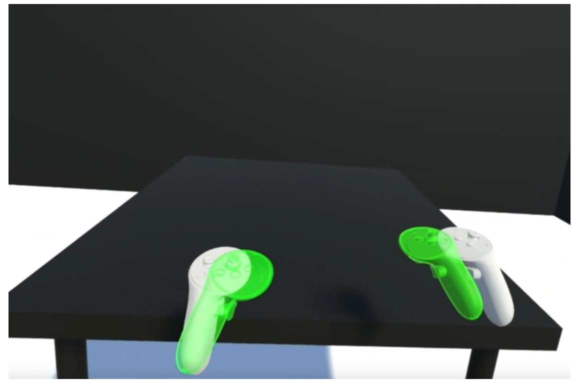
These are explored in-depth in the following sections.

3.1.1.1 Animation

Discrete and continuous movement are used in the beginning of every movement to show the user how to perform the motion. Discrete displays one static frame at a time, progressing sequentially from the start to the end of the motion. Continuous displays every seventh frame, initially showing only one and progressively increasing the number of visible frames as the movement continues. These styles assess the impact of information quantity on movement accuracy. In both cases, all frames are saved and analyzed, regardless of whether they are displayed. In discrete mode, as users match the current frame, it disappears, and the next frame appears, creating the illusion of fluid motion. In continuous mode, the matched frame just disappears (if it is visible). Video of the two animation types can be seen at `https://youtu.be/ieZxalfBxis?si=B1Ffpwrh4KGA3tX-`.



(a) Continuous



(b) Discrete

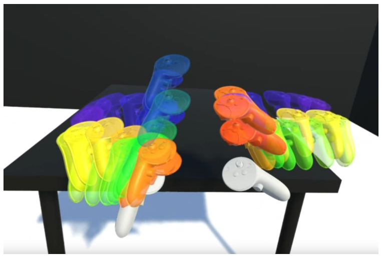
Figure 3.3: Animation types

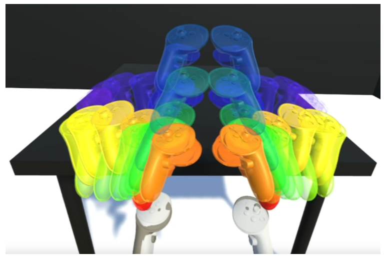
3.1.1.2 Hands

Unimanual (one hand) and bimanual (two hands) will also be accounted for to determine how the coordination of both hands affects the user's accuracy. Two routes were recorded for each movement, one for each hand, which will be used for the bimanual mode. For unimanual, users follow movements using only their right hand, regardless of dominance. With mirrored bimanual, both hands follow the left hand movement, which is replicated and mirrored for the right hand. Each hand follows its individual recorded movement sequence for asynchronous bimanual. Video of the three handed types can be seen at `https://youtu.be/ieZxalfBxis?si=JxFuu3TOP84tNXV9&t=21`.

3.1.1.3 Offset

Offset enables the user to see the hands from a different angle. This involves "ghost" controllers that are offset 0.5 meters forward from the actual controllers but follow the exact movements of the controllers. In addition, the tracing visualizations are moved forward the same amount as


(a) Asynchronous bimanual


(b) Mirrored bimanual

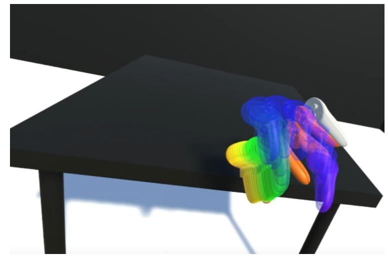
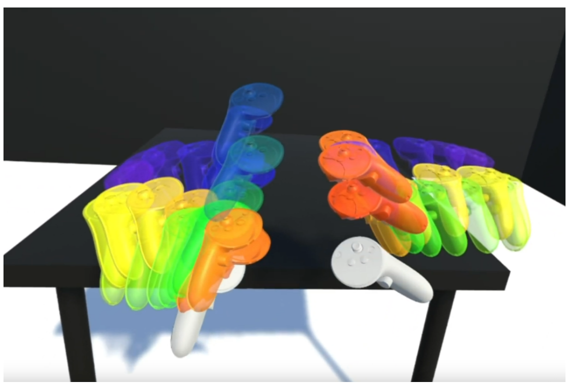

(c) Unimanual

Figure 3.4: Manual types


(a) In-Place

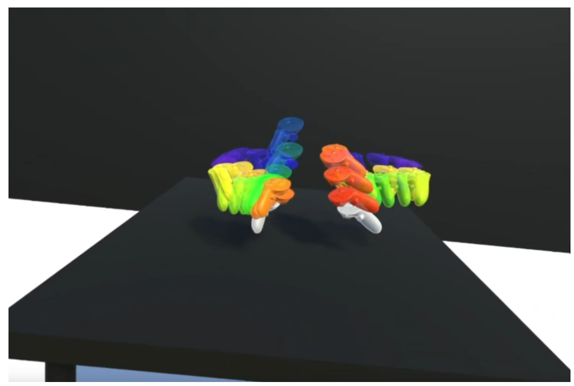

(b) Offset

Figure 3.5: Offset types

the "ghost" controllers, and users' representation of their real controllers are hidden to create the illusion that the offset hands are their hands. While offset mode is turned off, the traces are within reach of the users' controllers, and the user must follow the traces with their hands directly. Video of the close and offset visualization types can be seen at `https://youtu.be/ieZxalfBxis?si=zeeiQALgmLk6MAgE&t=46`.

3.1.2 Feedback

Each movement begins with an animation demonstrating the expected motion. The animation controllers follow a rainbow gradient to provide users with a temporal reference, aiding synchronization between hands. Upon successful movement completion, a confirmation jingle plays, the animation controllers reset, and position controllers reappear. If the user's hands exceed a 120-frame de-synchronization, a failure jingle plays, and the animation automatically replays to indicate a restart is required.

3.2 Participants

A total of 30 participants (22 males and 8 females) were recruited through an email list at the University of Central Florida and required to complete a questionnaire to ensure eligibility and gather basic demographic information. The eligibility requirements can be viewed at Appendix A.1. Participants ranged in age from 18 to 31 with a mean age of 21.6. 26 of the 30 participants (87%) were right-handed, 3 were left-handed (10%), and 1 was ambidextrous (3%). Participants were also surveyed regarding their prior experience with video games and virtual reality (Table 3.1). Half of users said they played video games often (weekly or daily), while 33% said the games they played often had a first-person perspective. Only 6 of the 30 (20%) stated that they owned a VR system, with the majority using a Meta Quest 2, the same model used in the study.

Table 3.1: Questionnaire Results

Question	None	Yearly	Monthly	Weekly	Daily
How often do you play video games?	3%	13%	33%	33%	17%
How often do you play first-person video games?	10%	23%	30%	23%	10%
How often do you play VR video games?	37%	37%	20%	3%	0%

3.3 Experiment Design

The tasks were designed to evaluate how different visualization configurations affect movement accuracy. A within-subjects design was employed, allowing each participant to experience all visualization conditions. This approach controls for individual variability and provides a more robust set of comparative data across conditions.

Prior to starting the trials, users received instructions and were given time to familiarize themselves with the VR environment and controls. Each participant completed a total of 36 trials, consisting of 3 unique movements presented under 12 different visualization combinations. To prevent learning effects or ordering biases, the sequence of combinations were randomized for each participant. Before each movement, users positioned their controllers within a set of opaque gray controllers. This action triggers an animation that demonstrates how to complete the movement. Once complete, users placed their hands back in the initial position to begin execution. Both hands follow the same gradient, and the participant is instructed to keep both hands on the same color at the same time, ensuring participants remain aware of the temporal aspect of the motion.

The independent variables were the offset, animation, and handed types, and the dependent variables were the position, rotation, and average scores.

3.4 Procedure

Participants are given instructions on how to use the program and then prompted to sit down, place the headset on their head, and adjust the straps as needed. The chair was placed in the middle of the room away from all other furniture, and the Roomscale boundary created a roughly 4’ x 4’ square around the chair. The user may move freely within the confines of the virtual environment using the character controls. The left controller stick is used for movement and the right controller stick is used for snap rotation, which has an increment of 10° and a 0.5 second delay between rotations. Users may click the Y button on the left controller to manually reset the current movement. They were given guidance by the researcher for the first three movements if needed, then were only helped if it was specifically requested.

Each participant must complete all three movement sequences across all 12 visualizations, resulting in 36 trials, estimated to take approximately 45 minutes. Between each visualization combination, a "pause" message is displayed to remind the participant to stop and complete the between-trial questionnaire. After completing all trials, a "done" message indicates completion, followed by the final between-trial questionnaire and the end-of-trial questionnaire.

3.5 Data Collection

Data from the simulation is saved in a .csv at the end of every movement, totaling 36 sections within each file. Each section contains a code which consists of the internal visualization code, an offset identifier, an animation identifier, a handed identifier, the movement code (0-2), the reset count, and the user-initiated reset count. The visualization code is a number 0-11 which aligns with one of the 12 visualization combinations and is used to tell the program what trial was chosen at random. For example,

8: offset_cont_asyc_0_3_1

means the section of the data is from the offset, continuous animation, and asynchronous bimanual combination, which has an internal code of 8. It is from movement 0 (the first movement), and the user was reset three times, one of those being a result of them hitting the reset button. This means the user was reset twice as a result of error.

For each frame in a movement, the following information is saved:

- Trial code
- Left position (x, y, z)
- Left position score
- Left rotation (x, y, z, w)
- Left rotation score
- Right position (x, y, z)
- Right position score
- Right rotation (x, y, z, w)
- Right rotation score
- Timestamp
- Score

3.5.1 Scoring

Accuracy was calculated based the distance between the correct position and rotation, and the user's hand. It must fall within a predefined allowance, with 0% representing the maximum allowable deviation and 100% indicating perfect alignment. Score for position and rotation are calculated independently, using the following formulas:

$$\text{Position: } 1 - (Vector3.Distance(correct, user)/positionAllowance)$$

$$\text{Rotation: } 1 - (Quaternion.Angle(correct, user)/rotationAllowance)$$

For example, assuming a position allowance of 0.25 meters, a correct Vector3 of $(0,0,0)$, and a user Vector3 of $(0.1,0.07,0.12)$ results in a distance of 0.17 and will have a score of:

$$1-(0.17/0.25)=0.32=32\%$$

Scores were calculated for every frame, and the overall score was computed as the average of the position and rotation scores. In the case of unimanual movement, the left hand information is populated with all zeros and is left out of the average.

CHAPTER 4: RESULTS

This chapter presents the findings from both the quantitative and qualitative analyses during the user study. The participants' motion data was recorded while they performed the given tasks, and heir subjective experiences were evaluated using a series of questionnaires. The findings provide a comprehensive view of how visualization design choices impact motor performance and user satisfaction, which can be found at `https://github.com/GabyShamblin/movement-visualization-data`. All data analysis and visualization was completed in R. Each set of data (position, rotation, overall) was tested for normal distribution, which was confirmed. Significance is defined as follows: . ($p < 0.1$), * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$).

4.1 User Performance

A repeated measures ANOVA using a mixed-effects model was conducted to compare the effect of each variable on user accuracy across conditions. The independent variables are offset, animation type, and the manual type. The user ID was added as a random effect, to account for individual variation. For the dependent variable, a mean score is calculated from each trial for each user and this is what will be used for subsequent calculations. Plotting this data This is written as an R formula which looks like:

$$score \sim offset * anim * hand + (1|user)$$

The analysis was performed assuming that in-place, continuous, and asynchronous bimanual were the default conditions (the Intercept in Table B.3). Each variable in Table B.3 represents a change from this baseline. For example, "Offset" refers to the offset visualization, "Anim" refers discrete animation, and "Hands" refers to mirrored and unimanual (which is further broken down in the "Hands" section). Mean scores and confidence intervals for the position, rotation, and overall average of each visualization type were calculated and plotted (Figure B.1, Figure B.3, Figure B.5).

Offset had a significant effect on position ($p < 0.001$), rotation ($p < 0.05$), and overall ($p < 0.001$), with in-place achieving slightly higher scores across all combinations. Animation type had a statistically significant impact on all scores as well ($p < 0.001$), with discrete animation yielding higher scores overall than continuous. There was a very slight increase for position, but rotation saw an increase of about 10% for discrete. Manual type had highly significant results for all scores as well ($p < 0.001$). Mirrored bimanual scored the lowest for overall and rotation scores ($p < 0.001$), followed closely by asynchronous bimanual. Mirrored had slightly higher position scores, but had less significance when paired with asynchronous ($p < 0.05$). Unimanual had the highest scores by almost 10% for all scores.

The interaction effect Offset:Anim (offset and animation) was not statistically significant, but Offset:Hands was slightly significant for position ($p < 0.1$). In-place unimanual had the highest scores of the other combinations by a small margin, followed closely by offset unimanual. Asynchronous and mirrored had about the same scores regardless of the distance of the visualization compared to the user. The interaction Anim:Hand (animation and hands) however, had a high significance ($p < 0.001$) for every score type. Discrete unimanual had the highest scores, with every other combination following the same patterns as the individual scores. The three-way interaction Offset:Anim:Hands was not significant.

4.2 User Experience

4.2.1 Between Trial Questionnaire

We performed an Aligned Ranks Transformation (ART) Analysis of Variance (ANOVA) to analyze each variable and the interactions between variables. The independent variables are the offset (in-place vs. offset), the animation type (discrete vs. continuous), and manual type (unimanual vs. mirrored bimanual vs asynchronous bimanual). The dependent variable is the user's score for each question. This analysis followed the formula:

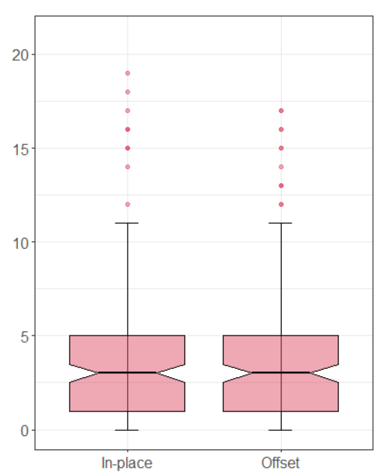
$$score \sim offset * anim * hand$$

The full questionnaire can be found in Appendix A.2.

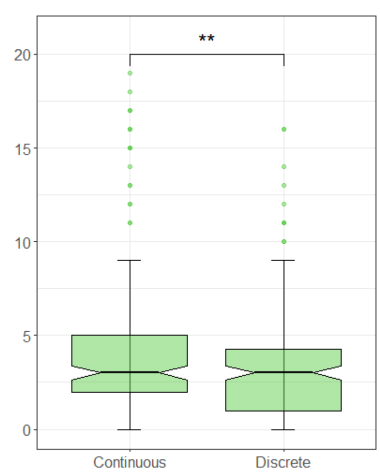
Manual type had a highly significant impact for how mentally demanding the task was ($p < 0.001$), as seen in Table 4.2. Specifically, Figure 4.3c demonstrates that unimanual received the lowest mental demand scores for this question by a large margin ($p < 0.001$), followed by mirrored bimanual. In addition, animation type received significance ($p < 0.01$), with discrete being less mentally demanding than continuous animation (Figure 4.3b). The offset visualization was not statistically significant and shows little difference on Figure 4.3a.

Table 4.1: How mentally demanding was the task?

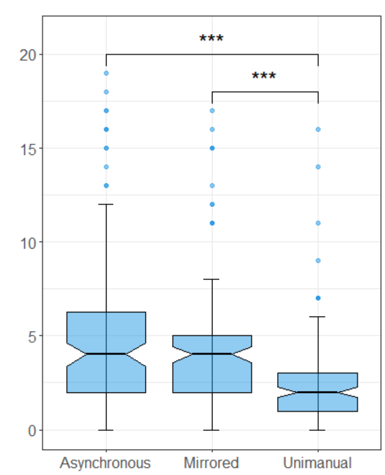
Variable	DoF	DoF Res.	F Value	p Value	Significance
Offset	1	348	0.689	0.407	
Anim	1	348	8.791	0.003	**
Hands	2	348	14.656	7.74e-07	***
Offset:Anim	1	348	1.61e-05	0.997	
Offset:Hands	2	348	0.558	0.573	
Anim:Hands	2	348	1.881	0.153	
Offset:Anim:Hands	2	348	0.193	0.824	
Hands					
Async - Mirrored		348		0.552	
Async - Unimanual		348		9.71e-07	***
Mirrored - Unimanual		348		3.75e-04	***



(a) Offset



(b) Animation



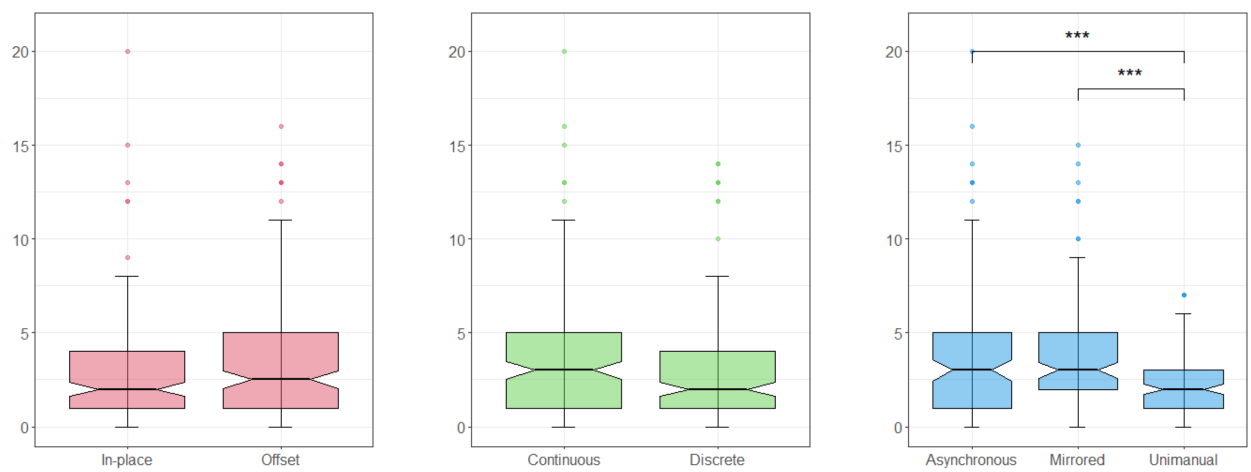
(c) Hands

Figure 4.1: How mentally demanding was the task?

For the physical demanding (Table 4.3), only handedness received any level of significance ($p < 0.001$). Results mirrored those of mental demand: unimanual was rated significantly lower ($p < 0.001$) and was followed by mirrored by a large margin (Figure 4.4c). The offset visualization was not statistically significant and shows little difference on Figure 4.4a.

Table 4.2: How physically demanding was the task?

Variable	DoF	DoF Res.	F Value	p Value	Significance
Offset	1	348	0.412	0.521	
Anim	1	348	2.082	0.150	
Hands	2	348	11.030	2.27e-05	***
Offset:Anim	1	348	0.053	0.817	
Offset:Hands	2	348	0.180	0.835	
Anim:Hands	2	348	1.083	0.340	
Offset:Anim:Hands	2	348	0.022	0.978	
Hands					
Async - Mirrored		348		1.000	
Async - Unimanual		348		1.01e-04	***
Mirrored - Unimanual		348		3.20e-04	***



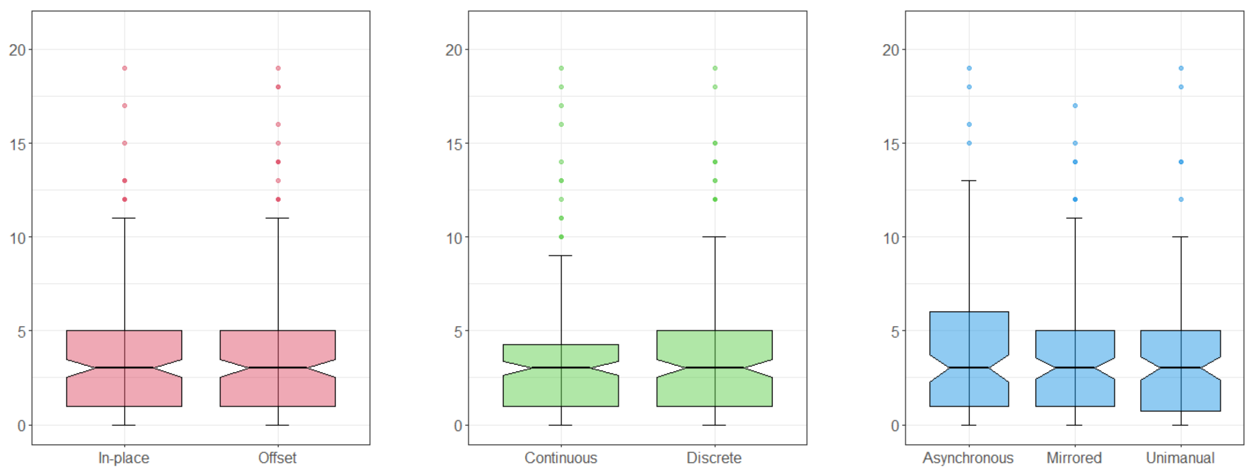
(a) Offset (b) Animation (c) Hands

Figure 4.2: How physically demanding was the task?

None of the visualization types affected the perceived pace of the task and no variables received significance.

Table 4.3: How hurried or rushed was the pace of the task?

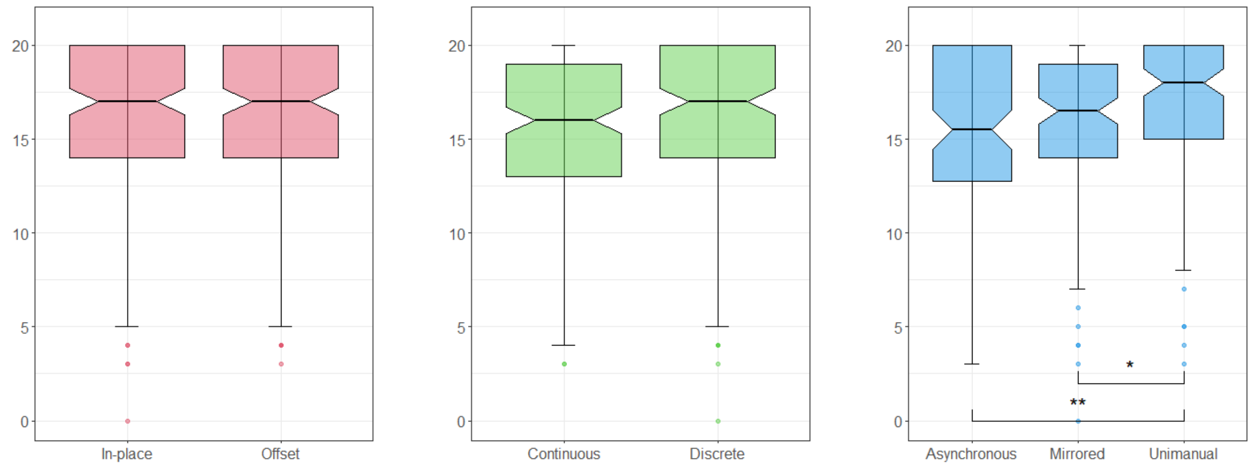
Variable	DoF	DoF Res.	F Value	p Value	Significance
Offset	1	348	1.591	0.208	
Anim	1	348	2.139	0.144	
Hands	2	348	1.306	0.272	
Offset:Anim	1	348	0.393	0.531	
Offset:Hands	2	348	0.143	0.867	
Anim:Hands	2	348	0.016	0.984	
Offset:Anim:Hands	2	348	0.023	0.978	
Hands					
Async - Mirrored		348		0.487	
Async - Unimanual		348		0.487	
Mirrored - Unimanual		348		1.000	



(a) Offset (b) Animation (c) Hands

Figure 4.3: How hurried or rushed was the pace of the task?

Users felt slightly more successful while using the unimanual than the mirrored handed visualization, but this result is less significant ($p < 0.01$) than the previous questions (Table 4.5). Asynchronous bimanual had a slightly lower median than unimanual ($p < 0.05$), but had a larger range of scores. The offset visualization was not statistically significant and shows little difference on



(a) Offset (b) Animation (c) Hands

Figure 4.4: How successful were you in accomplishing what you were asked to do?

Figure 4.6a.

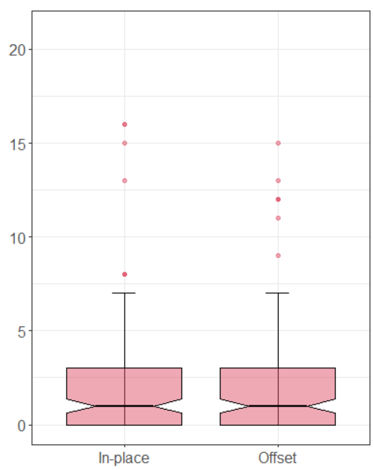
Table 4.4: How successful were you in accomplishing what you were asked to do?

Variable	DoF	DoF Res.	F Value	p Value	Significance
Offset	1	348	0.009	0.926	
Anim	1	348	3.084	0.080	
Hands	2	348	6.370	0.002	**
Offset:Anim	1	348	4.34e-04	0.983	
Offset:Hands	2	348	0.002	0.998	
Anim:Hands	2	348	0.502	0.606	
Offset:Anim:Hands	2	348	0.002	0.998	
Hands					
Async - Mirrored		348		1.000	
Async - Unimanual		348		0.003	**
Mirrored - Unimanual		348		0.014	*

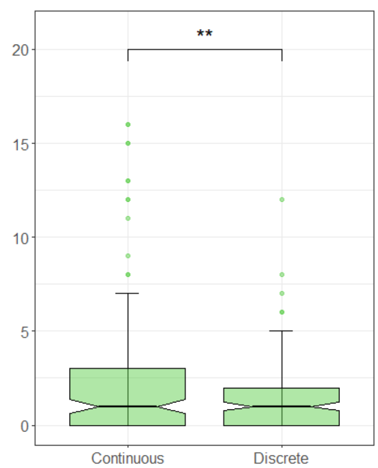
Stress was primarily associated with animation and manual type (Table 4.6). Discrete animation was significantly better than continuous animation ($p < 0.01$), having a smaller range of scores then the former. The distance between unimanual and asynchronous was more significant ($p < 0.01$) then unimanual and mirrored ($p < 0.05$), as also shown in Figure 4.7c. The offset visualization was not statistically significant and shows little difference on Figure 4.7a.

Table 4.5: How insecure, discouraged, irritated, stressed, and annoyed were you?

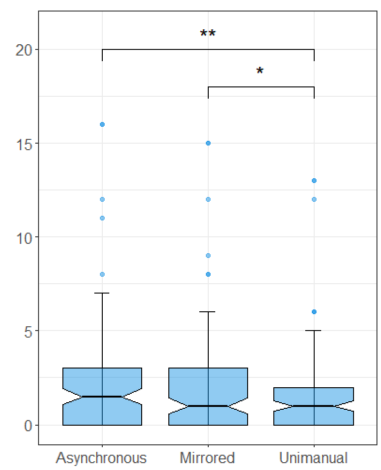
Variable	DoF	DoF Res.	F Value	p Value	Significance
Offset	1	348	0.002	0.969	
Anim	1	348	7.840	0.005	**
Hands	2	348	6.326	0.002	**
Offset:Anim	1	348	0.009	0.923	
Offset:Hands	2	348	0.379	0.685	
Anim:Hands	2	348	0.201	0.818	
Offset:Anim:Hands	2	348	0.123	0.884	
Hands					
Async - Mirrored		348		1.000	
Async - Unimanual		348		0.002	**
Mirrored - Unimanual		348		0.029	*



(a) Offset



(b) Animation



(c) Hands

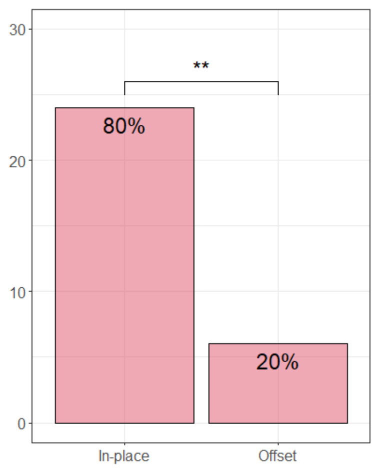
Figure 4.5: How insecure, discouraged, irritated, stressed, and annoyed were you?

4.2.2 End of Experiment Questionnaire

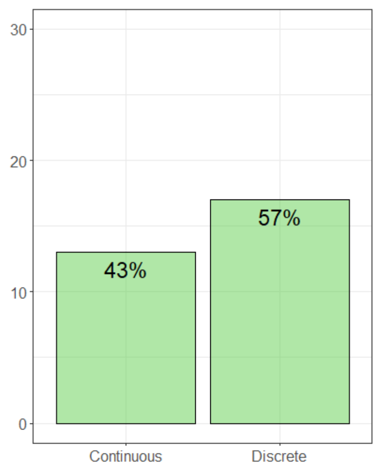
After experiencing all visualization combinations, participants were given a questionnaire about which techniques were preferred (Appendix A.3). Most users preferred in-place as opposed to offset (Figure 4.8a). Animation type preference was more evenly split, with a slight preference for discrete animation. Most users favored single-handed movements over the dual-handed movements, likely due to the increased coordination required for bimanual tasks. Asynchronous bimanual received the least positive response, ranking just below mirrored bimanual.

Table 4.6: End of Experiment

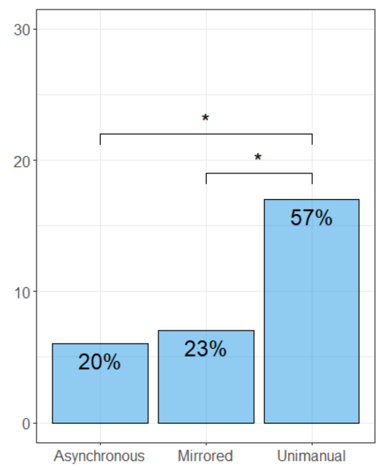
Variable	DoF	X-squared	p Value	Significance
In-place - Offset	1	10.8	0.001	**
Cont - Disc	1	0.533	0.465	
Async - Mirrored	1	0.077	0.782	
Uni - Async	1	5.261	0.022	*
Uni - Mirrored	1	4.167	0.041	*



(a) Which animation technique do you prefer?



(b) Which visualization technique do you prefer?



(c) Which handed technique do you prefer?

Figure 4.6: End of Experiment Questionnaire Results

4.3 Discussion

The results of this study highlight several key findings regarding the effects of different visualization techniques on user performance and perception on a VR-based movement task. The primary variables examined were offset (in-place vs. offset), animation type (discrete vs. continuous), and manual type (unimanual vs. mirrored bimanual vs. asynchronous bimanual).

Despite the between-trial questionnaire showing similar ratings for in-place and offset, the majority of users (80%, Figure 4.8a) preferred the in-place visualization when asked at the end of the experiment. This suggests that while offset may not have significantly impacted perceived mental or physical demand, stress, or performance during individual trials, the cumulative experience likely influenced user perception. Our first hypothesis offset will result in a higher accuracy was incorrect, as in-place yielded slightly higher scores ($p < 0.001$). This may be because the offset visualizations may have introduced a subtle sense of disorientation or disconnect, as users had to rely on information that did not align precisely with their proprioceptive feedback. This aligns with user's overall accuracy as well, as even though offset had a significant impact when it was the only changed variable ($p < 0.001$), it had little effect when combined with other factors and for rotation and position individually. Future research could explore whether familiarity with VR systems or extended exposure to offset visualizations influences user experience and adaption over time.

In terms of animation style, user preference was more evenly split between continuous and discrete. However, performance results demonstrated that discrete animation had significantly higher accuracy scores than continuous ($p < 0.001$). This confirms our second hypothesis, and aligns with previous research suggesting that breaking down complex movements into discrete steps can enhance learning and execution by reducing cognitive load [10]. The discrepancy between subjective preference and objective performance may indicate that some users found continuous animation to be more natural or engaging, even if it was less effective in guiding precise movements. Future studies could explore hybrid animation approaches that blend the benefits of both styles, such as showing a small amount of the path at a time that progresses as the user continuous through the motion.

The manual type had the most profound impact on both subjective and objective measures. Unimanual movements resulted in the highest overall accuracy scores and were rated as significantly less mentally and physically demanding compared to bimanual conditions ($p < 0.001$), which means we accept our third hypothesis. Both bimanual conditions were not significant from each other with regards to the questionnaires. Interestingly, asynchronous bimanual received the highest rotation accuracy scores, followed by mirrored and unimanual ($p < 0.001$). This suggests that users were more self-critical when coordinating both hands, possibly due to heightened awareness of minor inaccuracies when attempting to maintain synchronization. Asynchronous bimanual movements, on the other hand, introduced a greater challenge but also exhibited higher variability in user responses, indicating that some participants may have adapted more effectively than others. Given these results, future studies might consider implementing adaptive difficulty settings based on individual user performance. For example, if a user struggles with asynchronous bimanual movements, the system could introduce training phases, starting with unimanual movements and gradually increasing independence between hands. Additionally, investigating whether expertise in musical instruments, sports, or other activities that require bimanual coordination influences performance in this context could yield valuable insights.

Another important aspect of the study was the error correction mechanism, which required users to restart if one hand fell more than 120 frames behind the other. This system ensured that participants remained engaged with the task and maintained synchronization, but it may have also contributed to increased frustration or stress, particularly in bimanual conditions. The stress ratings indicated that discrete animation and unimanual movement were associated with the lowest stress levels, whereas asynchronous bimanual movements in a continuous animation style resulted in the highest stress. This suggests that providing more structured feedback in these challenging conditions could help mitigate frustration. Future implementations could explore alternative error correction strategies that provide real-time feedback instead of requiring a full reset. For instance, a dynamic difficulty adjustment mechanism could slightly relax accuracy thresholds when a user is struggling, allowing for smoother progression without sacrificing learning outcomes. Additionally, auditory or haptic feedback could be introduced to guide users toward correct positioning in real-time, potentially reducing the number of resets required and potentially reducing stress.

4.4 Future Research

The findings of this study have direct implications for the design of VR-based motor learning applications. The preference for in-place visualizations suggests that developers should be cautious when implementing offset-based visualizations, particularly for novice users. If offset representations are necessary, they should be accompanied by clear calibration or adaptation phases to help users adjust.

The superior performance of discrete animation suggests that step-by-step guidance is particularly beneficial for precision tasks, though user preference indicates a demand for more fluid representations. This suggests that VR training applications might benefit from hybrid animation techniques that are discrete, but use sections of continuous to highlight a clear path, providing both structure and natural movement flow.

Finally, the impact of manual type on both subjective and objective measures suggests that VR training programs should be tailored to user skill levels. Beginners may benefit from starting with unimanual tasks before progressing to mirrored bimanual movements and finally asynchronous movements as proficiency improves. Adaptive training systems that respond to user performance could provide a more personalized and effective learning experience.

CHAPTER 5: CONCLUSION

This study demonstrated that visualization techniques in VR significantly influence both user accuracy and subjective experience. While offset representations did not significantly impact performance, they were largely disliked. Discrete animation led to better accuracy but was not overwhelmingly preferred, suggesting a tradeoff between effectiveness and perceived usability. Bimanual movements, particularly asynchronous ones, were the most challenging, requiring greater cognitive and motor coordination. These insights can inform the development of VR-based training systems, emphasizing the importance of balancing user preference with performance optimization. Future research should explore adaptive feedback mechanisms, long-term adaptation to offset conditions, and hybrid animation approaches to further enhance VR training effectiveness. Furthermore, research could explore real-world applications of these findings in fields such as rehabilitation, skill training, and remote teleoperation, and how these VR visualization techniques translate to long-term skill retention.

APPENDIX A: EXPERIMENT QUESTIONNAIRES

A.1 Qualification Questionnaire

This questionnaire is filled out before the participant is allowed to schedule their participation time, to make sure they qualify and gather basic demographic information.

Eligibility Verification

Q1: I am 18-64 years old. ◯ Yes ◯ No

Q2: I have 20/20 vision with or without contacts and do not regularly wear glasses for corrected vision. ◯ Yes ◯ No

Q3: I have the ability to walk, extend both arms above my head, and use both hands. ◯ Yes ◯ No

Q4: I can read, write, speak, and understand English. ◯ Yes ◯ No

Q5: I am NOT pregnant. ◯ Yes ◯ No

Q6: I do NOT have a pre-existing serious medical condition (e.g., heart ailment, cancer, or other serious disease). ◯ Yes ◯ No

Q7: I do NOT have a pre-existing psychiatric condition (e.g., an anxiety or post-traumatic stress disorder). ◯ Yes ◯ No

Q8: I do NOT have any visual disabilities (e.g., blindness, color blindness, low vision). ◯ Yes ◯ No

Q9: I do NOT have any auditory disabilities (e.g., deafness, hard of hearing). ◯ Yes ◯ No

Q10: I do NOT have any neuropathy disabilities (e.g., hypersensitivity, numbness). ◯ Yes ◯ No

Q11: I do NOT have any neurological disabilities (e.g., autism, memory impairments). ◯ Yes ◯ No

Q12: I do NOT have any physical disabilities (e.g., amputation, tremors and spasms). ◯ Yes ◯ No

Q13: I do NOT have any recurring history of the following symptoms: Convulsions, Disorientation, Dizziness, Drowsiness, Excessive sweating, Eye pain or discomfort, Eye strain, Eye twitching, Fatigue, Impaired hand-eye coordination, Impaired sense of balance, Increased salivation, Involuntary movements, Lightheadedness, Loss of awareness, Motion sickness, Nausea, Seizures, Vision abnormalities (such as altered, blurred, or double vision). ◯ Yes ◯ No

Informed Consent Verification

Q14: Please fully review the informed consent form below before deciding whether to proceed with participation. https://drive.google.com/file/d/1f2BxMAlBDSG4Vc38E3jD7bpfkb6UBvox/view?usp=sharing

Q15: Have you read the information about the risks involved? ◯ Yes ◯ No

Q16: Have you read the information on who to contact with questions about the study? ◯ Yes ◯ No

Q17: Have you read the information about withdrawing from the study? ◯ Yes ◯ No

Q18: Have you read the information about how your data will be used? ◯ Yes ◯ No

Q19: Do you voluntarily consent to participate in this study? ◯ Yes ◯ No

Demographics Survey

Q20: What is your gender? ◯ Male ◯ Female ◯ Other ◯ Prefer not to say

Q21: What is your age? ________________

Q22: What is your height? ________________

Q23: Which hand is your dominant hand? ◯ Right hand ◯ Left hand ◯ Either hand

Video Game Survey

Q24: On average, how often do you play video games? ◯ None ◯ Yearly ◯ Monthly ◯ Weekly ◯ Daily

Q25: On average, how often do you play games with first-person perspectives? ◯ None ◯ Yearly ◯ Monthly ◯ Weekly ◯ Daily

Virtual Reality (VR) Survey

Q26: On average, how often do experience VR applications and games? ◯ None ◯ Yearly ◯

Monthly ◯ Weekly ◯ Daily

Q27: Do you own or possess a VR system? ◯ Yes (please specify) ____________ ◯ No

Email Address

Q28: What is your email address? We will contact you via email to schedule your in-person participation. ____

A.2 Between Trial Questionnaire

This questionnaire is filled out after experiencing each visualization technique, to a total of 12 timers per participant. It is based on the NASA Task Load Index (NASA-TLX) to determine how demanding the participant felt a task was on a scale from 0-20.

Q1: Rate your experience with the previous task:

How mentally demanding was the task? Very low ◯◯◯◯◯ Very high

How physically demanding was the task? Very low ◯◯◯◯◯ Very high

How hurried or rushed was the pave of the task? Very low ◯◯◯◯◯ Very high

How successful were you in accomplishing what you were asked to do? Very low ◯◯◯◯◯ Very high

How insecure, discouraged, irritated, stressed, and annoyed were you? Very low ◯◯◯◯◯ Very high

A.3 End of Experiment Questionnaire

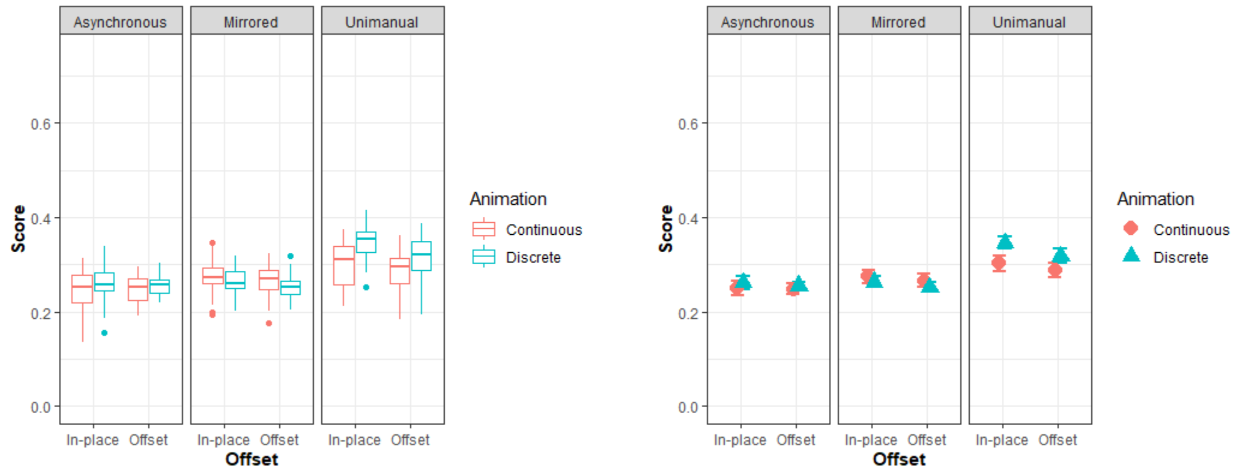
This questionnaire is filled out after completing all visualization techniques.

Q1: Which animation technique do you prefer? ◯ Discrete (one icon at a time) ◯ Continuous (all icons at once)

Q2: Which handed technique do you prefer? ◯ Single-handed ◯ Mirrored two-handed ◯ Asynchronous two-handed

Q3: Which visualization technique do you prefer? ◯ In-place (close) ◯ Offset (far away)

APPENDIX B: EXPERIMENT RESULTS



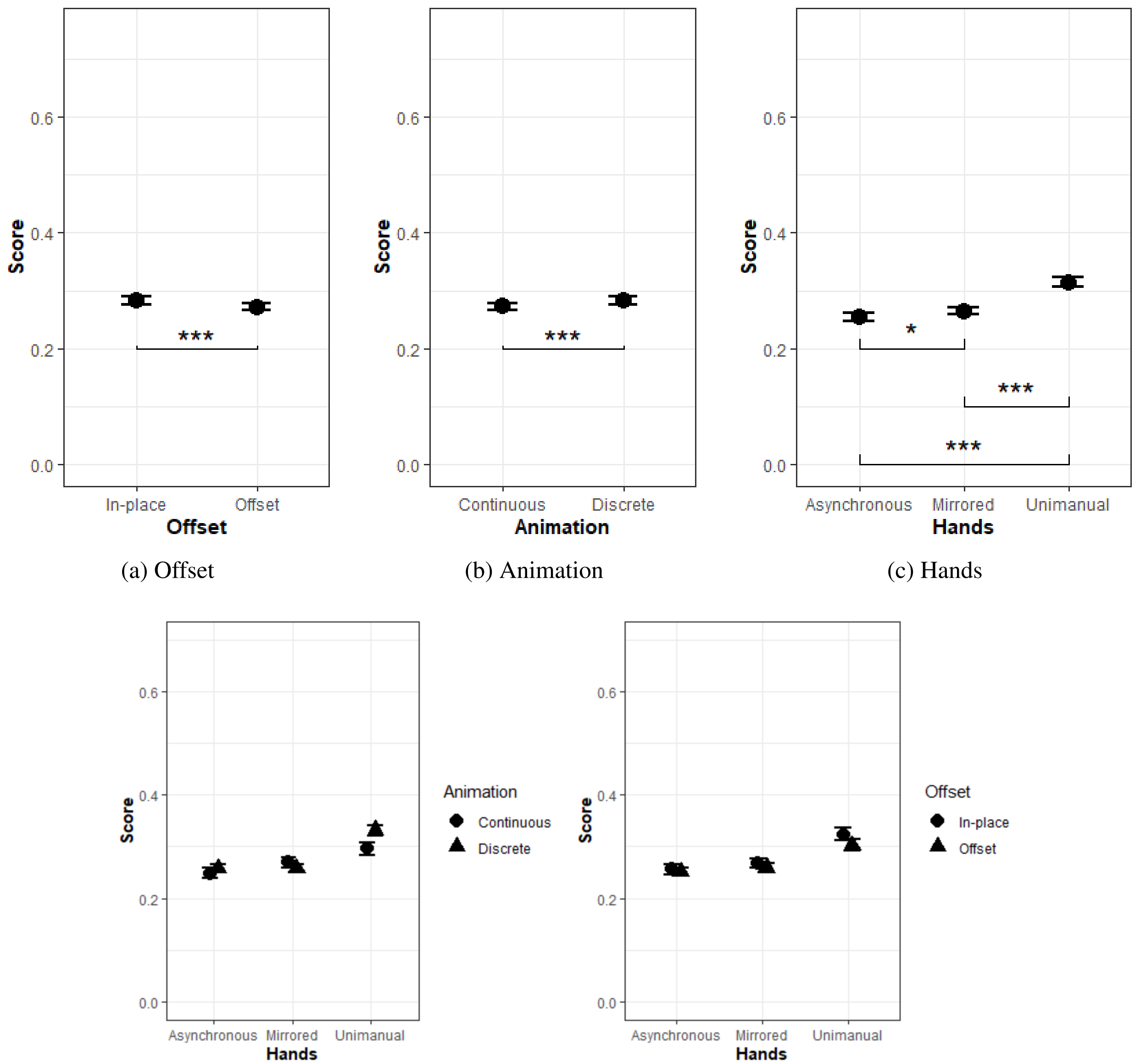
(a) Distribution of position scores for each trial

(b) Mean position scores of each visualization group

Figure B.1: The position scores

Table B.1: User position accuracy ANOVA results

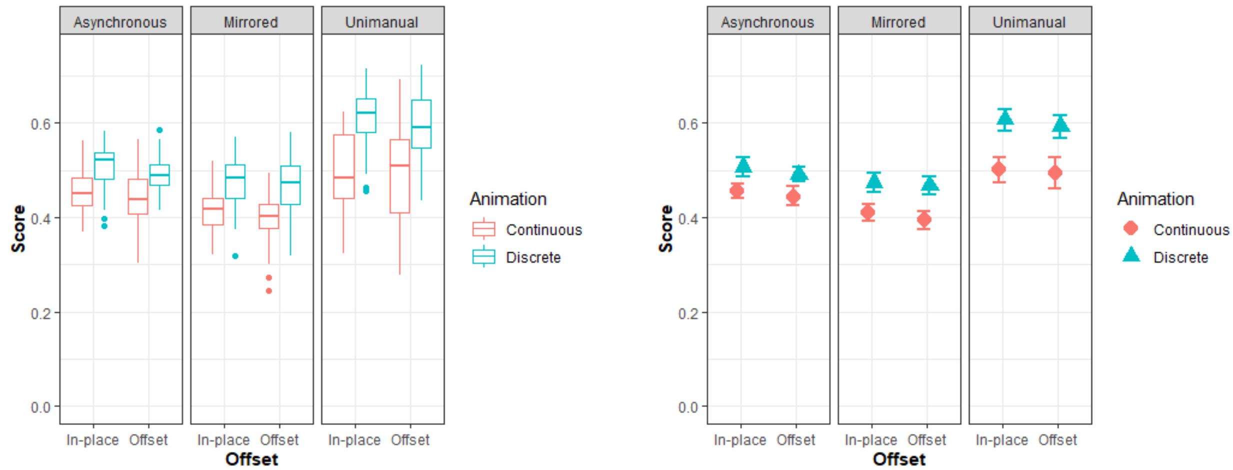
Variable	DoF	DoF Res.	F Value	p Value	Significance
(Intercept)	1	319	3832.793	<.001	***
Offset	1	319	14.008	<.001	***
Anim	1	319	12.847	<.001	***
Hands	2	319	145.621	<.001	***
Offset:Anim	1	319	1.280	0.259	
Offset:Hands	2	319	2.411	0.091	.
Anim:Hands	2	319	20.758	<.001	***
Offset:Anim:Hands	2	319	0.292	0.747	
Hands					
Async - Mirrored		319		0.019	*
Async - Unimanual		319		<.001	***
Mirrored - Unimanual		319		<.001	***



(a) Offset (b) Animation (c) Hands

(d) Animation:Hands (e) Offset:Hands

Figure B.2: The significant position results



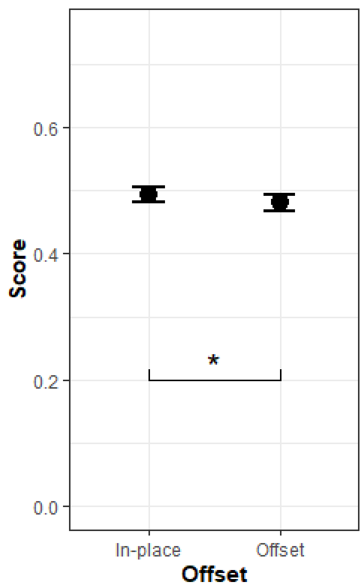
(a) Distribution of rotation scores for each trial

(b) Mean rotation scores of each visualization group

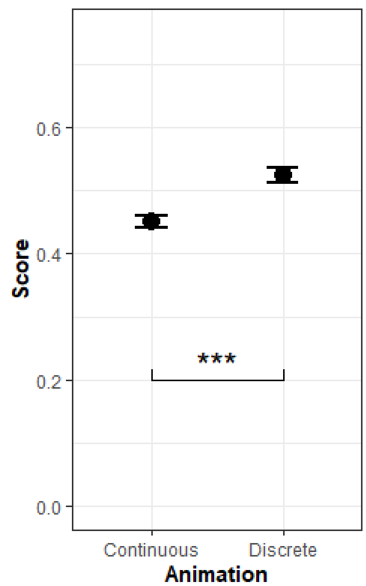
Figure B.3: The rotation scores

Table B.2: User rotation accuracy ANOVA results

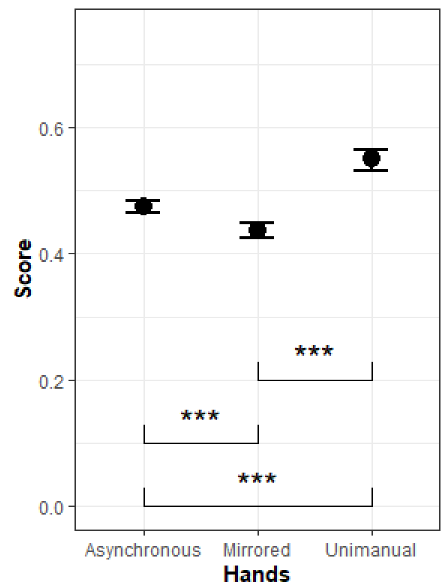
Variable	DoF	DoF Res.	F Value	p Value	Significance
(Intercept)	1	319	4403.027	<.001	***
Offset	1	319	4.419	0.036	*
Anim	1	319	217.614	<.001	***
Hands	2	319	149.080	<.001	***
Offset:Anim	1	319	0.039	0.844	
Offset:Hands	2	319	0.009	0.991	
Anim:Hands	2	319	9.590	<.001	***
Offset:Anim:Hands	2	319	0.211	0.810	
Hands					
Async - Mirrored		319		<.001	***
Async - Unimanual		319		<.001	***
Mirrored - Unimanual		319		<.001	***



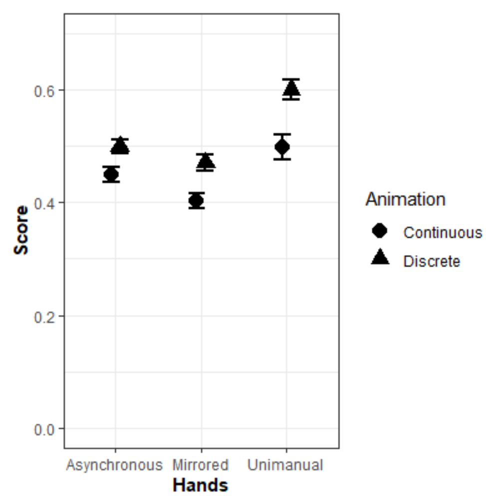
(a) Offset



(b) Animation

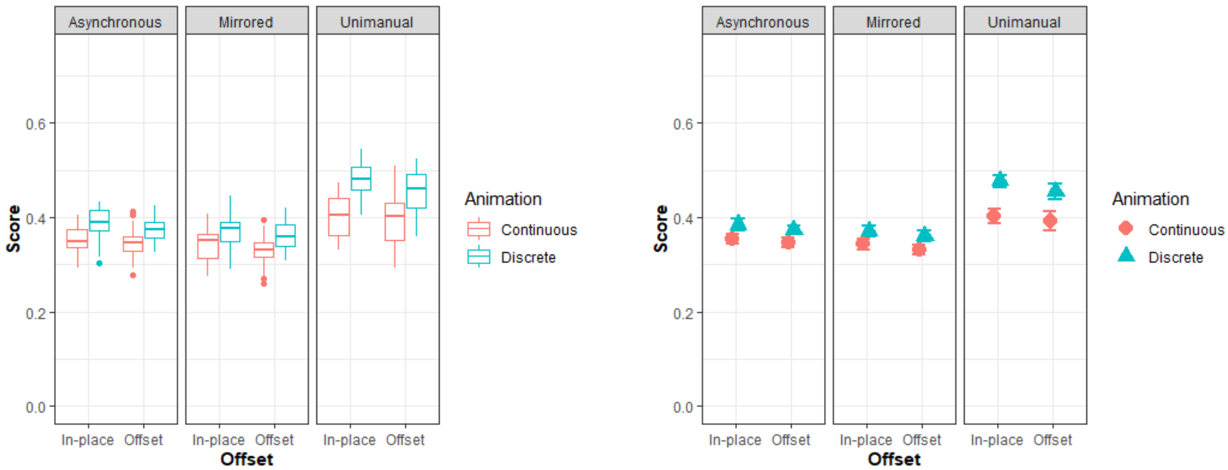


(c) Hands



(d) Animation:Hands

Figure B.4: The significant rotation results



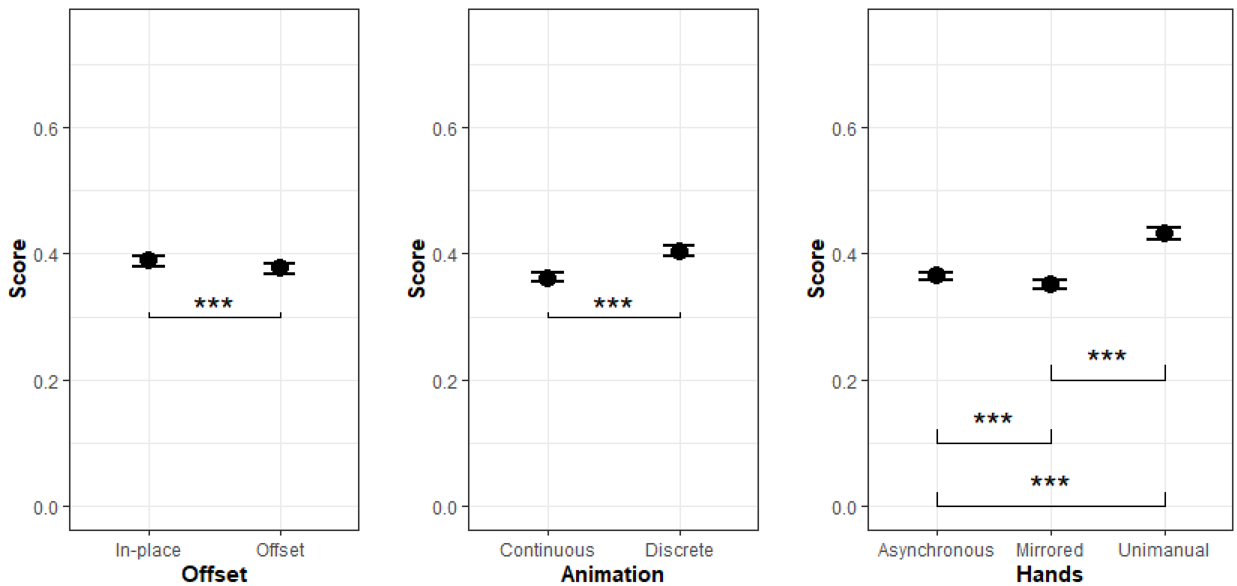
(a) Distribution of scores for each trial

(b) Mean scores of each visualization group

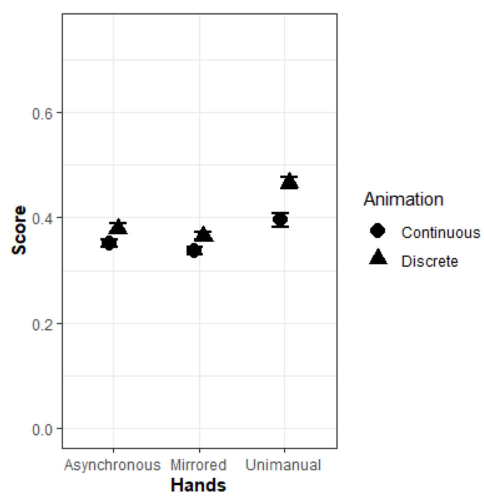
Figure B.5: The overall scores

Table B.3: User accuracy ANOVA results

Variable	DoF	DoF Res.	F Value	p Value	Significance
(Intercept)	1	319	6801.902	<.001	***
Offset	1	319	15.082	<.001	***
Anim	1	319	193.905	<.001	***
Hands	2	319	266.879	<.001	***
Offset:Anim	1	319	0.537	0.464	
Offset:Hands	2	319	0.461	0.629	
Anim:Hands	2	319	20.339	<.001	***
Offset:Anim:Hands	2	319	0.409	0.665	
Hands					
Async - Mirrored		319		<.001	***
Async - Unimanual		319		<.001	***
Mirrored - Unimanual		319		<.001	***



(a) Offset (b) Animation (c) Hands



(d) Animation:Hands

Figure B.6: The significant overall results

Table B.4: Position post-hoc analysis results (P - In-place, O - Offset) (C - Continuous, D - Discrete) (U - Unimanual, M - Mirrored bimanual, A - Asynchronous bimanual)

Pair	Z?	p Value	Significance
Anim:Hands			
CA - DA	-0.009	0.101	
CA - CM	-0.021	<.001	***
CA - DM	-0.009	0.108	
CA - CU	-0.046	<.001	***
CA - DU	-0.083	<.001	***
DA - CM	-0.012	0.030	*
DA - DM	<.001	0.974	
DA - CU	-0.038	<.001	***
DA - DU	-0.074	<.001	***
CM - DM	0.012	0.028	*
CM - CU	-0.026	<.001	***
CM - DU	-0.062	<.001	***
DM - CU	-0.038	<.001	***
DM - DU	-0.074	<.001	***
CU - DU	-0.037	<.001	***
Offset:Hands			
PA - OA	0.004	0.413	
PA - PM	-0.013	0.019	*
PA - OM	-0.003	0.528	
PA - PU	-0.068	<.001	***
PA - OU	-0.048	<.001	***
OA - PM	-0.017	0.002	**
OA - OM	-0.008	0.143	
OA - PU	-0.073	<.001	***
OA - OU	-0.052	<.001	***
PM - OM	0.009	0.090	.
PM - PU	-0.056	<.001	***
PM - OU	-0.035	<.001	***
OM - PU	-0.065	<.001	***
OM - OU	-0.044	<.001	***
PU - OU	0.021	<.001	***

Table B.5: Rotation post-hoc analysis results (C - Continuous, D - Discrete) (U - Unimanual, M - Mirrored bimanual, A - Asynchronous bimanual)

Pair	Z?	p Value	Significance
Anim:Hands			
CA - DA	-0.049	<.001	***
CA - CM	0.047	<.001	***
CA - DM	-0.021	0.019	*
CA - CU	-0.048	<.001	***
CA - DU	-0.150	<.001	***
DA - CM	0.100	<.001	***
DA - DM	0.028	0.003	**
DA - CU	0.001	0.907	
DA - DU	-0.101	<.001	***
CM - DM	-0.068	<.001	***
CM - CU	-0.095	<.001	***
CM - DU	-0.197	<.001	***
DM - CU	-0.027	0.003	**
DM - DU	-0.129	<.001	***
CU - DU	-0.102	<.001	***

Table B.6: Overall post-hoc analysis results (C - Continuous, D - Discrete) (U - Unimanual, M - Mirrored bimanual, A - Asynchronous bimanual)

Pair	Z?	p Value	Significance
Anim:Hands			
CA - DA	-0.029	<.001	***
CA - CM	0.013	0.014	*
CA - DM	-0.015	0.005	**
CA - CU	-0.046	<.001	***
CA - DU	-0.116	<.001	***
DA - CM	0.042	<.001	***
DA - DM	0.014	0.008	**
DA - CU	-0.017	0.001	**
DA - DU	-0.087	<.001	***
CM - DM	-0.028	<.001	***
CM - CU	-0.060	<.001	***
CM - DU	-0.129	<.001	***
DM - CU	-0.031	<.001	***
DM - DU	-0.101	<.001	***
CU - DU	-0.070	<.001	***

APPENDIX C: IRB APPROVAL LETTER

Institutional Review Board
FWA00000351
IRB00001138, IRB00012110
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

UNIVERSITY OF CENTRAL FLORIDA

APPROVAL

February 13, 2025

Dear Gabriela Shamblin:

On 2/13/2025, the IRB reviewed the following submission:

Type of Review:	Initial Study, Categories 6, 7a, 7b
Title:	The Impact of Visualization Styles on Movement Imitation Accuracy in Virtual Reality
Investigator:	Gabriela Shamblin
IRB ID:	STUDY00007550
Funding:	None, None
IND, IDE, or HDE:	None
Documents Reviewed:	• Between-Trial-Survey.pdf, Category: Survey / Questionnaire; • End-of-Experiment-Survey.pdf, Category: Survey / Questionnaire; • HRP-503-TLX- Protocol.docx, Category: IRB Protocol; • Online-Pre-Screening-Demographics-Email-Survey.pdf, Category: Survey / Questionnaire; • Recruitment-Flyer.pdf, Category: Recruitment Materials; • Scheduling-Email.pdf, Category: Other; • Study 7550 HRP-502-TLX-Consent-Adult (1) IRB edits.pdf, Category: Consent Form;

The IRB approved the protocol on 2/13/2025. Continuing review is not required.

In conducting this protocol, you are required to follow the requirements listed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system. Guidance on submitting Modifications and a Continuing Review or Administrative Check-in is detailed in the manual. If continuing review is required and approval is not granted before the expiration date, approval of this protocol expires on that date.

The IRB has approved the **waiver of documentation of informed consent** under 45 CFR 46.117(1)(c)(ii) for this project.

If this protocol includes a consent process, use of the time-stamped version of the consent form is required. You can find the time-stamped version of the consent form in the "**Documents**" tab under the "**Final**" column.

To document consent, use the consent documents that were approved and stamped by the IRB. Go to the Documents tab to download them.

When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Harry Wingfield
Designated Reviewer

LIST OF REFERENCES

[1] "Da Vinci Learning," *Intuitive Surgical*, Dec. 2022, https://www.intuitive.com/en-us/products-and-services/da-vinci/learning.

[2] "About Canadarm2," *Government of Canada*, Jul. 2024, https://www.asc-csa.gc.ca/eng/iss/canadarm2/about.asp

[3] P. Kazanzides, B. P. Vagvolgyi, W. Pryor, A. Deguet, S. Leonard, and L. L. Whitcomb, "Teleoperation and Visualization Interfaces for Remote Intervention in Space," *Frontiers in Robotics and AI*, Dec. 2021, doi: 10.3389/frobt.2021.747917

[4] K. Wormnes, W. Carey, T. Krueger, L. Cencetti, et al, "ANALOG-1 ISS – The first part of an analogue mission to guide ESA's robotic moon exploration efforts," *Open Astronomy*, vol. 31, pp. 5-14, Jan. 2022, doi: 10.1515/astro-2022-0002

[5] "ROV Jason," *National Deep Submergence*, Jan. 2024, https://ndsf.whoi.edu/jason/

[6] "Falcon," *Saab Seaeye*, Mar. 2025, https://www.saabseaeye.com/solutions/underwater-vehicles/falcon

[7] E. H. Korkut and E. Surer, "Visualization in virtual reality: A systematic review," *Virtual Reality (2023)*, vol. 27, pp. 1447-1480, Jan. 2023, doi: 10.1007/s10055-023-00753-8.

[8] A. Martin-Gomez, U. Eck, and N. Navab, "Visualization Techniques for Precise Alignment in VR: A Comparative Study," *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 735-741, Mar. 2019, doi: 10.1109/VR.2019.8798135.

[9] M. Fischer, C. Leuze, S. Perkins, J. Rosenberg, B. Daniel, and A. Martin-Gomez, "Evaluation of Different Visualization Techniques for Perception-Based Alignment in Medical AR," *2020*

IEEE International Symposium on Mixed and Augmented Reality Adjunct, pp. 45-50, Nov. 2020, doi: 10.1109/ISMAR-Adjunct51615.2020.00027.

[10] D. Coffey, F. Korsakov, M. Ewert, H. Hagh-Shenas, L. Thomas, A. Ellingson, D. Nuckley, and D. F. Keefe, "Visualizing Motion Data in Virtual Reality: Understanding the Roles of Animation, Interaction, and Static Presentation," *Computer Graphics Forum*, vol. 31, iss. 3, pp. 1215-1224, Jun. 2012, doi: 10.1111/j.1467-8659.2012.03114.x.

[11] S Kloiber, V. Settgast, C. Schinko, M. Weinzerl, J. Fritz, T. Schreck, and R. Preiner, "Immersive Analysis of User Motion in VR Applications," *The Visual Computer*, vol. 36, pp. 1937-1949, Aug. 2020, doi: 10.1007/s00371-020-01942-1.

[12] J. C. P. Chan, H. Leung, J. K. T. Tang and T. Komura, "A Virtual Reality Dance Training System Using Motion Capture Technology," *IEEE Transactions on Learning Technologies*, vol. 4, no. 2, pp. 187-195, Apr.-Jun. 2011, doi: 10.1109/TLT.2010.27.

[13] E. Charbonneau, A. Miller, and J. J. LaViola Jr., "Teach Me to Dance: Exploring Player Experience and Performance in Full Body Dance Games," *Association for Computing Machinery*, no. 43, pp. 1-8, Nov. 2011, doi: 10.1145/2071423.2071477.

[14] G. Sun, P. Muneesawang, M. Kyan, H. Li, L. Zhong, N. Dong, B. Elder, L. Guan, "An Advanced Computational Intelligence System for Training of Ballet Dance in a CAVE Virtual Reality Environment," *2014 IEEE International Symposium on Multimedia*, pp. 159-166, Dec. 2014, doi: 10.1109/ISM.2014.55.

[15] S. Martirosov, P. Horejsi, P. Kopecek, M. Bures, and M. Simon, "The Effect of Training in Virtual Reality on the Precision of Hand Movements," *Applied Sciences 11*, no. 17, pp. 8064, Aug. 2021, doi: 10.3390/app11178064.

[16] A. Nomoto, Y. Ban, T. Narumi, T. Tanikawa, and M. Hirose, "Supporting Precise Manuel-Handling Task Using Visuo-Haptic Interaction," *Association for Computing Machinery*, no. 10, pp. 1-8, Feb. 2016, doi: 10.1145/2875194.2875216.

[17] J. Bertrand, D. Brickler, S. Babu, K. Madathil, M. Zelaya, T. Wang, J. Wagner, A. Gramopadhye, and J. Luo, "The Role of Dimansional Symmetry on Bimanual Psychomotor Skills Education in Immersive Virtual Reality Environments," *2015 IEEE Virtual Reality (VR)*, pp. 3-10, Mar. 2015, doi: 10.1109/VR.2015.7223317.

[18] L. Jensen and F. Konradsen, "A review of the use of virtual reality head-mounted displays in education and training," *Education and Information Technologies*, vo. 23, pp. 1515-1529, Nov. 2017, doi: 10.1007/s10639-017-9676-0.

[19] S. Rourke, "How does virtual reality simulation compare to simulated practice in the acquisition of clinical psychomotor skills for pre-registration student nurses? A systematic review," *International Journal of Nursing Studies*, vol. 102, Oct. 2019, doi: 10.1016/j.ijnurstu.2019.103466.

[20] S. Pastel, K. Petri, C. H. Chen, A. M. W. Caceres, M. Stirnatis, C. Nubel, L. Schlotter, and K. Witte, "Training in virtual reality enables learning of a complex sports movement," *Virtual Reality (2023)*, vo. 27, pp. 523-540, Jul. 2022, doi: 10.1007/s10055-022-00679-7.

[21] G. Caccianiga, A. Mariani, E. De Momi, G. Cantarero, and J. D. Brown, "An Evaluation of Inanimate and Virtual Reality Training for Psychomotor Skill Development in Robot-Assisted Minimally Invasive Surgery," *IEEE Transactions on Medical Robotics and Bionics*, vo. 2, no. 2, pp. 118-129, May 2020, doi: 10.1109/TMRB.2020.2990692.