Effects of XR Technology on Motor Learning in Fencing

By

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ABSTRACT

Increasing benefits of utilizing immersive training environments for sports like basketball and baseball inspired a fencing coach to inquire its role in enhancing traditional coaching methods. This study investigates the potential of immersive training environments in augmenting traditional fencing pedagogy, which commonly involves mimicry of in-person mentors or videos and practice through recollection. Thirty participants with no prior fencing experience were taught the *advance-jump-lunge* sequence in various extended reality environments, using two common coaching styles: teaching individual sequence elements first and teaching the complete movement before its deconstruction. Initial findings suggest that subjects who learned individual components first generally demonstrated higher learning levels, supporting the part-task training strategy in fencing instruction, although no significant influence of learning environment type on learning levels was observed. This study provides valuable insights into fencing pedagogy and offers a roadmap for future research, which may include a detailed investigation of kinematic properties or additional data collection to track long-term effects and the learning trajectory of alternate movements.

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1. INTRODUCTION

Over the recent year, the application and investigation of extended reality (XR) technology have gained momentum in entertainment, education, construction, healthcare, and sports training, to enhance user experiences [1]. By overlaying virtual environments with the physical world to varying degrees, XR provides the opportunity to engage in highly realistic and interactive experiences.

In the realm of sports, athletes and coaches have increasingly embraced the integration of VR technology to optimize training conditions, to deliver comprehensive biofeedback, and to dissect game patterns. Virtual environments enable athletes to simulate game-like situations conveniently, thereby maximizing their training efficiency while reducing the risk of injury. Furthermore, VR technology aids coaches by gathering data, computing essential metrics, and offering feedback on potential performance improvements [2]. VR technology is applicable across all sports for its customizability to use cases.

Current applications of virtual reality (VR) technology span sports such as baseball, basketball, football, and tennis, facilitating the simulation of opponent movements, repetition of drills under consistent conditions, and focusing athletes' attention on critical aspects. Research continues to ascertain the benefits of immersive training environments. For example, it has been seen as superior to traditional methods for teaching students new to tennis. When comparing the two coaching approaches for mastering forehand and backhand oblique strokes, the performance of students trained in VR environments surpassed that of their counterparts in terms of scores and accuracy [3]. Preliminary research suggests that immersive training may be particularly advantageous for sports that necessitate extensive repetition and feature unpredictable in-game scenarios. Despite the proven benefits of VR training in certain disciplines, validation remains scarce in others, such as fencing—a sport characterized by intense training and rapid responses to unpredictable opponents, suggesting potential advantages of immersive training.

Another underexplored aspect of technology-driven sports training pertains to the specific type of technology employed. While most pedagogical approaches utilize VR to create fully immersive environments, the degree to which digital information is overlaid onto the physical world can be adjusted to suit diverse requirements. VR encompasses an entirely digital world, whereas augmented reality (AR) generates a hybrid environment that merges the real world with computer-generated elements. Mixed reality represents a blend of the two, and XR encompasses all forms of reality-altering technologies. Although VR has demonstrated performance improvements across various applications, the effects of each technology type warrant further investigation and comparison to determine the optimal learning environment. Such ideal conditions may vary depending on the application domain and users, but additional research could reveal patterns that facilitate informed decisions on the appropriate technology to employ in specific scenarios.

2. BACKGROUND

2.1 Motor Learning

Motor learning encompasses the processes that contribute to the acquisition of new motor skills. Fitts and Posner's model of motor learning distinguishes three stages to explain the development of these skills over time [4]. In the initial cognitive stage (1), an individual attains a foundational understanding of the proposed movement and the factors to consider while executing it. This stage is characterized by the acquisition phase, frequently dependent on verbal or visual guidance due to its high degree of error and inconsistency. Following the establishment of basic patterns, the associative stage (2) involves practice and refinement, consolidating the understanding and ensuring its persistence rather than being transient. Finally, the autonomous stage (3) is attained when the skill has been internalized, allowing for its execution with minimal cognitive oversight. At this stage, movements become adaptable, and the acquired knowledge can be applied across various contexts.

Typically, motor learning is classified into one of two forms: explicit learning and implicit learning. Explicit learning is a cognitively oriented process that facilitates the comprehension of task-related elements, such as rules and descriptors. This type of learning often develops the ability to articulate a motor skill as a series of steps. In contrast, implicit learning transpires without significant conscious awareness, leading to the inherent acquisition of a skill. An individual may achieve high automaticity through implicit learning, but they may struggle to verbalize the acquired skillset [4].

2.2 Sports Training

Motor learning can transpire through various means, including physical observation, verbal instruction, and even mental practice. In the context of sports training, particularly when acquiring new skills, procedural learning plays a predominant role. Procedural learning, a subtype of implicit learning, refers to the development of habits or muscle memory through repetitive practice [5]. As the primary learning method, repetition enables the measurement of learning through enhanced performance. Previous research has demonstrated that consistent practice of a singular movement can establish motor memory, and with sufficient repetition, an athlete can achieve automaticity, allowing for performance without significant conscious thought [6].

Coaching styles often differ in the sequence of instruction. Simpler movements are typically taught and practiced as a whole or as a continuous motion. Sports where whole practice is more prevalent include running and swimming. Conversely, more intricate concepts are frequently dissected into component parts and practiced incrementally before increasing in complexity. For instance, a golf swing may be taught as a sequence of backswing, pause, and forward swing. These two techniques are often joint into the whole-part-whole coaching method [7]. Employing this approach, an athlete would initially perform the entire movement in one continuous action. Subsequently, the movement would be deconstructed into simpler steps for detailed instruction, before being reassembled as a unified motion. Despite extensive research aimed at determining the most effective teaching method, there still lacks a definitive answer with outcomes seemingly dependent on factors such as the athlete's skill level and the complexity of the movement.

2.3 Fencing

Fencing is a one-on-one combat sport that is centered around scoring points by contacting the opponent with the tip of a sword-like weapon. Two fencers face one another on a ‘piste’, or a ‘strip’, use a weapon that is wired to the scoring board, and wear uniforms designed to detect points of the weapon and to protect athletes during contact [8].

Fencing is a highly strategic sport at high speeds and its physical techniques rely on combining rudimental movements to create offensive and defensive sequences. There are 3 types of fencing that differ in weapon design and scoring target and although the gameplay strategies and blade movement of each may vary, the fundamentals are relatively consistent throughout. To improve in fencing, whether it be scoring or blocking the opponent's attacks, fencers must practice repeatedly to establish complete control over one's movements. Swift and controlled footwork is necessary to move forward and backward efficiently because their locomotion is mostly constrained in one direction along the piste [9].

3. EXPERIMENTAL DESIGN

This study aimed to obtain preliminary findings from the integration of XR technology into fencing training methodologies. The overarching objective of examining fencing was to devise, if feasible, a training system or coaching tool to facilitate athletes in enhancing their training. Following the generation of ideas and hypotheses regarding potential advantages of training fencers in immersive environments, it was determined that the research should be conducted in stages due to variations in coaching approaches, existing skill levels, and movement types.

The initial phase of research concentrated on identifying correlations between the learning environment and the corresponding learning outcomes for people who have never fenced before. Participants with no prior fencing experience were recruited to minimize the influence of confounding variables and isolate the impact of each immersive environment.

3.1 Study Procedure

The initial step in formulating the study's structure involved determining the aspects and types of learning to be examined. The primary focus was on the subjects' ability to acquire a new movement through repeated practice and its dependence on the immersion environment. To concentrate on understanding the variations in learning, a single fencing sequence, comprising basic elemental movements, was selected for the entire study. A total of 30 subjects with no prior fencing experience were recruited for data collection to minimize bias.

Demonstrations of the movements learned by the subjects throughout the study were prepared across five different environments, each with an acquisition phase and a recall phase. During the acquisition phase, subjects were immersed in an AR or VR environment, observing an avatar, and asked either to simultaneously imitate the avatar's movements or to watch the avatar before replicating its actions. The two acquisition methods both employed physical observation but aimed to promote distinct cognitive learning approaches. The learning phase for each environment was followed by a recall phase, in which the subject was removed from the immersive environment while remaining in the headset to assess movement retention from that session. The state of being in the headset without immersion in a specific environment is referred to as 'passthrough.'

The advance-jump-lunge sequence was selected as the target movement due to its fundamental role in fencing. Comprised of three elemental components (advance, jump, and lunge), this sequence could be taught individually to construct the entire motion, and its components could still be clearly identified within a fluid advance-jump-lunge movement. Given the requirement that all subjects have no prior fencing experience, the advance-jump-lunge combination was deemed to possess an appropriate level of difficulty. It is a sequence of components rather than a single building block, yet simple enough for subjects to grasp the general aspects in one data collection session, which lasted approximately one hour of fencing.

Although the study originated from interests in XR technology in training, the 30 subjects were divided into two groups to also compare the effects of whole practice versus parts practice. Group 1 subjects employed a parts-then-whole approach, practicing the sequence's elements before integrating them into the complete motion. Group 2 subjects utilized the whole-parts-whole method, initially observing the entire sequence without context, then deconstructing it into component parts, and finally attempting the full sequence again after comprehending its constituent parts.

Ultimately, each subject had the opportunity to learn both the components and the connected sequence in each of the five immersive environments, followed by testing in passthrough. The immersion order was randomized for each subject to mitigate order bias. Table 1 below outlines the flow of actions for the two groups of subjects.

Group 1	Group 2
∨ Element Block	∨ Sequence Block
Advance (*x5*) Jump (*x5*) Lunge (*x5*) (*x5*) *environments* Connect all elements in *Passthrough* (*x3*)	Adv_j_lunge (*x10*) ↳ Immersed (*x7*) and in *Passthrough* (*x3*) (*x5*) *environments*
> Sequence Block	> Element Block
> Sequence Block	> Sequence Block

Table 1: Breakdown of trials for each subject group. Group 1 starts with the Element Block (blue) where advance, jump, and lunge are learned separately, and then proceed to the Sequence Block. Group 2 starts with the Sequence Block (green) where the entire advance-jump-lunge movement is learned as one movement. The elements are then taught afterwards.

3.2 Subject Setup

Subjects were equipped with Force Sensitive Resistors (FSRs), infrared markers for motion capture, and a Varjo mixed reality headset for immersion and eye tracking.

Force Sensitive Resistors (FSRs) are sensors composed of a material whose resistance alters in response to applied loads such as pressure, weight, or squeezing [10]. As a result, they are frequently employed to measure relative changes in force and their rates, enabling the detection of contact and movement. In this study, FSRs were utilized on the subjects' shoe soles to record internal rhythm and weight shifts throughout the trials. As illustrated in Figure 1, a total of 8 FSRs were positioned under the heel, outer ball, inner ball, and big toe of both feet.

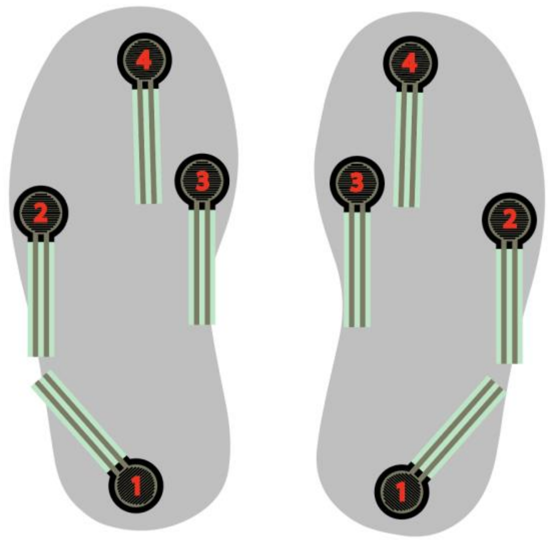
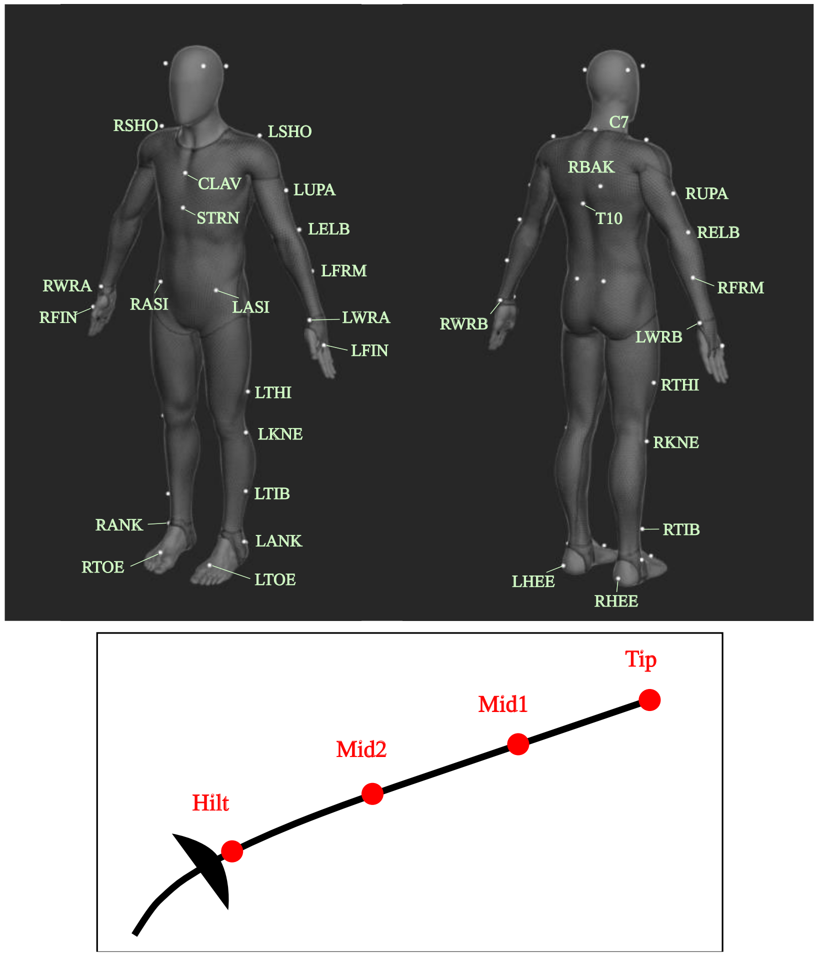


Figure 1: Force Sensitivity Resistor (FSRs) placement on shoe soles. The circular portion detects the pressure under the (1) heel, (2) outer ball, (3) inner ball, and (4) toes. They are placed on both feet.

Subject motion data were captured using infrared reflective (IR) markers and OptiTrack cameras, which emit infrared light to determine the precise location coordinates of the markers. OptiTrack's PrimeX 13 cameras emit 850 nm infrared light that reflects off spherical markers covered in 3M 7610 reflective tape. These cameras receive reflections as 2D images with 1280 x 1024 image resolution at a 240 Hz frame rate and combine images captured from various angles around the room to ascertain position coordinates in 3D with ±0.2 mm accuracy [11]. The built-in conventional full body biomechanics markerset from OptiTrack was adhered to for marking and capturing the entire body's locations. Additionally, the subject was equipped with a fencing weapon, which was marked and tracked using IR tape. Figure 2 below illustrates all 39 points on the skeleton and the recorded locations along the weapon, from the hilt to the tip.

a)



b)

Figure 2: All markers that were tracked using motion capture during data collection. OptiTrack's conventional skeleton markers are labeled on the model in (a) and the points that were tracked along the weapon are labeled in (b).

Lastly, all subjects were situated in a Varjo mixed reality headset for the entirety of the study to ensure the consistency in subject conditions outside of the type of immersion. The Varjo XR-3 provides "true-to-life mixed reality" visuals at over 70 ppd resolution and with a field of view of 115^o to provide a highly realistic immersive environment. The XR-3 was also used to monitor gaze path, where subjects are looking when learning, at 200 Hz [12].

3.3 Learning Environments

The acquisition of the advance-jump-lunge sequence was assessed in a total of five distinct learning environments: Memory, 2D Video, 360 Video, Avatar in AR, and Avatar in VR. All environments were presented using the Varjo XR headset to maintain consistency in physical equipment and visibility across the different scenarios. Figure 3 below depicts the environments from a subject's point of view.

Memory and 2D Video were designed to emulate current training methods that involve following a coach or mentor. A flat video of an advanced fencer performing the move was displayed on one of the walls, simulating the experience of watching a video on a TV. In the *2D Video* environment, subjects were asked to mimic the move in real-time, while in the *Memory* environment trials, subjects were instructed to replicate the move from memory after watching the videos.

The *360 Video* environment featured a recording of the entire room during the performance of an advanced fencer. Subjects were immersed in the video in virtual reality and asked to replicate the fencer's movements simultaneously.

The two avatar environments showcased a fencer avatar repeatedly executing the advance-jump-lunge in the center of the room. The augmented reality environment allowed subjects to see the avatar placed in the real world, while the virtual reality environment immersed subjects onto a fencing piste or playing strip with the avatar. In both environments, subjects could explore various positions around the avatar and were asked to reproduce the movements concurrently as they were being demonstrated.

Figure 3: A subject's view of the 4 learning environments through the Varjo XR-3 headset: (a) 2D video, (b) 360 video in VR, (c) Avatar in VR, and (d) Avatar in AR.

3.4 Fencing Avatar

The learning environments in which subjects participated were generated from recordings of an experienced fencer. A fencing coach was present during data collection to ensure proper movement and to act as an opponent, maintaining consistent directions for the fencer. The fencer performed various basic fencing movements, both as elemental components and smooth sequences, while equipped with infrared reflective (IR) markers, FSRs, and electromyography (EMG) sensors for comprehensive body monitoring. These sensors captured the physiological data of a trained athlete, which served as a reference when analyzing subjects' recordings.

Following data collection, a full-body photogrammetric 3D scan of the fencer was obtained using the Lenscloud scanner. The scanner instantaneously captured two sets of 120 images, which were processed to generate a 3D model suitable for animations [13]. The motion capture data of the fencer's skeleton was then labeled and extracted to animate the model accordingly. These avatar simulations were employed in the AR and VR learning conditions.

The other environments utilized video footage from a 360 camera positioned at the center of the room during data collection. The complete view of the recordings served as the '360 Video' environment, immersing the subject in a VR environment identical to the room with the fencer. The 360-view recordings were subsequently converted to 2D videos, focusing only on the fencer, to replicate the "TV" experience in the "2D Video" and "Memory" environments.

4. EVALUATION METHODS

Primary interested in measuring the learning of a common fencing movement, advance-jump-lunge, the analysis is mainly directed to the Sequence block trials. The Elements block was a time for subjects to understand details of the movement and learning is measured from the complete sequences.

4.1 Data Processing

Before conducting any numerical analysis, the raw motion capture data was labeled according to the markerset depicted in Figure 2 and organized for easy accessibility. Each trial, or recording, contained multiple repetitions of an action and thus needed to be segmented into portions that only included moments when a subject was performing an action. Identifying the start and end times for each action was essential for further analysis.

After labeling the IR markers on the subjects and weapon and exporting all raw data, the start and end frames were determined by examining the motion capture data. The 'start' of the move is defined as the moment the subject is about to initiate movement, while the 'end' is defined as the moment the subject completes the movement. For smooth advance-jump-lunge movements, the end would be the moment the front foot lands after the lunge. By analyzing the front foot's position data, the lunge's end could be identified, as the position would momentarily become stationary before retreating to the starting position. This would also be the moment when the body's momentum stops in order to change directions.

Upon closer inspection of the FSR data during the transition phase, instances of instability and balancing struggles were frequently observed: the center of mass would continue shifting forward after the feet had stopped moving due to the body's momentum not having fully ceased, causing the upper body to tilt forward. Consequently, the end times determined from position data were refined to the moment of initial impact upon landing the lunge, in order to eliminate any excess noise in the weapon trajectory that might arise from regaining balance, such as wobbles and sudden drops from tilting forward. Figure 4 shows a segment of FSR data for the front foot during one advance-jump-lunge, with each line representing the pressure reading of each FSR placed on the sole, as shown in Figure 1. The black vertical lines indicate the times determined from motion capture, while the bolder purple line represents the refined end of the movement. Each action now has a start and end time that can be used for referencing its corresponding data in the raw files.

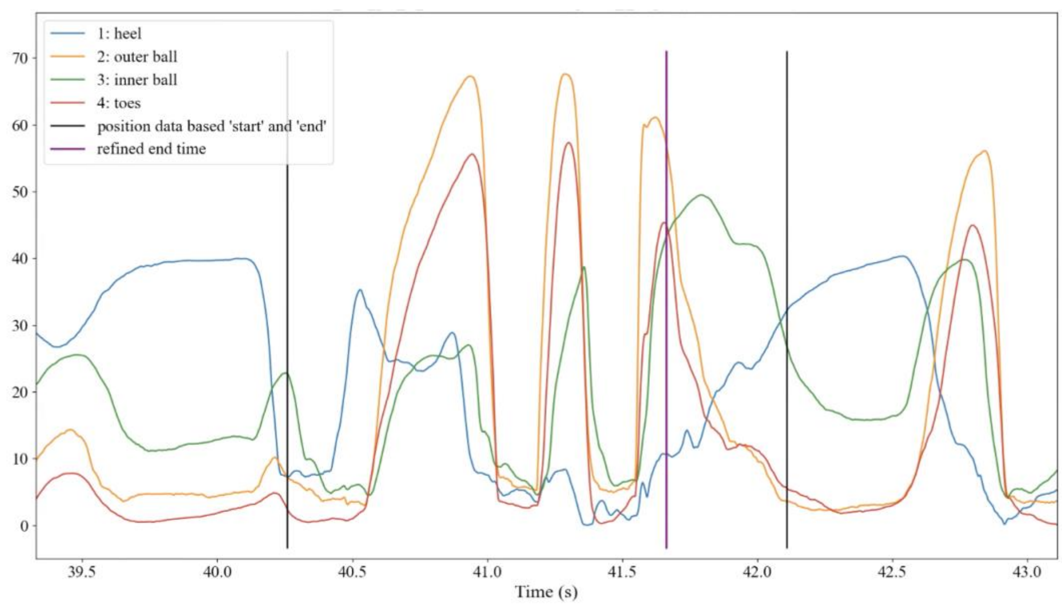


Figure 4: FSR signals of the front foot plotted against time during one advance-jump-lunge. The blue, orange, green, and red data are the pressure on the heel, outer ball, inner ball, and toes, respectively. The vertical lines are the start and end of the action determined from the position data of toe marker, shown in black, and refined based on FSR readings for the initial strike of the foot, shown in purple.

4.2 Movement Visualization

The breakdown of the movements were used for the motion capture data was initially visualized in Blender in an organized fashion to identify any noticeable patterns and to gain insights into potential analysis techniques for subsequent steps. During this stage of data visualization, the focus was on the front toe marker (RTOE or LTOE) and the weapon tip (Tip) throughout the complete advance-jump-lunge sequences. The front toe's path served as an indication of the direction and total distance traveled during the movement, while the tip was used to observe the stability and consistency of the subjects' movements.

The extracted start and end times for each advance-jump-lunge attempt facilitated easy access to the individual paths of each marker during each action. To plot these segments in 3D in a visually comprehensible manner, they were translated using principal component analysis (PCA) to align them all in the same direction. PCA is employed to reduce the dimensionality of a dataset by identifying the principal axis or direction of a cluster of points in a coordinate space [14]. A change of basis is then performed on the dataset to assign the principal basis a new direction. In order to align the direction of all markers tracked in each action, PCA analysis was conducted on the front toe marker segment to determine the principal direction of every advance-jump-lunge and to translate the paths to start on the y-axis, move in the positive x direction, and remain above the z=0 plane. All other markers present in the action were then rotated accordingly. Figure 5 exemplifies how one subject's data could be visualized using this method. This example presents the front toe and weapon tip marker paths during all advance-lunge-jump actions completed by one subject, color-coded by the environment in which the action was performed.

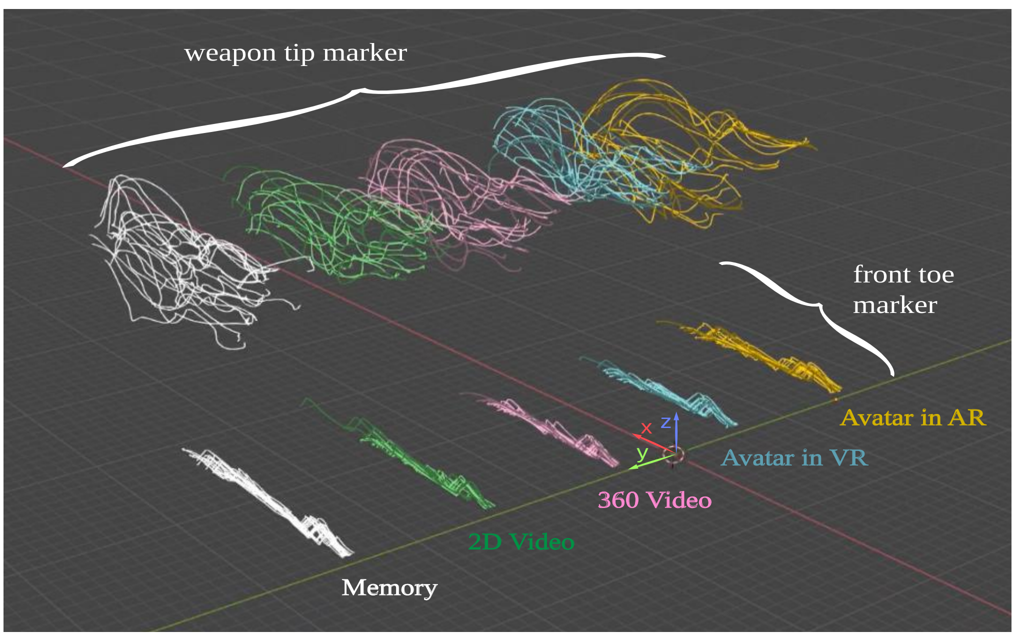


Figure 5: Motion capture data visualization in Blender during every single advance-jump-lunge completed by one subject. The paths lined up along the y-axis, travelling relatively parallel to the x-axis, and on the $z = 0$ plane, are the paths of the front toe marker after aligning each of their principal directions. The cluster of paths “in the air” above the toe paths are the locations of the tip of the weapon. Each of the actions are categorized by its environment and the actions of each group were color-coded and plotted overlaid on one another. White for *memory*, green for *2D video*, pink for *360 video*, blue for *avatar in VR*, and yellow for *avatar in AR*. Each color, except white, have 2 shades in the plot and the darker shade paths are for those completed in *passthrough* to test retention after each immersion.

Plotting actions grouped by learning environment was used to seek general patterns within each environment and any reoccurring differences between environments across subjects. The actions were then also graphed individually in chronological order.

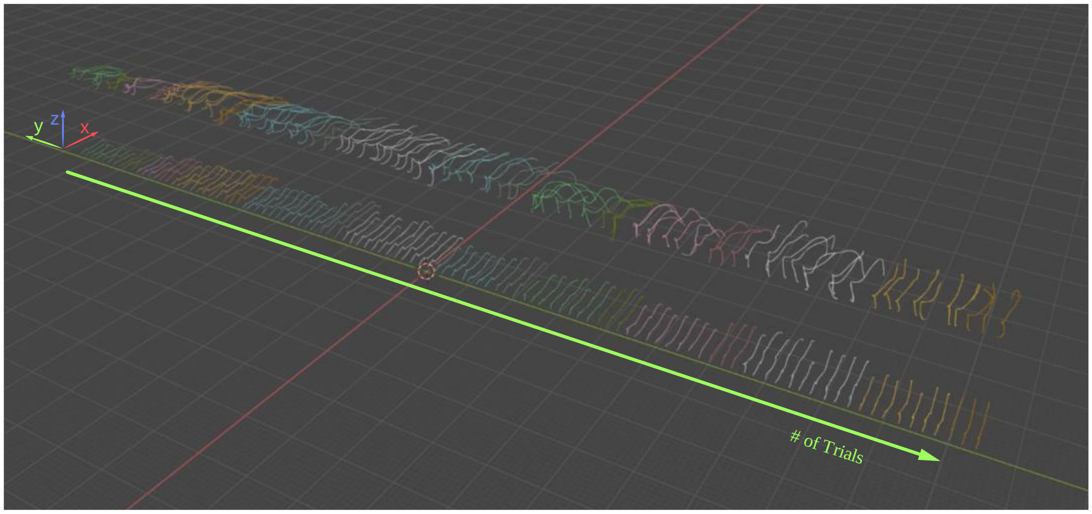


Figure 6: Same motion capture data visualization of the front toe and weapon tip markers as figure 5 but plotted individually in order of occurrence. They are still color-coded by environment, along with its respective passthroughs, traveling in the +x direction, and progressing with time in the -y direction.

4.3 Learning Metrics for Advance-Jump-Lunge

In order to measure and compare the learning of a single movement sequence across various learning environments, it is essential to define what constitutes 'learning.' The characteristics of a proper advance-jump-lunge must be determined to identify the calculations needed for analyzing the data of each performed action. For the scope of this paper, the analysis is at the Tier 1 level, which seeks to answer broad 'yes or no' questions within each attempted advance-jump-lunge to roughly categorize them as 'successful' or 'unsuccessful' attempts. These criteria were verified by a fencing coach and were evident in the reference fencer's physiological recordings.

One of the features used to determine the 'success' of the advance-jump-lunge attempts was the subject's rhythm during each attempt. The sequence that the subjects are attempting to learn consists of three elemental moves called 'advance,' 'jump,' and 'lunge.' Although these moves are smoothly connected and performed as a single movement in the 'sequence' block trials, the subject's FSR recordings should still display three "bounces" for each step in the sequence. This rhythm check was used to simply indicate if each action attempt consisted of all three parts and thus could be considered an advance-jump-lunge sequence, yielding a 'yes' or 'no' response. It is important to note that this is solely a cadence check based on FSR data and does not reflect the quality or correctness of each component. Figure 7 shows examples of both successful (a) and unsuccessful (b) scenarios by highlighting each 'bounce' within the sequence actions with colors.

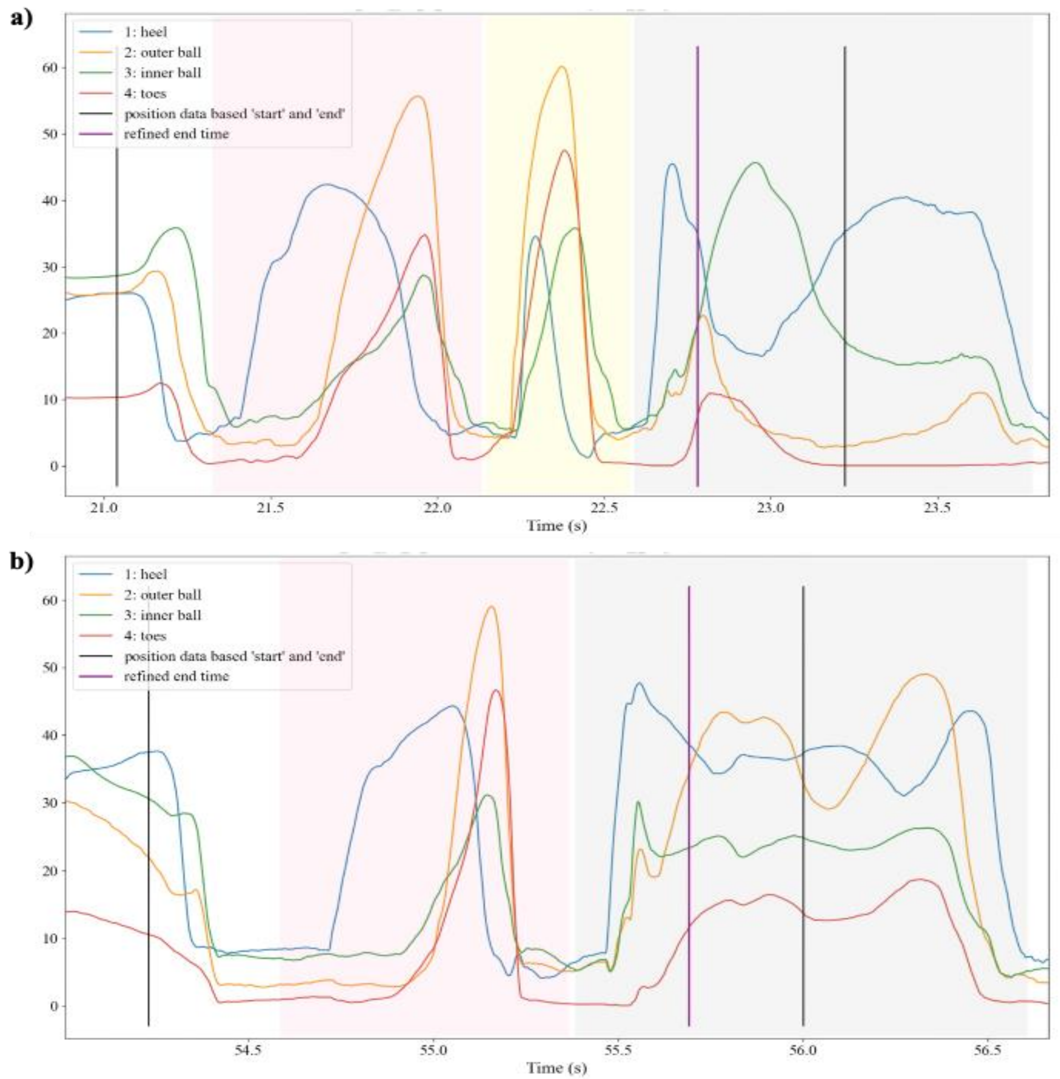


Figure 7: Advance-jump-lunge rhythm check with front foot FSR data. Each indication of a movement at the foot, the 'bounces', is boxed and counted in brown. Action (a) has 3 clear strikes with the front foot, getting categorized as 'successful', and the front foot in action (b) only strikes twice, unsuccessful. The duration of each step of the foot is highlighted with a different color: pink, yellow, or gray.

These two sample segments of FSR data in Figure 7, represent the most commonly observed patterns: three beats and two beats in the movement. In panel (a), the first strike shaded in pink corresponds to the advance, the second strike shaded in yellow is the jump, and the third strike shaded in gray is the final lunge. In panel (b), the front foot only makes two strikes. If an action had only two beats, it typically consisted of either an advance followed by a lunge or an advance, jump, and then a forward extension of the weapon for the lunge without moving the feet. The four individual signals and their correlations can be examined more closely to identify other characteristics.

One piece of information that can be derived from the relationship between the four sensors after plotting the FSR data is the type of landing during the lunge portion. With the FSR configuration described earlier in Figure 4, the FSR signals of each foot, comprising four signals plotted against time, can be analyzed to determine which part of the foot makes the initial strike when landing the lunge and how weight shifts across the feet throughout the action. Generally, most landings could be classified as either a 'heel strike' or a 'toe strike'. A lunge that initially made contact with the ground on the heel and then leaned onto the toes was considered a 'heel strike,' while a lunge with the front portion of the foot making initial contact with the ground, often followed by a weight shift onto the heels, was considered a 'toe strike'. The heel strike was deemed the 'successful' case as it was associated with a more confident and stable lunge. Figure 8 illustrates the FSR data of the front foot as it lands a lunge for both a heel strike and a toe strike. If the heel signal spikes first and then decreases while the pressure on the toes and ball of the foot increases, it is a heel strike. Conversely, if the toes, inner ball, or outer ball signal spikes first and the heel reading is significantly lower, it is considered a toe strike.

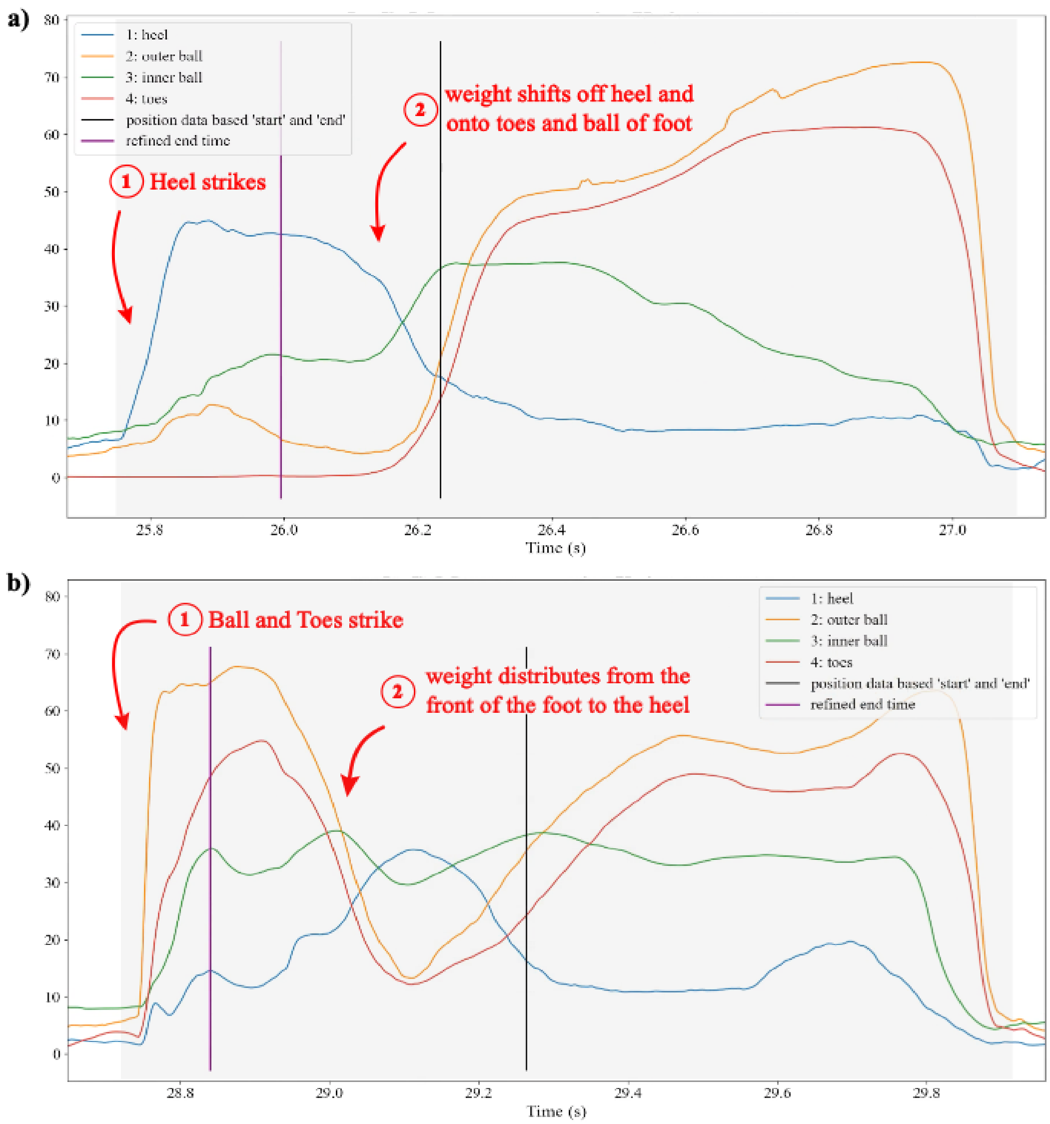


Figure 8: FSR data of the front foot while landing a lunge, specifically shaded in gray. Lunge (a) is considered a *heel strike* because the force on the heel, the blue line, sharply increases first and then slowly decreases while the rest of the foot, orange, green and red lines, starts applying pressure as the heel signal decreases. On the other hand, lunge (b)'s landing strikes the outer ball and toes first while the heel applies no pressure until the pressure under the ball and toes decrease, making it a *toe strike*.

The quality of each advance-jump-lunge and the learning progress of each subject will be assessed using these two evaluation methods for the analysis presented in this paper. In this study, an advance-jump-lunge is considered "good" or "proper" if the movement consists of three 'beats' and the front foot lands on its heel during the lunge.

5. Results and Discussion

With an aim to investigate the performance and learning of an advance-jump-lung sequence, this studying primarily focuses on analyzing sequence trials rather than those of the individual elements. It is to gain insight for how complete sequences should be orchestrated. Analysis initiates with the visualization of actions in a three-dimensional space, progressing to a comprehensive evaluation based on two key characteristics: action rhythm and the style of lunge landing.

5.1 Pattern Visualization

Motion capture data visualization of the feet and weapon markers mentioned above were utilized to gather inspiration for advance-jump-lunge metrics to analyze. he feet markers served as a general guide to the forward movement of the body during the sequence, while the weapon paths were analyzed for any evidence of temporal learning.

Upon examining these visualizations, both for individual subjects and collectively, it appeared that some subjects' feet markers were influenced by the type of learning environment. Figure 9 presents a bird's-eye view of the front foot marker trajectories for all sequences performed during acquisition by one subject, grouping these paths by their corresponding environment. This perspective emphasizes the distance traversed by the front foot during the complete advance-jump-lunge sequence. Initial observations suggested the shortest distance traveled occurred in VR, the longest in Memory, with an incremental gradient in between.

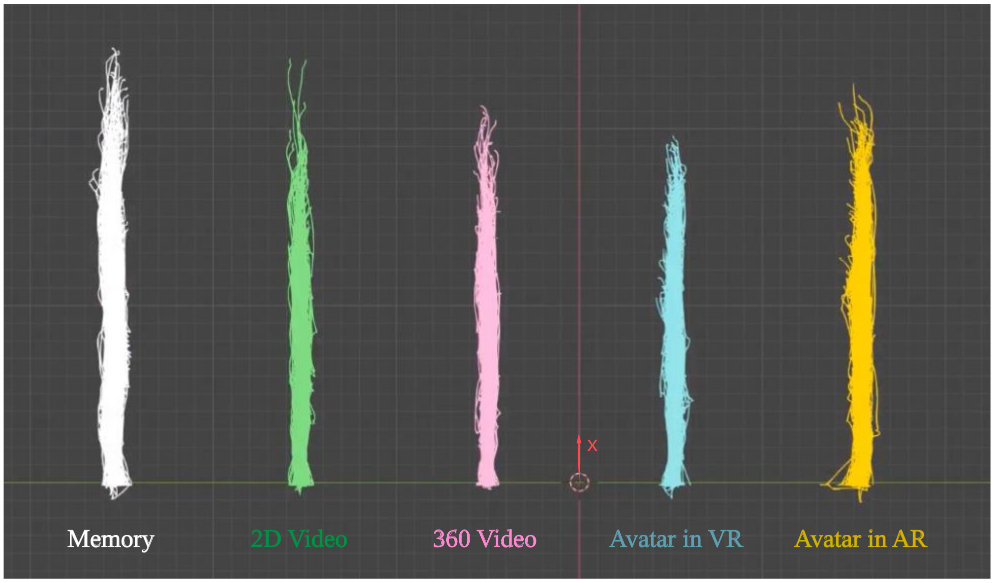


Figure 9: Front toe marker paths during all advance-jump-lunge of one subject. They are rotated and mapped to all travel along the positive x-axis direction and then grouped by its learning environment.

Subsequently, we computed the numerical distances traveled in each sequence action using the translation of the front foot toe marker. These distances were categorized by the modality in which they were performed, normalized by dividing by the group average, and then contrasted as depicted in Figure 9.

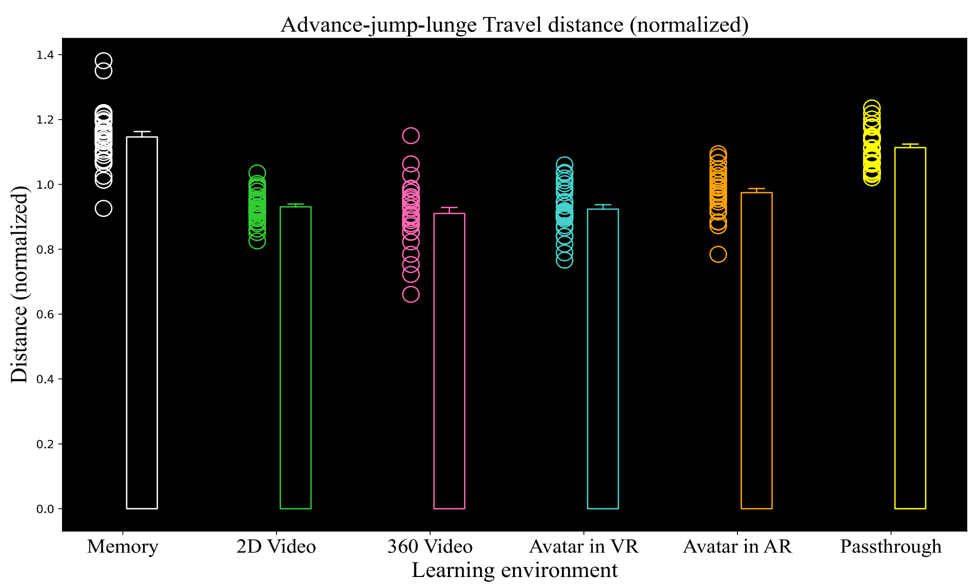


Figure 10: Normalized distance traveled during each advance-jump-lunge, categorized by its learning environment. Each action's distance is plotted as circles and the average distance traveled in each environment are plotted with a bar graph.

Upon investigating disparities and parallels across the learning environments, the degree of immersion emerges as a potential determinant for variations across modalities. From VR to AR to passthrough, the extent of digital simulation diminishes while the observed translocations during the movements increased. The distances traveled during the actions performed in AR were significantly longer ($p = 0.0021$) than those executed in VR. Memory and Passthrough modalities then motivated movements significantly larger, with $p < 0.0001$ for both, than those in AR as well. A possible explanation is that when immersed in a VR simulation, subjects are deprived of any visual feedback regarding their movements or immediate environment, which might induce a sense of insecurity. Conversely, in AR, subjects have a digital avatar superimposed on their actual surroundings, promoting a sense of safety and fostering longer strides with greater confidence. In memory or passthrough settings, subjects are fully engrossed in self-monitoring their movements, resulting in larger, more confident strides.

Initial visualization of the motion capture data during the execution of the advance-jump-lunge sequences suggests a potential preference for AR environments over VR, possibly due to enhanced comfort and safety for the fencers. However, to substantiate these correlations and draw a conclusion about the influence of XR technology on the quality and learning efficiency of fencing movements, it is necessary to measure and analyze additional metrics, beyond travel distance.

5.2 Effect of Immersion

Majority of the data, computations, figures, and findings were organized by learning environment type, as the principal objective of this study was to explore the correlation between immersive environments and their associated motor learning levels.

After determining 'yes' or 'no' for rhythm check and 'heel strike' or 'toe strike' for landing type for each identified advance-jump-lunge attempt across all subjects, the results were initially plotted using a raster plot to visualize all outcomes simultaneously. Figure 11 below depicts a raster plot for each learning metric, with each row displaying the results of all actions completed by an individual subject. The outcomes are represented through vertical lines of two different sizes: the taller or full-size tick mark indicates either a successful identification of three pulses in the FSR data during rhythm check or a heel strike ascertained from analyzing lunge landings. The shorter lines in the plots represent the opposite results of each analysis: a cadence count other than the three beats in an advance-jump-lunge, and a lunge with a toe strike.

Panels (a) and (c) plot the responses for each action in chronological order along the x-axis to examine learning over time. Panels (b) and (d) group the actions according to their corresponding learning environment and then plot them in chronological order. Each action's associated environment is indicated by the line's color: white for memory, green for 2D video, pink for 360 video, blue for avatar in VR, and orange for avatar in AR. The distinction between the acquisition stage and recall stage, or each environment except memory, is represented by the shade of the color: actions performed to test retention after acquisition in an immersive environment are plotted with a darker shade of that environment's color.

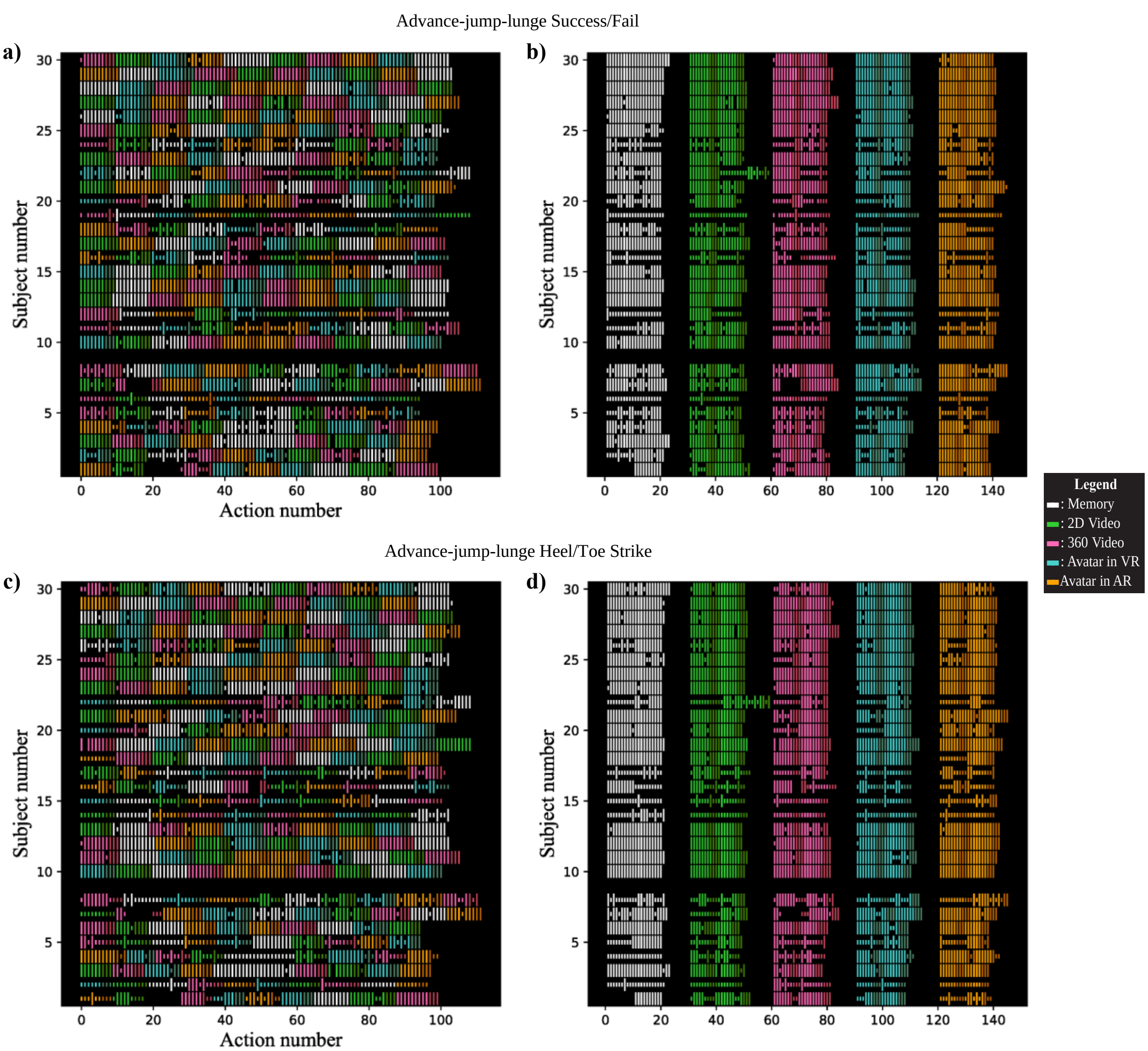


Figure 11: Raster plot displaying all results of the evaluated learning metrics. Plots (a) and (b) contain the results of the rhythm check: taller lines for actions that successfully consisted of 3 components, and shorter ones for those that did not. (c) and (d) are the results of determining the landing type of the lunges: full-size ticks for heel strike and shorter ones for toe strike. Each row of ticks represents the results of one subject. Plots (a) and (c) display them strictly in chronological order while (b) and (d) groups them according to its acquisition environment and then in chronological order for each group.

Each row in the raster plot reveals the learning progression of each subject regarding the advance-jump-lunge sequence, observed within approximately one hour of their initial exposure to the movement. Various learning progressions can be discerned, including subjects who quickly learned a specific style of advance-jump-lunge (regardless of its correctness), those who intermittently switched forms, and those who demonstrated overall inconsistency. The relationship between the two characteristics within individual subjects also varied, with some displaying a direct relationship where proper rhythm and heel strike occurred together, and others exhibiting an inverse relationship.

For example, when examining the progression as a function of time and learning environment in Figure 11(b) and 11(d), Subject 22 demonstrated more advance-jump-lunges with proper rhythm in the latter half of the trials but had more actions with a heel strike in the first half. The raster plot served as a tool for visualizing the raw characterization results to identify potential correlations before performing calculations.

However, while this form of results provides a wealth of information and reveals patterns between environments for individual subjects, it is challenging to generalize across all subjects. In pursuit of the goal to identify varying results across learning environments, each action was labeled with its corresponding subject and the environment in which it was performed for all computations. From the rhythm-check data, accuracy was calculated as the ratio of 'yes' responses to the total number of actions. For the lunge landing determinations, the ratio of heel strikes to the total number of actions was calculated. These ratios were computed for each subject's performance in each environment. Figure 11 presents the results of each learning condition through a combination of a bar graph and scatter plot. The scatter plot displays each subject's success rate and heel strike rates per category, while the bar graph illustrates the average rates in each environment with error bars.

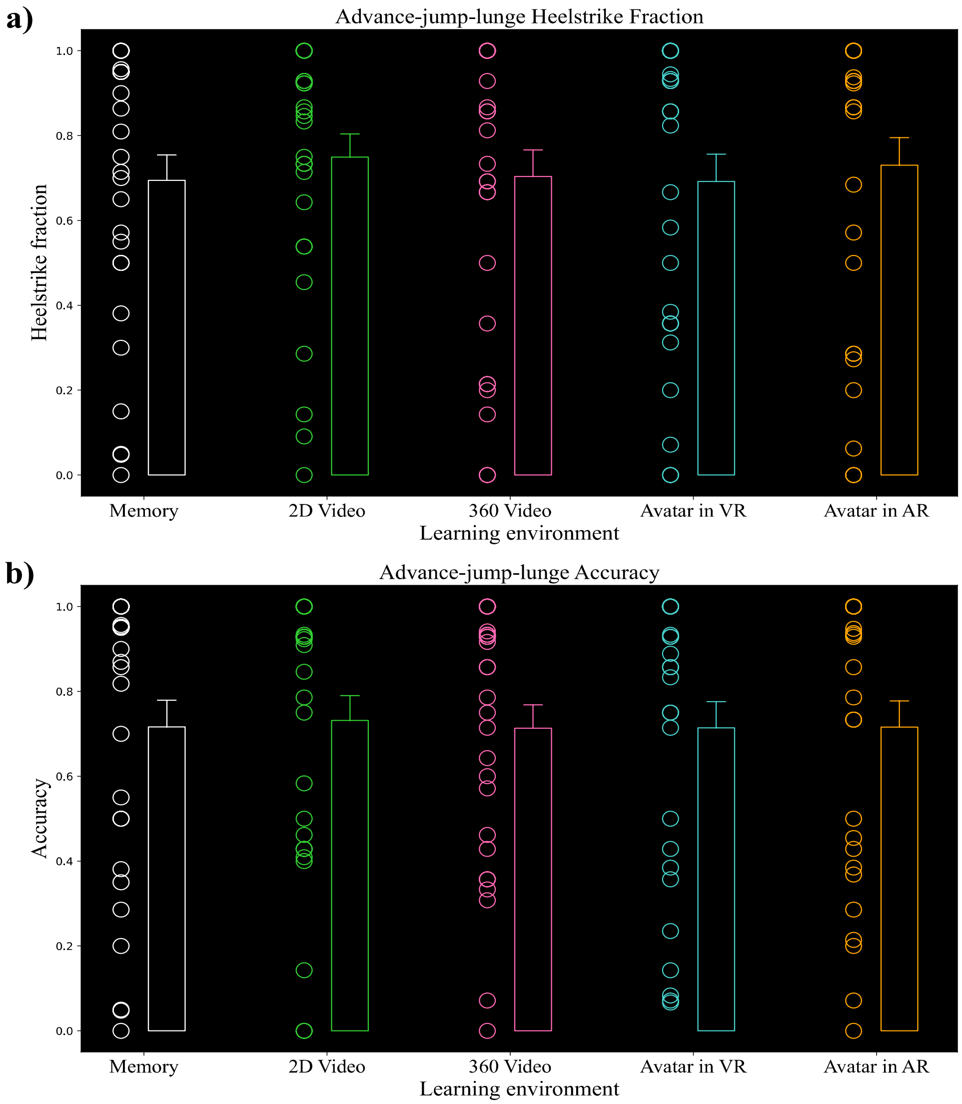


Figure 12: Scatter-bar graph of each subject's accuracy of replicating the proper rhythm of an advance-jump-lunge sequence in (a) and each subject's rate of heel strikes in (b), both categorized by the environment that the action was performed in. Each subject's performance is plotted, per category, as the circles and their values are averaged and graphed as a bar graph and its error bar.

The findings from these figures may clarify why it was challenging to discern generalizations from the raster plot. The raster plot organized by subject and learning environment displayed a variety of potential relationships and their hypothetical causes, yet none were consistently evident across all subjects. The average 'success' rates, executing an advance-jump-lunge with the proper tempo and heel strike, showed no significant differences between learning environments. P-values of paired t-tests conducted between modalities for each of the modalities are listed in Table 2. Although the results of movement visualization hinted at the possibility of differing behavior between AR and VR environments, both metrics were learned to a similar extent across all environments and subjects.

Accuracy		**Heel-strike Fraction**	
Avatar in AR	2D Video	Avatar in AR	2D Video
Avatar in VR	360 Video	Avatar in VR	360Video
$p = 0.9556$	$p = 0.5667$	$p = 0.2603$	$p = 0.2377$

Table 2: Calculated p-values from paired t-tests comparing avatar in AR and avatar in VR, and 2D video and 360 video for both the accuracy and their heel-strike fraction. None of these comparisons are deemed significant because the p-values are all larger than 0.05.

Although the aim was to identify advance-jump-lunge metrics to determine the 'best' immersive technology for teaching fencing moves, the absence of a clear 'winner' still offers valuable insights. One possible explanation for the insignificant results is that the effect of immersion is subject-dependent. The progress of learning fencing movements, and potentially other sports techniques, may rely on various factors, such as the athlete's background and preferred learning style, which ultimately influence how immersion impacts the individual. This would lead to an 'ideal' learning environment for each person, but not a universally applicable answer.

Moreover, the analysis performed on this dataset so far focuses on general aspects of each subject's actions and measures learning in a more qualitative manner by examining specific features in each action. Future steps should involve refining the criteria for a "good" advance-jump-lunge by analyzing the fencer's data. Possible examples include identifying general shapes that certain marker paths should follow, patterns in FRS readings that reveal weight shifts throughout the action, center of mass velocity calculations, elastic energy flow cycles within the body, and other kinematic properties. These features should be extracted from and compared between the avatar and all subjects. Error computations for all features can then be employed to redefine a 'proper' advance-jump-lunge and re-measure learning across environments.

5.3 Effect of Teaching Style

Subjects of this study were assigned to one of two groups to compare the effects of two common teaching styles: group 1 used parts-then-whole practice, group 2 used whole-parts-whole practice. The two coaching methods were also compared according to the results of evaluating advance-jump-lunges based on their rhythm count and lunge striking type. The same type of analysis, as the one used to compare learning environments, is conducted again to now compare across subject group types.

Initially, a raster plot is generated and color-coded by subject group type to identify any visually noticeable patterns between subjects in each group. Figure 13 below presents the same rhythm check results as in Figure 11(a) and lunge strike type outcomes as in 11(c), with subjects of group 1 displayed in white and subjects of group 2 in peach. The longer lines still denote the proper rhythm (a) or heel strike (b), and the shorter ticks indicate an incorrect rhythm count (a) or toe strike (b) in the corresponding graphs.

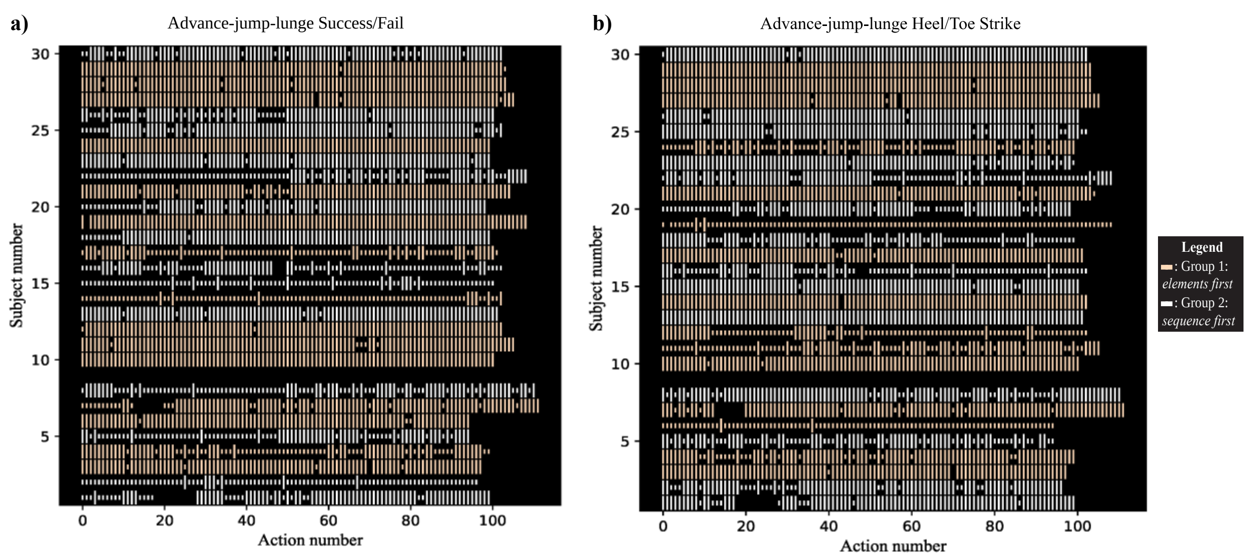


Figure 13: Results of the FSR-based rhythm count check (a) and the results of FSR-based lunge type classification (b), both color coded by subject group type. The action types of those executed by subjects in group 1 are shown in peach and those by subjects in group 2 are in white.

Color coding the results according to group type accentuated possible relationships that were not visible when grouped by learning environment. For example, when color coded by learning environment, it was noticeable that some subjects were able to grasp the two concepts from the start of the study and continued to repeat them throughout the majority of the trials, but it did not seem to be affected by the learning environment. Now that the subjects are grouped, it appears that most of those subjects are of group 1, especially in plot (a). This hinted at the possibility of finding a significant difference in accuracy and heel-strike rate between the two groups.

The accuracy, fraction of actions with proper cadence, and the ratio of heel strikes were computed again for all actions of each subject. The same metrics were used to compare the two coaching methods by categorizing the individual results according to their group number. Figure 14 displays the 2 ratios computed for each subject and grouped by their respective learning method. Elements first for group 1 and full sequence first for group 2.

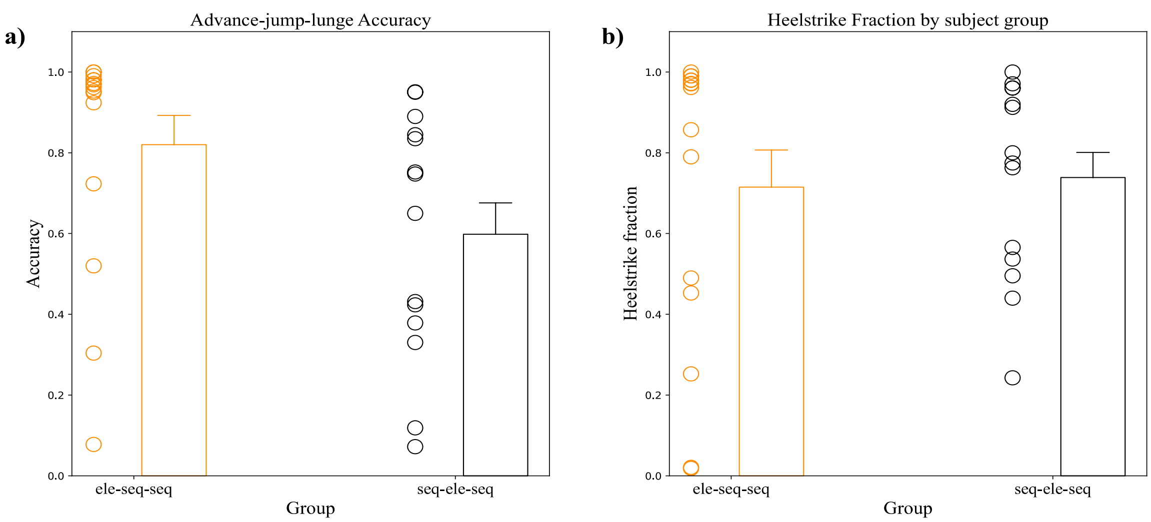


Figure 14: Accuracy of advance-jump-lunge according to action cadence (a) and the portion of heel strikes (b), averaged per subject and per group type, elements first or sequences first. In both plots, individual subjects are plotted with circles and each group's average is shown with a bar graph.

When comparing the same two metrics of advance-jump-lunge across teaching methods, different results were observed. The likelihood of executing a heel strike, as shown in Figure 14(b), was similar for both groups of subjects, but the accuracy of completed advance-jump-lunges was significantly higher ($p = 0.0083$) for those who learned the individual components first compared to those who learned the full sequence first.

Noticing a non-negligible effect of coaching style on rhythmic accuracy, the raster plot in Figure x(a) was further analyzed in a different manner. Instead of performing calculations within rows of the raster plot for subject-based analysis, calculations were conducted along columns at each action number. 'Scoring' successful 3-step advance-jump-lunges with a 1 and all others with a 0, the results were smoothed by averaging all scores of each repetition and then passed through a low pass filter. By separating subjects based on their group, the resulting learning levels of the subjects in each group were plotted as a function of action number in Figure 15.

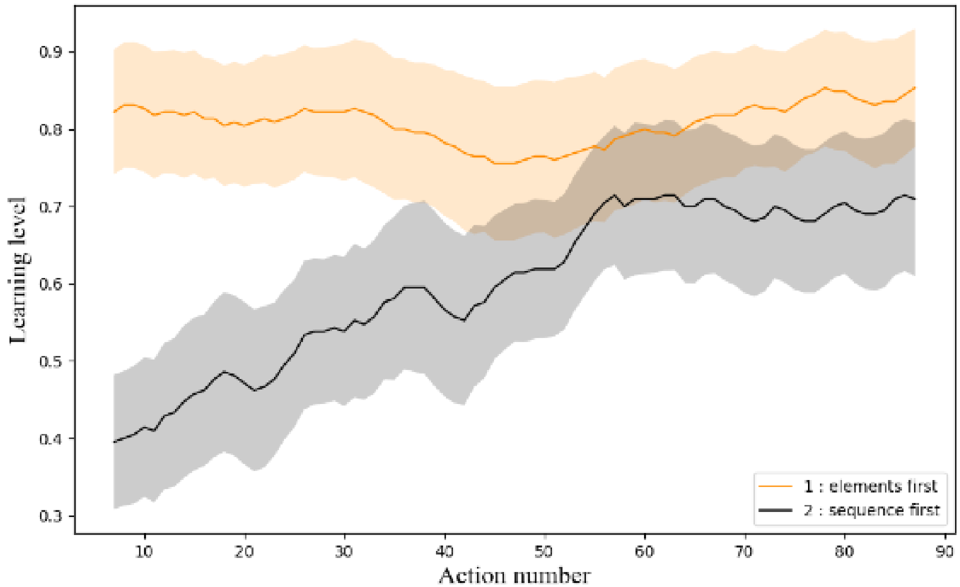


Figure 15: Learning levels calculated for each repetition of advance-jump-lunge across all subjects. The average learning progress of those who learned elements first are shown in orange and those who learned sequence first are displayed in black. The shading around the lines are the respective standard deviations.

Up to this point, based on the identified advance-jump-lunge metrics, the two coaching approaches seem to influence learning, as illustrated in Figure 15. The learning level for subjects who were taught elements first began with high accuracy, approximately 0.8, and maintained relative consistency over numerous repetitions. In contrast, subjects who learned the sequence first typically started with lower accuracy, around 0.4, but experienced rapid improvement until beginning to plateau during the latter half, approaching the level of group 1 subjects.

Considering the structure of Sequence and Element Blocks within the study, the advance-jump-lunge sequences under analysis belong to two distinct Sequence Blocks. For group 1 subjects, elements first, both sequence blocks transpire after establishing the sequence components, yielding higher accuracy in terms of action rhythm. Inversely, subjects in group 2 learn the sequence first, with elements being taught between the two sequence blocks. This order appears to manifest in the learning curve's behavior midway through the actions. During the initial sequence block, subjects seem to commence with uncertainty about the task and learn as the trials progress, as evidenced by the increasing learning levels from action numbers 1 through 50 in Figure 15. Subsequently, subjects learn the individual elements before repeating the sequences. The learning levels during the second sequence, approximately the latter half of actions, remain mostly constant.

In general, learning is observable during both block types within the study, but predominantly during the block presented first. The outcomes of teaching sequence first can be observed in Figure 15, and although not explicitly illustrated, it can be reasonably deduced, by comparing against group 2 subjects' data, that learning takes place in the elements block before executing their first seamless advance-jump. Nevertheless, when examining the learning levels of both groups toward the study's conclusion, subjects who learned elements before connecting them consistently exhibit higher learning levels. This leads to several questions to be investigated, possibly in future data collection sessions: Does learning the entire sequence before its elements impede overall learning? Will both groups eventually attain the same learning level after more repetitions? Is a single session of data collection sufficient for measuring learning, or should subjects return for multiple sessions?

Implementing the study with two subject groups to distinguish teaching methods offered some insights into the optimal approach for teaching fencing to those who are just beginning. Based on a single day of learning, subjects who learned individual components first generally exhibited higher learning levels, bolstering the case for part practice in fencing training. However, these findings are not conclusive, as the learning progress was only measured for a specific movement sequence and for immediate learning after initial exposure. One potential suggestion for further data collection is to reinvite the same subjects to assess their progress over time and analyze any long-term effects of the two coaching styles. Subjects should also learn additional sequences of varying styles to validate the effects observed for advance-jump-lunge. Additionally, the subject group type, elements first or sequence first, should be randomized for each movement to mitigate bias from previous experiences.

6. CONCLUSION

Interested in expanding the existing research about the effects of immersive technologies in sports training, a study was designed to seek ideal learning conditions for fencing training. Specifically focusing on the advance-jump-lunge sequence, the study monitored how motor learning levels changed with the type of immersive environment, and the type of teaching.

It was found that subjects who learned individual components first generally demonstrated higher levels of learning, supporting the argument for parts practice in fencing training. However, the results also indicated that although subjects may feel different emotionally, no significant differences were found in the learning progress when comparing various immersive environments, suggesting that the ideal learning environment may be dependent on individual factors such as an athlete's background or preferred learning style.

Despite the insights gained from this study, there are limitations that must be acknowledged. First, the data analysis only identified 2 metrics of the subjects' advance-jump-lunge attempts. More measures need to be identified to better quantify movement performance, measure learning, and compare accuracy with the avatar fencer's movements. Second, the learning progress was only measured for one specific movement sequence and for immediate learning after the first exposure. Consequently, it is necessary to conduct further research to better understand the long-term effects of different coaching styles and their applicability to other movement sequences and styles.

Possible future research directions arise from the relationships found and identified limitations of this study procedure. Deeper kinematics analyses, such as center-of-mass velocity and elastic energy flow cycles, may provide guidance on refining the definition of a 'proper' advance-jump-lunge. Additional data may be collected by reinviting the same subjects to measure progress over time or to teach them a variety of fencing sequences. Re-evaluating learning afterwards may provide more insight on how learning conditions affect motor learning levels. Each subject's "best" learning environment should also be calculated and compared with their preferred conditions.

Ultimately, this study has provided valuable insights into the teaching methods for fencing and has laid the groundwork for future investigations into the optimal approach to training individuals with no prior experience. By further exploring the relationship between coaching styles, immersive environments, and motor learning, researchers and coaches may develop more effective and tailored training strategies that maximize learning outcomes for fencers and potentially other sports as well.

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