VisCourt: In-Situ Guidance for Interactive Tactic Training in Mixed Reality

Liqi Cheng
lycheecheng@zju.edu.cn
State Key Lab of CAD&CG
Zhejiang University, China

Hanze Jia
hzjia1118@gmail.com
State Key Lab of CAD&CG
Zhejiang University, China

Lingyun Yu
Lingyun.Yu@xjtlu.edu.cn
Xi'an Jiaotong-Liverpool University
Suzhou, Jiangsu, China

Yihong Wu
wuyihong@zju.edu.cn
State Key Lab of CAD&CG
Zhejiang University, China

Shuainan Ye
sn_ye@zju.edu.cn
State Key Lab of CAD&CG
Zhejiang University, China

Dazhen Deng
dengdazhen@zju.edu.cn
School of Software Technology
Zhejiang University, China

Hui Zhang
zhang_hui@zju.edu.cn
Department of Sports Science
Zhejiang University, China

Xiao Xie*
xxie@zju.edu.cn
Department of Sports Science
Zhejiang University, China

Yingcai Wu
ycwu@zju.edu.cn
State Key Lab of CAD&CG
Zhejiang University, China

Figure 1: An example usage scenario of VisCourt: (1) Utilizing the navigation view, incorporating a basketball tactic board for supporting tactic learning and setup. (2) Following the tactic breakdown, players engage in a step-by-step tactic preview with a ghost. (3) Employing a set of in-situ tactic guidance both on the court or on players aids to execute the tactic.

*Corresponding author: Xiao Xie, xxie@zju.edu.cn

UIST '24, October 13–16, 2024, Pittsburgh, PA, USA

ACM ISBN 979-8-4007-0628-8/24/10
https://doi.org/10.1145/3654777.3676466

ABSTRACT

In team sports like basketball, understanding and executing tactics—coordinated plans of movements among players—are crucial yet complex, requiring extensive practice. These tactics require players to develop a keen sense of spatial and situational awareness. Traditional coaching methods, which mainly rely on basketball tactic boards and video instruction, often fail to bridge the gap between theoretical learning and the real-world application of tactics, due to shifts in view perspectives and a lack of direct experience with tactical scenarios. To address this challenge, we introduce VisCourt, a Mixed Reality (MR) tactic training system, in collaboration with a professional basketball team. To set up the MR training environment, we employed semi-automatic methods to simulate realistic 3D tactical scenarios and iteratively designed visual in-situ guidance. This approach enables full-body engagement in interactive training sessions on an actual basketball court and provides immediate feedback, significantly enhancing the learning experience. A user study with athletes and enthusiasts shows the effectiveness and satisfaction with VisCourt in basketball training and offers insights for the design of future SportsXR training systems.

CCS CONCEPTS

• **Human-centered computing → Visualization**.

KEYWORDS

Immersive Training, SportsXR, Mixed Reality, In-Situ Visualization

ACM Reference Format:

Liqi Cheng, Hanze Jia, Lingyun Yu, Yihong Wu, Shuainan Ye, Dazhen Deng, Hui Zhang, Xiao Xie, and Yingcai Wu. 2024. VisCourt: In-Situ Guidance for Interactive Tactic Training in Mixed Reality. In *The 37th Annual ACM Symposium on User Interface Software and Technology (UIST '24), October 13–16, 2024, Pittsburgh, PA, USA.* ACM, New York, NY, USA, 14 pages. https://doi.org/10.1145/3654777.3676466

1 INTRODUCTION

In competitive team sports, a tactic represents a series of specific actions among a team to achieve a short-term goal [64, 67]. Basketball is a typical team sport, and effective tactics are essential to improve a team's performance. However, learning basketball tactics is challenging for players due to the complexity of the tactics. Furthermore, each tactic may have different what-ifs depending on the specific situation. Different tactic training methods are therefore designed to help players learn tactics effectively [62].

Conventional tactic training in basketball primarily involves imagery training, such as coaches using a basketball tactic board (BTB) to explain tactics, as well as players watching tactic videos. Afterward, the coach organizes the players to practice on the court. However, due to the passive nature of watching BTB or videos, there exists a gap between imagery training and real-world tactic practicing. Players often need to transform the 2D tactic imagery into complex 3D coordination among multiple players when practicing tactics. Such a gap usually causes unsuccessful tactic practices and repeat training. This motivates us to explore an improvement to address the gap in comprehending and executing tactics.

We collaborated with a university-level professional basketball team, involving both coaches and players, to identify existing gaps and improve the training process. Thereby we identified two primary challenges. **The first challenge is to support interactive learning of tactical movements.** Immersive training methods have been proven effective in sports by offering athletes a way to engage with realistic game scenarios and situations [26, 39]. For tactic training, a straightforward approach is to watch tactic videos in immersive environments to enhance imagery training [62]. However, the lack of interaction with the real world and safety concerns associated with large-scale movements in virtual reality (VR) limit its usage in practical training.

The second challenge is to enhance users' learning experience and tactical comprehension with guidance. Existing embedded visualizations have been utilized in sports videos [77] and live games [38] to eliminate context switching and reduce distractions [68]. However, tactic training is a more complex scenario requiring perspective shifting and changes in the user's motion state. Thus, it is impractical to apply existing visualizations directly. Designing in-situ guidance to assist players in accessing augmented tactical information remains an open question.

To address the first challenge, we create an immersive training environment where users can simulate collaboration or opposition with virtual players at the team level on a basketball court, thereby enhancing their spatial and situational awareness. This setup allows for individual tactic training without the need for coaching or feedback from teammates. Training in this way offers an engaging first-person perspective experience (FPP) while also providing augmented information from a third-person perspective (TPP).

To address the second challenge, we proposed a design space of in-situ guidance visualization and interaction for MR team sports training. To validate this concept, we began with a user-centered design process, followed by summarizing a design framework for in-situ visualization guidance. We then iterative design and develop VisCourt, with a focus on basketball tactic training. VisCourt provides a progressive training routine and supports individual scrimmage training for various tactical what-if scenarios on a real-world court. Finally, we conducted user studies to verify the usability and effectiveness of simulated tactical training in VisCourt.

In summary, our main contributions are the following:

(1) identify gaps in the current two-step tactic training routines derived from a user-centered formative study.
(2) propose VisCourt, a semantic movements training method in MR that supports comprehension in practice.
(3) detail four design aspects of in-situ guidance visualization and interaction design in tactical contexts.
(4) evaluate the overall user experience of VisCourt, along with lessons learned from feedback.

2 RELATED WORK

In this section, we review relevant research, including immersive sports training and in-situ visualization for movement data.

2.1 Immersive Sports Training Methods

Extended reality (XR)—encompassing virtual reality (VR), augmented reality (AR), and mixed reality (MR)—has seen rapid advancements and shown potential in enhancing training experiences. Immersive training enables users to receive augmented visual feedback [23, 70] and interact within a real-world setting. In contrast to industrial [7], safety [55], and medical training [56], sports training needs freedom of movement and performance review.

VR facilitates sports participation despite real-world constraints, with studies [6, 21, 47] and products like Eleven Table Tennis [5] seeking to create immersive sports experiences through gameplay and integration across various training disciplines [40, 61, 62]. Yet, the limitations of VR, including a confined psychological and physical scope [19] for engaging in physical activities and the challenge of large-scale movements without real-world environmental perception [51], suggest it is more suited to stationary endeavors.

For AR sports training, Lin et al. [39] employed AR to provide situated visualization for basketball free-throw trajectories. Jan et al. [26] conducted Tai Chi training offering motion guidance to users, while Wu et al. [70] utilized visual cues to assist at-home workouts. However, the limited field of view (FOV) [24] of current AR devices and the difficulty of discerning virtual images under outdoor sunlight [41] restrict the training environment's scope.

Mixed Reality (MR) integrates virtual information into the real-world environment, effectively narrowing the gap between the user and the virtual world. Tian et al. [59, 60] utilized MR for group-based Tai Chi instruction, while Kim et al. [28] developed outdoor soccer training to improve passing skills. Nevertheless, few studies [46] applied MR to multi-person practical training in team sports.

The aforementioned works primarily address individual motor skill levels [39, 40, 70] without achieving a comprehensive understanding of dynamic coordinated tactical comprehension or emphasizing cognitive skills. Tsai et al. [62] developed a VR basketball training system, comparing VR with traditional methods and demonstrating VR's feasibility and effectiveness for enhancing tactic imagery training. However, team training, an indispensable component of tactical training, often requires large-scale player movements, which are constrained in VR. Therefore, our work aims to simulate a realistic training environment, offering users a full-body engagement training experience that enables individual completion of team training tasks. Exploring and developing how to use MR for individual scrimmage tactic training to enhance the sense of spatial and situational awareness is the goal of our work.

2.2 In-Situ Visualization for Movement Data

Situated visualization is connected and displayed within its environment [29, 35]. Kim et al. [31] expanded on this term through the introduction of physical data referents, which include real-world entities and spaces. Thus, they characterize two foundational classes (situated and embedded). Existing works on embedded visualization for movement data [32], especially about sports [18, 37], primarily focus on augmenting video and place visualizations at specific fixed locations, without direct correspondence to physical referents. Additionally, most of these are used for conveying insights [77] or game viewing [38] from a third-person perspective. Hence, due to the shift in perspective and the lack of referents, their design space cannot be directly applied in in-situ environments [25].

Integrating situated visualization with visual analytics introduces highly interactive and real-time exploration capabilities [14], leading to the development of immersive analytics tools [57]. A significant portion of research in this field leverages in-situ visualization within mixed reality environments to analyze spatio-temporal data [13], with human movement being a notable example. Pearl [43] explores the analysis of movement data in relation to surrounding areas of interest within a simulated exhibition context. Similarly, AvatAR [52], which combines 3D trajectories with virtual avatars, provides valuable insights into human motion data analysis. Despite the limited discussion [73] within the visualization community regarding the relative motion between visualizations and viewers, few studies have explored situated visualization in motion [72, 74].

Our research is dedicated to establishing a set of design practices focused on in-situ guidance for user movement in MR. In the following sections, we present our user-centered approach to developing an interactive tactic training system in section 3 and section 4. We then introduce VisCourt in section 5. In addition, we present the user study in section 6 and the reflection in section 7, focusing on the "What-Ifs" scenarios and the in-situ visualizations.

3 FORMATIVE STUDY

In this section, we present our formative study with domain experts to obtain a comprehensive picture of tactic training in basketball. Our aim is to identify the pain points in current training routines.

3.1 Mocap for Tactic Simulation

Drawing on EasyMocap [1, 20] for multi-person, multi-view motion capture, we first set up the capture environment around an indoor basketball half-court. We used seven lightweight and portable GoPro HERO8 cameras for recording. In collaboration with a university-level professional basketball team, we initially acquired a 60-minute video recording of the tactical training routine. Then we invited ten players from *the First Team* to perform four tactics they were familiar with and the what-ifs: Spain pick and roll, UCLA cut, Horn twist, and Pistol with flare. Each tactic was executed for an average duration of 10 seconds and performed three times. After the capture, the coach reviewed the multi-view videos to select the best execution as the standard data. We utilized state-of-the-art computer vision (CV) models for automatic 3D reconstructions of both the ball and players. Thus, we created initial 3D tactical scenarios for user experience and subsequent guidance design and development.

3.2 User Interview

Participants. We conducted interviews and user testing of the 3D prototype with 4 basketball coaches (C1-C4; Age: 28–47), each with at least three years of tactical coaching experience, and 4 professional basketball players (A1-A4; Age: 20–25; male=2, female=2).
Procedure. Each semi-structured interview lasted around 30 minutes. We collected participants' backgrounds and inquired about their tactic training routine. Subsequently, we showed them three video clips selected from the recorded training, each about 1 minute in length, showcasing both offensive and defensive tactic scenarios. We encouraged participants to think aloud about their typical routine and any challenges they encountered. For coaches, our inquiries focused on the criteria they used to evaluate the effectiveness of tactic training and the frequent mistakes athletes make. With the athletes, we discussed their overall training experiences and recent performance, including instances where they encountered challenges in coordinating with teammates during play execution.

We invited participants to engage with our initial simulated 3D tactical scenarios to follow the avatar's movements (without guidance) and collected their feedback on any confusion, requirements for additional information, or problems they encountered when using our prototype (more details in our supplementary materials). The initial feedback confirms the necessity of guidance. Finally, we encouraged them to discuss the potential enhancements.
Findings and Discussions. All participants (from 5 different teams) reported that tactic training is a regular part (at least twice a week), including learning new tactics to expand their tactical knowledge and adaptability (C2,C3). They also stated that they would first watch the static **basketball tactic board** and follow the coach's explanation of dynamic tactical progression. In a few cases, C3 and A1 mentioned that *"Apart from the coach's guidance, the player who initiated the tactic would also start managing the BTB for tactical simulations and communicating with teammates."* After that, some teams employed **augmented tactic videos** as an additional tool for tactic training. At the end of the training, the coach usually arranged multiple players to simulate tactic execution repeatedly

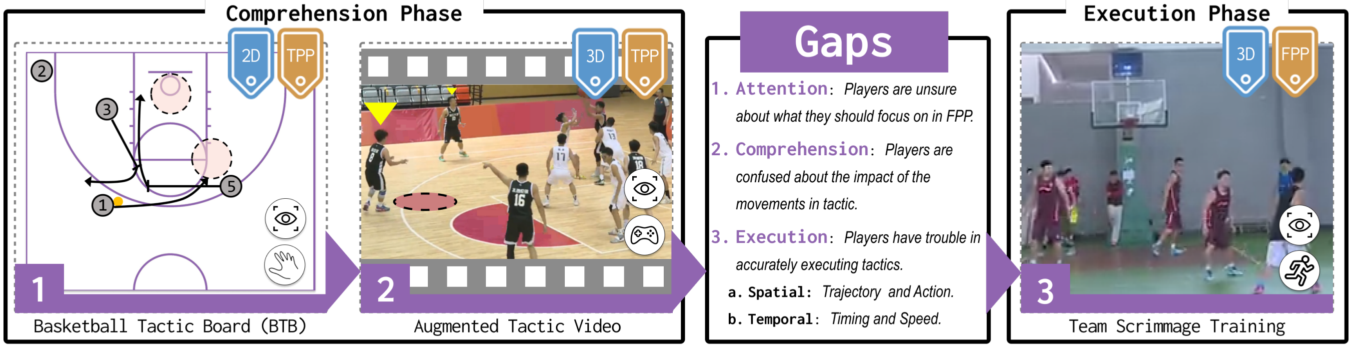

Figure 2: The current tactic training routine begins with players observing 1) BTB and 2) Augmented tactic videos, followed by 3) Team scrimmage Training. This process encompasses two distinct stages: the Comprehension Phase and the Execution Stage.

on the court for **team scrimmage training**. C1 emphasized, *"contrasting with passive observation, this is the most crucial part in the training session."* **However, it was noted that individual tactic training was limited to repeating observational learning and did not include the execution of tactics on the court.**

It is clear that the tactic training routine evolved from a *passive, observation* approach to an *immersive* ,*interactive* process. This progression, moving from 2D visualizations to 3D hands-on practice, and viewing from third-person perspective (TPP) to first-person perspective (FPP), would significantly enhance engagement and effectiveness. This evolution can be categorized into two stages: the **Comprehension Phase** and the **Execution Phase** (Figure 2). We also identified the difficulties may encounter, as follows:

- **F1: Augmented Tactical Information and Context Presented Separately.** Players receive insights on tactical adjustments—such as shifts in formation or the emergence of open spaces—mainly from BTB or instructional videos. However, this information does not directly link to specific, real-world tactical scenarios. A common comment among participants was *"Although I understood the BTB or video, I still made mistakes during execution."* This points to a notable gap between the comprehension of tactical information and its practical execution.
- **F2: Setup Diverse Tactical Scenarios is Challenging.** For players, tactical scenarios help them learn tactics and allow them to create a mental model of teammates or opponents. Insufficient player participation or unfamiliarity with the tactics can significantly challenge the players in executing tactics.
- **F3: Providing Feedback Immediately During Training is Difficult.** The absence of real-time feedback results in difficulty for players to self-correct. As A2 and A4 expressed, *"I couldn't keep up with the team's pace, what's worse is I didn't know how to adjust."* Moreover, immediate feedback from coaches is often not available and is provided through verbal instructions [39].
- **F4: Player's Attention Shifts in View Perspectives** Switching perspectives inevitably leads to shifts in players' attention. A2 and A3 expressed that when viewing tactic videos, *"I pay more attention to the ball handler."* However, during tactic training, it's crucial to focus on the current roles of the players involved.
- **F5: The Effectiveness of Physical Referents for Guidance is Limited.** Physical referents are commonly employed in individual training, but their use is constrained by the limited space, making it impractical to deploy many of them. Moreover, these physical referents provide less information.

3.3 Video Data Analysis

To explore the augmented tactical information that players require and to understand how current tactic videos guide players, we collected a total of 46 augmented tactic videos. This included the top 20 English basketball tactical explanation videos with augmented visualizations on YouTube (searched using keyword combinations such as "Breakdown video + Basketball" and "Tactic video + Basketball" [77] after which coaches manually cleaned up the selection) and 26 videos from the team's playbook. Under coaching, we sliced these videos into pieces and categorized the tactics. Our corpus ultimately included 79 tactics and their what-ifs, detailing 112 tactical scenarios. Our goal is to enhance the guiding role of visual information in MR tactical scenarios, complementing the need for coach or teammate coordination guidance. We conducted a qualitative analysis of this corpus. Based on in-depth interviews, we first standardized the content that needed to be annotated for each video clip: the types of augmented tactical information, the timing and reasons for their augmentation, and the number of steps in each tactical scenario. We invited four experts (C1,C2,A1,A3). They independently reviewed and segmented the videos following this process: each segmented 1/2 of the videos and verified another 1/2 of the videos segmented by others [77]. Disagreements were resolved through open-meeting discussions following our coding book (more details for statistical information refer to our supplementary materials). Finally, we came to statistical information on two aspects, namely, Situations Aspect and Data Aspect. The design framework was further refined in the iterative discussion.

3.4 Summary of the Gaps

- **Attention:** *Players are unsure about what they should focus on in FPP.* It is crucial to consider the attentional limitations of players in motion and potential line-of-sight obstructions, which may cause players to miss critical information. Additionally, integrating virtual content with the real environment can create visual noise, leading to confusion and reduced focus. This could adversely affect players' training experience, making tactical information difficult to assimilate.
- **Comprehension:** *Players are confused about the impact of the movements in tactics.* Understanding tactics is a focal point in tactic training. Missing the context or losing augmented tactical information can lead to inaccuracies in comprehension. As C1 mentioned, *"Seeing open spaces in videos is simple, but the challenge lies in seizing these opportunities on the field."* All interviewed

athletes mentioned that they sometimes *"do not understand the impact of their movements."* This is partly because it might not have been noticed, and partly because such impacts are implicit and difficult to discern through observation alone.

- **Execution:** *Players have trouble accurately executing tactics.* Ensuring successful execution is essential for tactical training. Performance reviews and movement data analysis are effective methods for evaluating players' tactical skills [69]. We identified that common errors in execution often involve inaccuracies in both spatial and temporal aspects, specifically categorized as:

(1) **Spatial**: Trajectory and Action.
(2) **Temporal**: Timing and Speed.

However, unlike motor learning [45], tactic training places a greater emphasis on **comprehension**. As C1 mentioned, *"Unlike rigidly executing accuracy as in drills, tactics in real games are variable and require flexible decision-making based on the situation."*

4 DESIGN EXPLORATION

An important question is how to display data for guidance within situated [72]. We summarize design goals and then propose a design framework in three aspects: situations, data, and referent [10, 71].

4.1 Design Goals

The aim of tactic training is to enhance players' tactical skills. We characterized four design goals based on the above findings.

- **G1: Providing a progressive tactic training routine.** Although MR training environments present 3D tactical scenarios, gaps remain between comprehension and execution. To bridge these gaps, we need a progressive training routine. Unlike traditional routines that separate these phases, a progressive routine allows comprehension of TPP to assist FPP execution.
- **G2: Collecting motion data for diverse 3D tactic scenarios.** To support immersive tactic training, our tool needs to provide diverse 3D tactical scenarios for simulation, encompassing all players' motion data and basketball trajectory.
- **G3: Uncovering and visualizing augmented tactical information for in-situ guidance.** The impact of tactical changes is reflected in the augmented tactical information. Although tactic videos have already displayed this data, it's crucial to integrate it with tactical scenarios, such as one's own movement data and the opponents' form changes. Our tool should provide in-situ guidance to enhance users' situational awareness.
- **G4: Giving intuitive feedback immediately.** To enhance individual training under 3D tactical scenarios and provide players with precise goal specifications, our tool should offer intuitive visual feedback in motion to players in real-time, eliminating the need for coaching staff or teammates to be present.

4.2 Design Framework

4.2.1 Overview. We divided the design of in-situ guidance into four questions. At the **Situations** aspect, we addressed *"When to display in-situ guidance"* for a tactic breakdown. At the **Data** aspect, we summarized *"What augmented tactical information should be presented for guidance"* within specific situation. At the **Object** level, we proposed *"Where the guidance can be laid out on"* in MR. For the last question "Which visual types to use", we conducted design iterations in the prototype of VisCourt (refer to section 5).

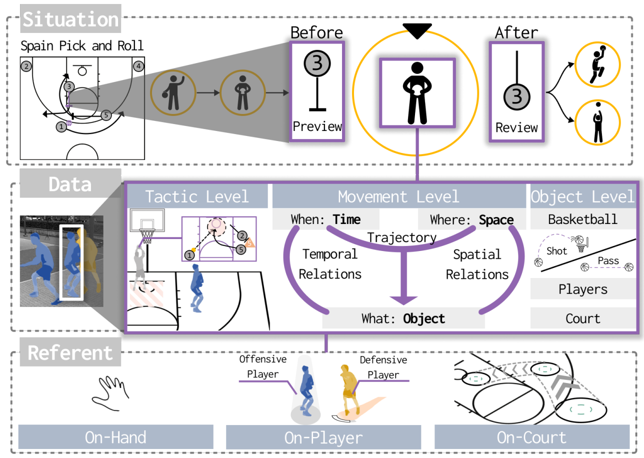

Figure 3: We proposed a design framework for visualizing in-situ guidance for tactic training in MR, focusing on three aspects: situations, data, and referent.

4.2.2 Aspect I: Situations (When). The situation describes the specific moment of scenarios in the tactic. A tactic comprises multiple scenarios [62], often divided by specific movements [34], thereby breaking down complex tactics [11]. Despite the existence of alternative scenarios, the execution of tactics is linear, represented by a flowchart for the Spain Pick and Roll, as shown in Figure 3. We divide a tactic scenario into three situations: ***Preview (Before movement), Moving (In movement), and Review (After movement)***. Following discussions with coaches (C1-C4), we categorized the trigger in preview and the subsequent changes in review.

Preview: Before movement. In tactic training, the focus is on the player-related movement triggers. These previews determine the timing and order of executing movements.

- After the predefined gesture or signal, execute *Tactic A*. (6/79)
- After *Player A* completes specific basketball technical movement (eg., receives the ball or sets a screen), *Player B* moves. (48/79)
- After *Player A* reaches a specific area, *Player B* moves. (55/79)

Moving: In movement. Player executes the movement.

- *Player A* moves to a specific area and performs a *Technical Action*.

Review: After movement. We categorize the impact of movement into two types. However, the changes induced in practice are not singular. For instance, in a man-to-man defense, off-ball movement [69] can lead to the movement of defending players, altering the defense form and creating open spaces for shooting or passing.

- Causes changes in *Players'* position (21/79) and actions (27/79).
- Causes changes in defense form (30/79).
- Causes open spaces (47/79) on the *Court*.

4.2.3 Aspect II: Data (What). Data refers to augmented tactical information. With a similar proposal for learning, we refer to Chen et al.'s [77] classifications from high to low semantic levels and identify the data needed by players from FPP while in movement.

Tactic Level. A tactic leads to a specific tactical goal. In basketball offensive tactics, this goal generally refers to ***"The Specific player A has a shooting opportunity in open spaces."*** Region of Interest is the representation of an open space. The tactic-level data presents the rationale behind a tactic, explaining the key factors contributing to its efficiency. However, tactics are flexible and variable. There exist what-ifs, thus providing players with additional knowledge and understanding to adapt their decision-making accordingly.

- *What-if* scenarios represent the variations of a tactic in response to different situations (26/79).
- *Region of Interest (ROI)* is a defined space within the real-world environment [43], determined based on the division of basketball court areas. It signifies the open spaces on the court (30/79).

Movement Level. A *movement* refers to a strategic action taken at a specific time within a confined area [33], either individually or in coordination with teammates. Movement data, as a form of spatio-temporal data, encompasses information categorized into three components according to the triad scheme: *Where: Space, When: Time, and What: Object* [43]. Inspired by human movement analysis works (eg. PEARL [43]), we integrate a model [8, 50] that describes movement data into the guidance design. This model delineates the three components of spatio-temporal information, along with their characteristics and relations. Specifically, we narrow the object component down to the basketball context. We initially categorized augmented tactical information into three types: ***Spatial Relations, Temporal Relations, and Trajectory***. The design goal of in-situ guidance is to direct players in training, fundamentally classified as mover-oriented tasks [9] at the movement level. Due to the complexity of tactics and various relations between movements, it's challenging to encompass all relations. Therefore, for each type, we selected one tactical data as our proof of concept.

- **Spatial Relations** refer to how certain spatial relations among positions or players may occur based on movements [8, 16].
  - *Defense Form* reflects the defensive formations (21/79) and the dominant areas (19/79) of defenders [38]. The changes indicate alterations in defenders or defense schemes.
- **Temporal Relations** for time units are also known as ordering relations. It involves the relationship and coordination of group movements within a tactic's timeline [8].
  - *Timing* refers to the moment executing movement and involves the duration it takes (21/79). As the saying, "The ball arrives as the player does," which is crucial in team coordination.
- **Trajectory** (45/79) represents the spatio-temporal position of the player. Trajectories encompass *positions (62/79), speeds (15/79), directions (13/79)*, and other attributes. Due to the complexity of real-game situations, players are not expected to strictly follow the predetermined trajectory during training.

Object Level. The object data encompasses the physical attributes of objects, including: the basketball, the players, and the court. Since the court is static, we only consider the changing ROIs. For the ball, our focus is primarily on the spatio-temporal data of the ball such as shots and passes, as these often represent key steps in tactics. Due to the involvement of numerous players, which can diminish the first-person experience, we categorize the associated players into key offensive players, key defenders, and other players [17].

4.2.4 Aspect III: Referent (Where). The referent is the virtual entities (players) and physical entities [43] (basketball, court, and user) in the MR training environment [65]. Referents are of significant interest in this work due to their ability to lay out visual guidance. Placing visualization on the basketball is not feasible in FPP because the ball is constantly in motion. Moreover, the emphasis should be on the positions of the opposing players rather than the ball. Therefore, we categorized the layout of in-situ guidance into three types: ***On-Hand, On-Player, and On-Court***.

4.3 Summary

This design framework assists in defining players' requirements for in-situ guidance in scenarios by clearly identifying aspects: Situations, Data, and Referents. Thus, with only coach annotations on these, we can determine the elements for visualization except situated visual types [35]. This framework allows us to focus on iteratively refining the design space for in-situ guidance(section 4).

5 VISCOURT

In this section, we designed VisCourt, our immersive tactic training system developed to improve tactical skills.

5.1 Augmented Tactical Information Processing

To extract augmented tactical information, our data processing pipeline encompasses semi-automatic tactic breakdown and uncovering data complemented by coach annotations.

(1) *Tactic Breakdown*: We utilize a skeleton-based method [44] for action recognition and segmentation with minor manual clean-up. We integrated different what-ifs into a flowchart (Figure 3).
(2) *Augmented Tactical Information*: The 3D player motion data already includes the movement trajectory. We can compute *positions, speeds, actions, and directions* from the trajectory.
   - *Region of Interest (ROI)*: We divided the court into various areas [66] and annotated the regions that require attention during movements, especially open spaces. We calculated the shooting percentages for each shooting region, as defined by Official NBA Stats [2], based on historical shot records.
   - *Defense Form*: We calculate the dominant area [15, 69] for each player first. Based on the positions, we identify the man-to-man defenders and potential help defenders. We then determine the defensive formation [38].
   - *Timing*: Based on annotations, we identify the trigger logic between movements.

   For movement triggers in the preview and resulting impacts in the review, we invited three coaches (C1, C3, C4) to annotate based on the design framework manually. All coaches conducted a cross-check to ensure accuracy and completeness.

5.2 In-Situ Guidance Design Iteration

We categorized in-situ guidance according to the design framework (Figure 3). We initially proposed the designs based on the insights from video analysis, and relevant studies on augmented videos [17, 77], E-Sports games [3], and situated design patterns [35, 38, 39] in 3D. Then we invited two coaches (C3, C4) and two athletes (A1, A3) to assess whether these designs met their needs and addressed their challenges in section 3. After each discussion, we collected feedback and revised our designs. Following several iterations, we determine the design space in the four collected tactics.

5.2.1 Guiding Users' Attention. To assist athletes in identifying tactical details, we start with a tactic breakdown, using ***BTB*** (on-hand) as a navigation view to present an overview at the tactic level. This approach helps users establish a connection between co-located 2D views and situated 3D scenarios [27]. At the movement level, users need to pay attention to specific movements in each scenario [40], such as taking a shot, setting a screen, or making a pass. We use floating *labels* (on-player) and corresponding movement position ***glyphs*** (on-court) to help users identify movements that impact

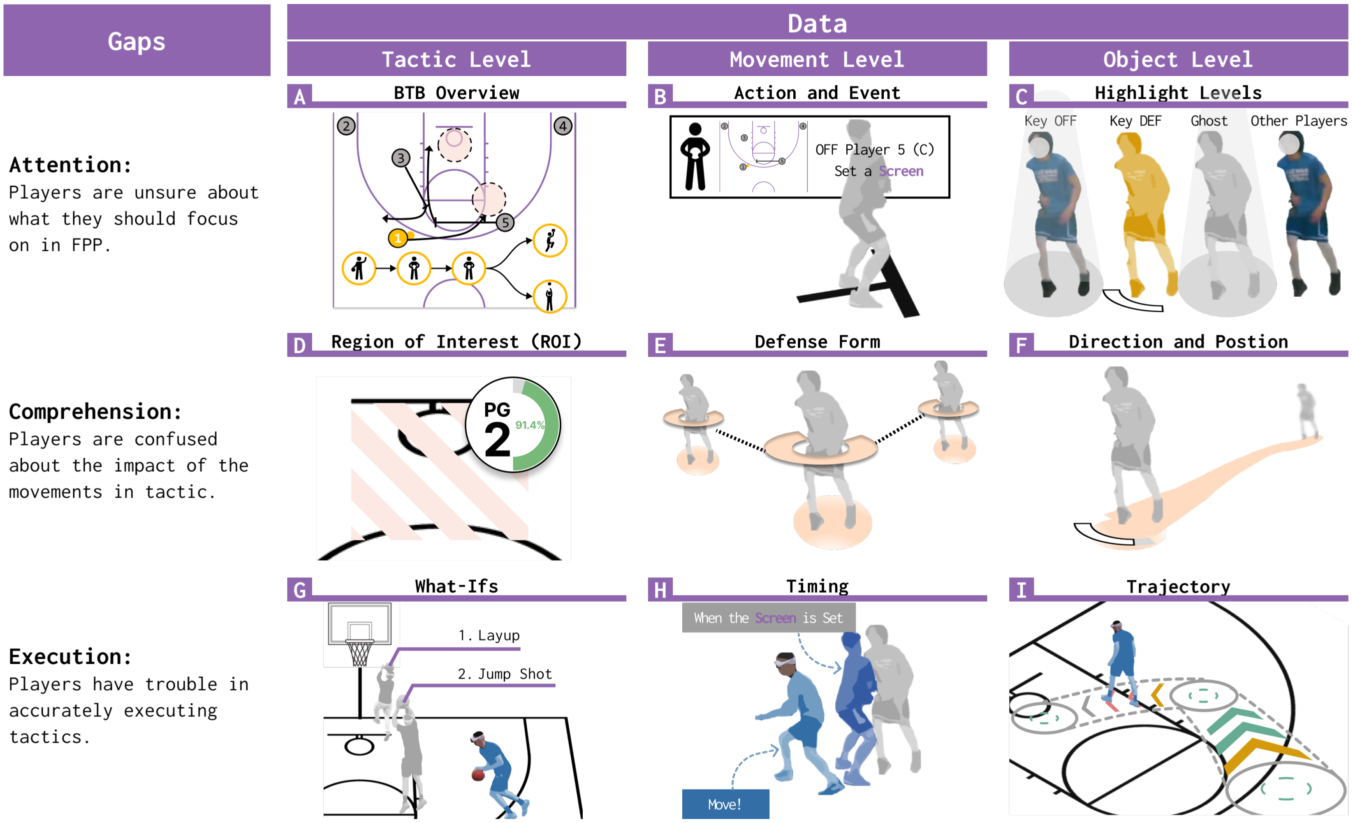

Figure 4: Our design space for in-situ guidance in basketball tactic training is based on the partitioning of the data and the gap.

decision-making. On the object level, referring to the players' importance ranking proposed by Chen et al. [17], we categorize and set different highlight levels for associated players in the FPP. This includes categorizing into key offensive players, key defenders, and other players based on suggestions from coaches and players. Additionally, we design a ***ghost*** [35] representation of the current player being acted by the user in the preview phase.

5.2.2 Showing Impact of Tactic. The impact of tactical movement unfolds in a layered, causal relationship. We explain our design considerations from low to high semantic levels.

- *Changes of Defenders' Direction and Position.* The most direct effects are observed at the object level, influencing the movement and position of defenders. Our design represents defenders' paths and positional changes with ***trajectory*** (on-court)-the thicker the line, the more recent the position. For direction, we adopted the well-regarded "defense shield" [17] design. We represent the defender's direction and distance from the corresponding offensive player with an arc-shaped ***glyph*** (on-court). The orientation of the arc matches the defender's direction, with white indicating the current direction and grey indicating the previous. The arc's length reflects the distance. Moreover, we iterated on incorporating other data, such as speed or 1-on-1 relationships. However, user feedback in an FPP context suggested, *"It's quite obvious who is defending me; there's no need for connected lines."*
- *Changes of Defence Form.* Changes in a defender's movement lead to alterations in the team's overall defensive formation. We set a dominant area to represent a player's capacity to occupy the court. This is visualized as a circular ***glyph*** (on-court) that fades from a darker color at the center to lighter outward, placed under the feet of defenders. The dominant area also helps to detect the mistake of being too close to the defender. The defensive formation reflects the team's defense scheme. We used hollow circular ***glyphs*** (on-player) placed around the waist of players, connected by dotted ***lines***. Users crossing these lines would face a pinch from defenders at both ends of the line. During tactical execution, movements by defenders can cause them to be too far apart or blocked by others, changing the original form.
One alternative design involved placing a defense Voronoi diagram, used for analyzing players' off-ball movement efficiency in 2D [69], directly onto the court. However, this design covered the entire court and failed to specify key defenders. Another alternative highlighted the associated defenders' enclosed area [38], improving the TPP game viewing experience. However, the large enclosed area could also cause visual clutter. Moreover, our final design focuses on enabling users to perceive changes in the defense form to find breakthroughs or off-ball movement opportunities, rather than concentrating on the coverage area.
- *Changes of ROIs.* Changes in the defense form lead to the emergence of open spaces on the court. We highlight these ROIs with rectangle ***glyphs*** (on-court) filled with stripes, aligned with the standard court lines. We positioned circular ***panels*** (on-court) next to the ROIs to display the scoring efficiency at that position and the player role (e.g., PG: point guard) executing the shot. As A1 mentioned, *"The highlight of ROIs enhances my memory of the tactic, allowing me to quickly spot open spaces on the court."*

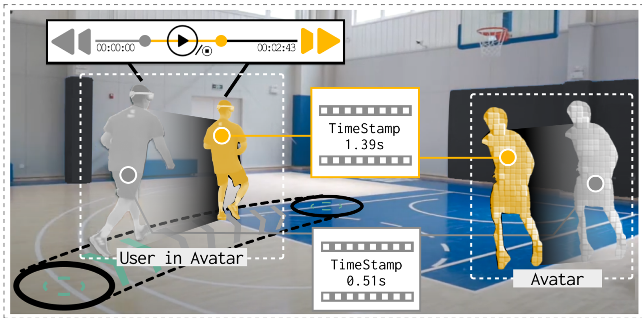

Figure 5: Users can achieve playback control (play, pause, and rewind) in VisCourt through positional movement. We employed color coding to represent different times.

5.2.3 Guiding Users' Movement. Guiding users to correctly execute tactics is a fundamental usage. For each movement, we use a combination ***glyph*** (on-court) to represent the start and end positions. The green dashed circle indicates the precise position, while the grey solid circle represents a reasonable position range (set to 0.5m). The use of arrows to denote ***trajectory*** (on-court) is a natural design choice [30]. We visualize the trajectory that users need to follow as a 0.7m [63] wide line (deviating beyond this threshold or encroaching upon a defender's dominant area is considered incorrect). Within this trajectory, arrows encode speed and direction: green indicates a speed faster than the standard, red denotes a slower speed, and yellow signals the user to accelerate. Additionally, we added slanted and semi-transparent grey planes along the edges of the trajectory lines. This provides users with a simulated sense of constriction, guiding them to move within the designated path.

The timing of execution is crucial. We set a pause before the triggers for preview. We designed a ***ghost*** to show the various tactical scenarios resulting from different decision-making. Additionally, the simultaneous ghost provides users with a reference for subsequent movements, assisting them to follow and execute.

5.3 Interaction

VisCourt offers the following interactions to improve usability:
Tactic Navigation. Users can choose different tactics, training sessions (learning or practicing), or specific situations within a tactic by tapping on a virtual navigation panel.
Playback Control by Positional Movement. Following the requirements of coaches and athletes, we divided the step-by-step training session into preview, moving, and rewind phases (Section 4.2.1), inspired by bullet time [58] effects. VisCourt enables the play, pause, and rewind of tactical movements for the entire scenario through the positional movement of the user. Using the PICO4 HMD, we capture the user's real-time coordinates, mapping them to distances on a fixed trajectory (similar to a playback progress bar) to control playback. Users move along a predetermined trajectory corresponding to the avatar they acted, with moving forward indicating play, moving backward for rewind, and standing still for pause (as shown in Figure 5). This allows users to walk and watch the evolution of the entire tactic simultaneously, achieving a true "step-by-step" experience. This interaction model has been positively received in our iterative design process, as A3 mentioned, *"I had no prior experience using VR controllers, and walking while watching on the court is very intuitive."*

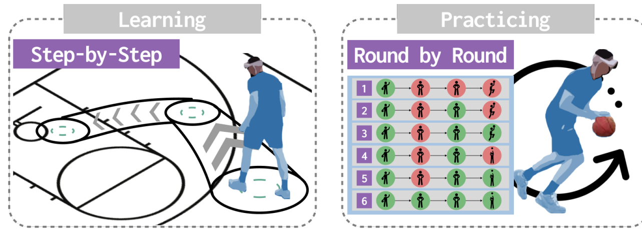

Figure 6: Training routine in VisCourt involves a step-by-step learning and repeated round by round practicing.

Perspective Control. VisCourt offers three perspectives: a 2D co-located top-down view, a 3D situated third-person perspective, and a 3D situated first-person perspective. Users can watch BTB animations on the navigation panel. They can enter the first-person perspective of an avatar to receive guidance. VisCourt allows users to switch avatars or step out to observe tactical changes from any position and observation angle on the court. Other interaction modalities [36], like voice or gaze control, could naturally facilitates perspective adjustments. Future studies could explore the effectiveness of different perspectives in training to understand how these modalities enhance or affect learning outcomes.
Tactic What-Ifs Control. By integrating positional movement-driven playback control with perspective switching, VisCourt enables users to control tactical what-ifs within situations. For example, a user can exit the current acting avatar, walk into another avatar in the current situation where decision-making is involved, and execute different movements. This changes the original tactical development and leads the user into another variant.

5.4 Training Routine

We developed a progressive training routine in an MR environment for tactical training (G1), acknowledging that completely altering athletes' training habits is impractical. Building on the traditional routines, VisCourt introduces an overview of the tactic initially, followed by a step-by-step learning session for comprehension, and concludes with repeated practicing sessions for execution. This progressive routine facilitates gaining a tactical overview in a global 2D view and an immersive perception of tactical scenarios in 3D.

5.4.1 Step-by-Step Learning Session. After obtaining a memory image from an overview provided by the BTB, users first engage in step-by-step learning. We segmented a player's complete movement into individual fragments to facilitate learning. In this session, users can switch to any avatar or disembodiment, gaining different perspectives. Users control playback through moving, including pause, play, and reverse. We also offer a navigation view for clicking to switch tactical scenarios, enabling users to repeatedly learn the same step and achieving a correspondence between co-located 2D and situated 3D perspectives.

5.4.2 Round-by-Round Practicing Session. After the learning session, users can engage in round-by-round repeated practicing, keeping pace with the team's tactical execution and deepening their understanding. Unlike before, VisCourt eliminates unnecessary guidance during practice, retaining only the parts that guide movements to ensure fluent repetitive training. User performance data is collected via an MR Head Mounted Device (HMD) during tactical execution. Errors exceeding a threshold are indicated in red, while

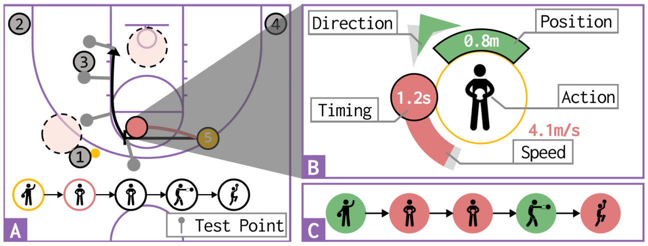

Figure 7: In the practicing session, (A) the complete running route of the player, along with its test points. (B) The movement data (position, speed, timing, and direction) was recorded. (C) The performance review of each step.

normal execution is shown in green, allowing users to quickly receive feedback. Data for each step is encoded in a glyph (Figure 7). Furthermore, users can switch tactics or sessions at any time.

5.5 Hardware and Software

The proposed VisCourt system was implemented using the Unity 2021.3.15 game engine [4] and the XR Interaction Toolkit. We used PICO4 to run the VisCourt program. The PICO4 weighs 295g and supports a field of view of 105°. It has a dual-eye resolution of 4320x2160 and supports mixed reality effects in RGB color mode.

6 USER STUDY

We conducted a user study, aiming to evaluate whether basketball players (including professionals, youth athletes, and enthusiasts) can effectively engage in VisCourt, and observe their training process to gather insights for future improvements of SportsXR.

6.1 Participants

The study was conducted in person within a half-court basketball setup measuring 47 feet by 50 feet, accommodating both outdoor and indoor environments. This setup mirrored traditional tactical training environments, enabling us to evaluate VisCourt's effectiveness. To ensure a diverse study group, we recruited 12 basketball players, including both male and female athletes. Four participants were amateur basketball enthusiasts (E1-4, Average Age: 22.25 years, SD=0.96). Additionally, we invited eight professional players from a university team. All of them had no physical limitations and had never experienced symptoms of motion sickness. Among these, four were youth players from the Youth Team (Y1-4, Average Age: 17.25 years, SD=0.5), and the remaining four were professional players from the First Team (P1-4, Average Age: 21.50 years, SD=1.29). This participant mix allowed us to study the system's effectiveness across different levels of professional expertise from the players' perspective. Moreover, two of them (E1,P2) had prior experience using HMDs for immersive games. Each participant received $15 as compensation for their participation.

6.2 Procedures

Due to the results from previous studies [62] (effectiveness of immersive training) and our prototype's user testing (necessity of guidance), we focused on the VisCourt training experience across different skill levels. The study comprised two parts and lasted about 40 minutes. The first part focused on the overall experience and training outcomes with VisCourt. We introduced VisCourt and its usage to the participants, ensuring they were comfortable with the system without our guidance. Based on the coach's suggestion, the "Spain Pick and Roll" [48] is a classic team coordination tactic, encompassing key events such as screening, passing, and shooting, which broadly cover our in-situ guidance design. We then selected this tactic for the 12 players to train on. Initially, each player watched a 2-minute video of a coach explaining tactics using a tactical board, followed by a 5-minute augmented tactic video. After that, participants proceeded with their tactical training using the PICO4. The duration of the step-by-step learning session was fixed at 5 minutes, followed by a test in a round-by-round practice session. During the test, participants were restricted to executing the ball handler's movements in the current Spain Pick and Roll scenario, with the test conducted over three rounds, each about 10 seconds. In the second part, participants were asked to complete a post-study questionnaire. This questionnaire collected their subjective ratings on the overall system, in-situ guidance in tactical scenarios, and the Sport Engagement Scale (SES). We employed the think-aloud protocol to gather feedback on the entire experience. As compensation for participation, each participant was paid $15.

6.3 Measures

We collected quantitative data on user subjective ratings through post-study questionnaires to assess the overall experience and each in-situ guidance design condision. We recorded and analyzed the trajectory of each practice made by users to conduct a performance review. Finally, we employed the Sport Engagement Scale (SES) to measure the level of engagement within VisCourt.

6.3.1 User Perceptions of VisCourt.

- Overall User Experience of VisCourt. We initially evaluated the effectiveness of VisCourt for tactical training across seven dimensions using a 7-point Likert Scale: 1) Helpfulness, 2) Fun to Use, 3) Felt in Control, 4) Training Capability, 5) Likely to Use, 6) Comfort Level 7) Real-World Applicability.
- Usability of In-Situ Guidance and Interactions. For each in-situ visualization for guiding tactic training within our design space, we gathered subjective ratings across four dimensions using a 7-point Likert scale. These dimensions encompass helpfulness, understandability, and funness. The final dimension was tailored based on the gaps and included aspects such as "guiding my attention", "guiding my comprehension", or "guiding my execution". Regarding the two primary interactions provided by VisCourt (Playback and Perspective Control), we applied the first three dimensions mentioned above, while the last dimension assessed whether these embodied forms made users "feel in control".

6.3.2 Quantitative Analysis of Training Performance Review. Our quantitative analysis included overall quality assessed by four coaches and analysis of collected trajectory data. These data were continuously gathered during the practice phase. Trajectories are commonly analyzed in sports [69]. However, it is adequate for the trajectories to be roughly similar, with more emphasis on the start and end points, direction, and speed. Thus, we followed standard analytical approaches and focused on analyzing low-level indicators, which were broken down from overall movement trajectories.

- Overall Performance. Tactical training is not merely about mechanical movements, assessing whether players execute tactics well is a challenging task, and it's difficult to quantify through fixed performance indicators [62]. Therefore, we invited the coaches mentioned above to score each round of the participants' practice sessions. The scores ranged from 1 to 5, where 1 indicated unsuccessful tactical execution and 5 indicated execution consistent with the standard movement. We utilized both multi-view third-person and players' first-person perspective videos to demonstrate each player's tactical execution to the coaches. To ensure the reliability of the results, we shuffled the training information and concealed player backgrounds, making the coaches' scoring more impartial. We calculated the average scores, and the results are shown in Figure 10.

- Indicators for Position, Speed, and Timing. We utilize standard motion data as our benchmark. During execution, our focus lies on whether players can reach specified positions within the designated time, rather than solely on precise trajectory. To achieve this, we employ a method of setting test points (Figure 7) to gather motion data. We calculate the Euclidean distance between the actual player position at corresponding tactical time points and the standard data position to measure positional deviation. For the aspects of speed and timing, we followed the coaches' emphasizing that *"Seizing opportunities to move into open spaces for shooting is crucial."* As the ROI (open space for shooting) is not always available, timing can indicate whether a player capitalizes on the spatial advantage [42]. Entering too early alerts defensive players to cover, while entering too late results in missing. The speed reflects the player's tactical execution and fluidity [12]. For instance, in the fast breaks tactic, gaining a speed advantage within the ROI can lead to a higher scoring rate. Therefore, we recorded the instantaneous speed and the time when they entered the ROI. Given the specific tactical scenarios utilized for testing, although there are many tactical variations of the "Spain Pick and Roll", we focused on scenarios where the ball handler has scoring opportunities within the restricted area for our tests.

6.3.3 Engagement Measurement. The Sport Engagement Scale (SES) [22] is a reputable instrument for assessing engagement within sports contexts. SES conceptualizes engagement as a positive psychological condition encapsulated by three dimensions: vigor, dedication, and absorption, each measured by five questions on a 7-point scale during participation in sports activities [22]. User feedback yielded positive averages across all dimensions (Vigor: 5.75, Dedication: 5.68, Absorption: 5.67), indicating that VisCourt successfully engaged users in basketball tactic training.

6.4 Study Results

We present the ratings for the overall user experience of VisCourt and then delve into the feedback regarding guidance design and interaction. Then, we summarize the performance review.

6.4.1 The overall user experience of VisCourt for training was predominantly positive. The results of the overall user experience, as shown in Figure 8.A, indicates that the majority of participants deemed VisCourt as "helpful" and "fun", experienced a sense of control during its use, and acknowledged its "training capability" for tactical training. Moreover, a substantial number of users expressed a likelihood of utilizing VisCourt for tactic training purposes. Apart from the positive feedback received at the software level, some primary concerns stem from the comfort and generalizability of current MR devices. In terms of comfort, 67% of the participants

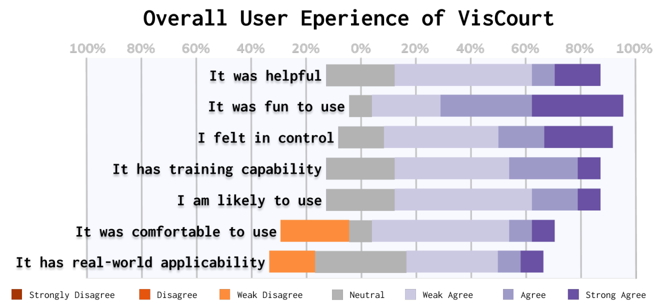

Figure 8: Overall user experience of VisCourt.

reported feeling comfortable. Lastly, 50% of users were confident in VisCourt's applicability to real-world training contexts. The two youth players (Y2,Y3) expressed concerns about the potential limitations of MR HMD usage to contribute to myopia or exacerbate existing myopia, which may not be suitable for adolescents.

- *In-situ visualizations for guiding user attention in training are more helpful when they are more attractive and can be laid out on more referents.* Participants rated positively on the helpfulness of each in-situ guidance. For guiding players' attention, the avatar highlight level was considered the most helpful and useful. P1 appreciated our use of projection to highlight key players, saying, *"The spotlight effect allows me to immediately focus on teammates who are breaking into open spaces."* Although the use of a co-located overview and labels was not as engaging as avatar highlighting, all participants found it to be the most intuitive and easy-to-understand method. *"This may be because of our previous habit of watching tactical boards,"* as P3 mentioned. Considering that users hardly checked the BTB during movement, some participants found it less helpful because *"Unlike the mini-map in MOBA games, it's hard for me to use my peripheral vision to simultaneously look at the 3D scene and BTB."* Overall, in-situ guidance within VisCourt addressed the issue of attention loss in complex scenes due to an overload of virtual content.
- *For guiding user comprehension of the impact of tactics, ROI visualization was considered significantly effective in all aspects.* Among the three types of tactical change guidance, perceiving defensive shifts is straightforward in 3D, but challenging in 2D video. There was a difference in rating on defense form between enthusiasts and professional players. As P4 mentioned, *"In reality, the defense form is not fixed and is greatly influenced by the player's abilities, but it still reflects the pressure the defenders put on me."* On the other hand, E1 commented, *"Noticing changes is crucial for me, and I prefer to score through switches."* However, what is easily noticeable as open space from a top-down 2D perspective can become challenging to discern in an in-situ environment due to obstructions or a limited field of view. ROI assists users in quickly *"identifying tactical open spaces"* and *"understanding the tactical goal"*, highlighting shooting opportunities within the tactic play.
- *Ghosts and trajectories for guiding movement are engaging and easy to comprehend.* The in-situ visualization used for guiding execution is the most frequently employed. The design pattern [35] of using trajectories to guide user movement is still considered the most effective. Y3 and P1 mentioned, *"The use of red and green colors helped me better control my speed."* E3 agreed with setting a wider trajectory width because *"tactics are not about rigidly following a path."* Additionally, the method of using planes

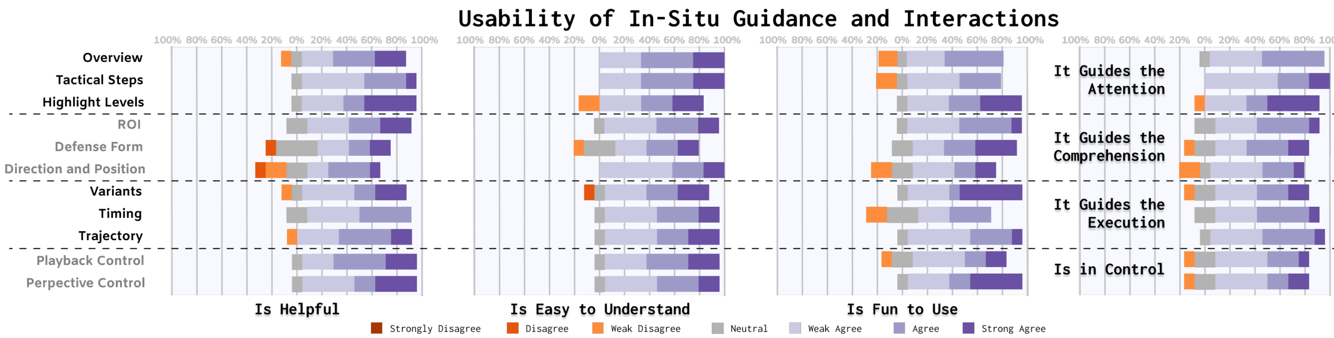

Figure 9: Usability of in-situ guidance and interactions for each in-situ visualization condition.

to constrain movement paths to prevent entering a defender's dominant area was also well-received by several players.

On the other hand, displaying various what-ifs through ghosting was found to be more helpful and engaging. The use of ghosts to show different branches was the most interesting to users. As E2 mentioned, *"I try to experience all the branches, which helps me understand the entire tactical evolution."* Regarding timing, an abstract concept, we used a pause feature to let users perceive the moment to move. However, Y3 commented, *"Too many pauses disrupt the continuity of movement."* Nevertheless, in subsequent round-by-round practicing sessions, Y3 agreed with our division of the VisCourt training routine, indicating a balance between structured learning and maintaining the flow of movement.

- *Movement-based interactions are useful in tactic training.* Both playback control by positional movement and perspective control received positive ratings for being helpful and providing a sense of control. Without the need for a VR controller, participants naturally used their movement to control the learning process while training. "While I walk slowly, time just stops here, and I can look around at this moment, which is very interesting," commented by Y1 and Y4. P1 and P4 appreciated the ability to enter the perspective of teammates or opponents to review the current situation. The method of using visual guidance as an interactive medium aligns with the needs of tactical training, demonstrating the effectiveness of integrating intuitive movement controls and perspective shifts into MR tactical learning environments.

6.4.2 Performance Review of Practicing in VisCourt. All 12 participants (6 indoor, 6 outdoor) completed the training routine. We calculated the overall performance of three groups (professional players, youth players, enthusiasts), as well as the average interpolation distance to test points, and the timing and speed of entering open space areas, based on the measurements mentioned above.

The results indicated that (Figure 10) three rounds of practice within VisCourt could effectively improve the quality of tactical execution, as evidenced by the significant reduction in distance error to each test point in the third round compared to the first. We paid special attention to the timing and speed of participants entering the ROI, finding that, after three sessions, most participants were able to better grasp the movement positions of ball handlers. Professional players became fully acquainted by the end of the learning session, showing no significant changes during training and fluctuating within the normal range of performance. Timing emerged as a noteworthy topic. For professional players, "*being faster than the intended timing*" is not always advantageous.

6.5 Implications for Future SportsXR Training

Next, we discuss the design implications we learned.

- *Ghost for preview via playback control shifts the learning to exploratory.* An interesting aspect of our design is the introduction of ghosts in the preview to depict key movements related to decision-making. Users can freely switch and enter any branch, exploring what-ifs under different situations. This approach transforms learning tactics into active exploration. By enabling users to visualize and interact with these tactical what-ifs, we encourage a more immersive experience, fostering a more engaging and motivating approach to tactical training.
- *Guiding user attention is important for in-situ visualization.* Overlaying virtual content onto real environments can cause visual overload and confusion, potentially leading to virtual reality sickness. By guiding user attention to a few key objects, users can effectively process the in-situ guidance, enhancing the learning experience and minimizing cognitive overload.
- *Identifying the referents in scenarios matters for in-situ design.* Different sports contexts have different referents. To develop in-situ visualizations for a specific environment, these unique elements need to be identified first before proceeding with design.
- *Bullet time is useful for sports training.* Bullet time is a concept from gaming, where action is slowed down to allow for dodging during a frozen moment. In VisCourt, users can step out of avatars during bullet time to observe players and examine potential outcomes, thereby enhancing their perception of situations.

7 DISCUSSION

7.1 Feasibility of VisCourt

Although the user study has demonstrated the usability of VisCourt, we extend the discussion of the feasibility:

- **Applicability**: VisCourt can support training in both indoor and outdoor environments, accommodating diverse experience levels. However, its application to real-world situations may be limited by the mocap tactical samples.
- **Generalizability**: The findings from the development of VisCourt are applicable to other team sports contexts, such as soccer. These include the design considerations of in-situ visualization. Moreover, by adapting the gathered scenarios, the design framework can be expanded to other position-based MR guiding scenarios like rescue exercises or theater rehearsals.
- **Scalability**: The modules are scalable, such as supporting real-time motion reconstruction of video recordings to expand the tactic database or even enhance the spectator experience.

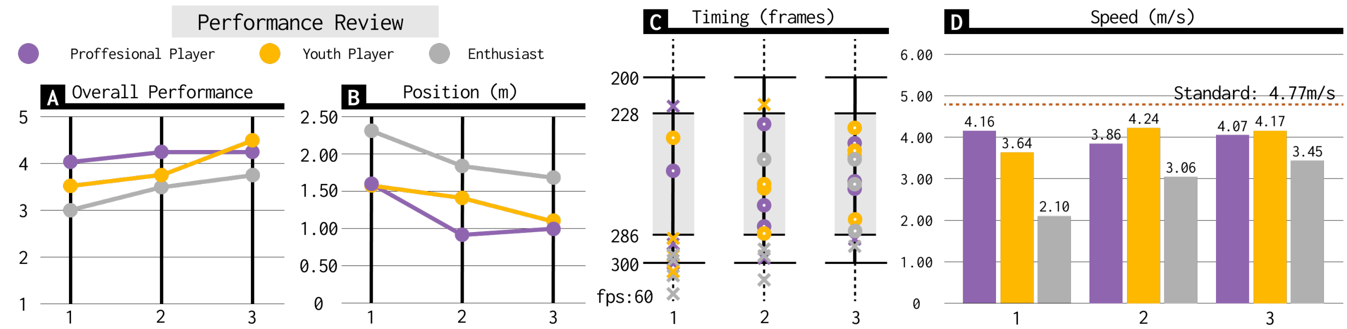

Figure 10: The Performance Review consists of four parts. A) Overall Performance, B) Distance for fixed test point, C) Timing and D) Speed when participants move into the open space.

7.2 What-If Scenarios in MR Tactic Training

In a basketball tactic, the player's choices (e.g., continuing to dribble or passing the ball) significantly determine the subsequent development of the play. Nevertheless, it is difficult for the player to understand the differences between these options due to the fast-paced and dynamic nature of basketball, which makes it hard to replicate the on-court situation at the decision point [76].

Fortunately, training in MR offers such potential. In a manner similar to playback, trainees can easily revisit the specific decision point and compare the differences. This in-presense approach quantifies the vague concept of *"experience in executing a tactic"* in a measurable way. In other words, it allows players to gain a more comprehensive understanding of the various what-ifs of a tactic, thus effectively improving their on-field vision and decision-making ability. However, it is clear that the current shaping of the "decision point" concept still relies on actual filming, which limits the number of possible choice branches. In the future, by incorporating generative models to dynamically link the basketball scenarios displayed in MR with the trainees' choices, there will be a significant enhancement in the perception of What-If scenarios.

7.3 Situated Visualization in Motion

While there has been works focusing on visualization in movement data for analysis or coaching [43], most of it is set in a stationary context, with few discussions on the design of visualization in motion [72]. Moving is considered the relative motion between visualizations and viewers, thus providing assistance to users during movement or serving as a form of feedback for user actions. In 2D videos or flat surfaces, laying out augmented information on specific semantic segmentation objects is straightforward. However, dynamically identifying objects and rendering visualizations in real-time remains challenging in 3D environments, such as AR or MR. With the development of HMDs, these effects are improving, making visualization in motion a topic worth exploring. VisCourt, as a proof of concept for in-situ visualization during user movement, has demonstrated its training capability through user studies. Visualization in motion extends beyond simply providing movement suggestions or feedback to users. A potential area of research could explore using visualization in motion to convey useful information for collaboration in multi-person sports scenarios [49], such as organizing fire drills. This approach could enhance coordination and strategy execution in team settings, opening new avenues for the application of immersive technologies in sports and beyond.

7.4 Limitations and Future Work

We reviewed the current limitations of VisCourt and considered feasible solutions for future work.

- *Drawbacks of visual guidance*: In sports training, relying solely on visual guidance has its limitations, such as the distraction issue or guidance being out of view. Considering the advantages of other guidance methods, such as audio [53, 54] or physical feedback [75], our future work involves integrating multiple methods to provide suitable forms of guidance at different sessions.
- *Limited user support*: Currently, VisCourt only supports individual training, lacking collaborative training capabilities. Our future work will address the current limited user support by tackling visual confusion and synchronization issues that may arise in MR multi-player environment.
- *Predefined Tactic Simulation*: Relying solely on motion capture for tactic simulation is not sufficient. To overcome the limitation in enriching tactical content of what-ifs, we will use generative algorithms for game simulation, such as multi-agent reinforcement learning, which can be more effective.
- *Tutorial Creation Heavily*: To address the limitation of the current manual annotation process through our design framework by coaches, we will explore using domain-knowledge agents for automated tutorial creation based on segmentation from match videos and expertise from tactical domain specialists..

8 CONCLUSION

In conclusion, this study explored the design space of in-situ visualization for guidance in basketball tactic training . We collaborated with both coaches and players to identify existing gaps in current training routines and design goals for immersive training. Drawing on these design considerations, we developed VisCourt, that enables users to emulate collaboration or competition with virtual players within various tactical scenarios on the court, thereby enhancing their spatial and situational awareness. The overall user experience of VisCourt was assessed through user studies confirming the effectiveness and practicality. In the future, we aim to extend our in-situ visualization practices to broadly application in motion.

ACKNOWLEDGMENTS

The work was supported by NSFC (U22A2032, 62202424, 62272396), and the Collaborative Innovation Center of Artificial Intelligence by MOE and Zhejiang Provincial Government (ZJU).

REFERENCES

[1] 2021. EasyMoCap - Make human motion capture easier. Github. Retrieved December 12, 2023 from https://github.com/zju3dv/EasyMocap

[2] 2022. NBA Stats. Retrieved March 18, 2024 from https://www.nba.com/stats/

[3] 2022. NBA2K23. Retrieved March 11, 2024 from https://nba.2k.com/2k23/

[4] 2022. Unity Technologies. Retrieved April 05, 2024 from https://unity.com/

[5] 2023. Eleven vr table tennis. Retrieved February 25, 2024 from https://elevenvr.com/en/

[6] Anna Akbaş, Wojciech Marszałek, Anna Kamieniarz, Jacek Polechoński, Kajetan J. Słomka, and Grzegorz Juras. 2019. Application of Virtual Reality in Competitive Athletes – A Review. *Journal of Human Kinetics* 69, 1 (2019), 5–16. https://doi.org/10.2478/hukin-2019-0023

[7] Hibah Qasem Alatawi, Nouf Albalawi, Ghadah Shahata, Khulud Aljohani, A'aeshah Alhakamy, and M. Tuceryan. 2023. Augmented Reality-Assisted Deep Reinforcement Learning-Based Model towards Industrial Training and Maintenance for NanoDrop Spectrophotometer. *Sensors (Basel, Switzerland)* 23, 13 (2023), 6024. https://doi.org/10.3390/s23136024

[8] G. Andrienko, N. Andrienko, P. Bak, D. Keim, S. Kisilevich, and S. Wrobel. 2011. A conceptual framework and taxonomy of techniques for analyzing movement. *Journal of Visual Languages & Computing* 22, 3 (2011), 213–232. https://doi.org/10.1016/j.jvlc.2011.02.003

[9] Natalia Andrienko and Gennady Andrienko. 2013. Visual analytics of movement: an overview of methods, tools and procedures. *Information Visualization* 12, 1 (2013), 3–24. https://doi.org/10.1177/1473871612457601

[10] Benjamin Bach, Ronell Sicat, Hanspeter Pfister, and Aaron J. Quigley. 2017. Drawing into the AR-CANVAS : Designing Embedded Visualizations for Augmented Reality. In *Workshop on Immersive Analytics, IEEE Vis*.

[11] Shawn L Berman, Jonathan Down, and Charles WL Hill. 2002. Tacit knowledge as a source of competitive advantage in the National Basketball Association. *Academy of management Journal* 45, 1 (2002), 13–31. https://doi.org/10.5465/3069282

[12] Gedas Bertasius, Hyun Soo Park, Stella X. Yu, and Jianbo Shi. 2016. Am I a Baller? Basketball Performance Assessment from First-Person Videos. *2017 IEEE International Conference on Computer Vision (ICCV)* (2016), 2196–2204. https://doi.org/10.1109/ICCV.2017.239

[13] Wolfgang Büschel, Anke Lehmann, and Raimund Dachselt. 2021. MIRIA: A Mixed Reality Toolkit for the In-Situ Visualization and Analysis of Spatio-Temporal Interaction Data. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–15. https://doi.org/10.1145/3411764.3445651

[14] Sebastian Büttner, Michael Prilla, and Carsten Röcker. 2020. Augmented Reality Training for Industrial Assembly Work - Are Projection-based AR Assistive Systems an Appropriate Tool for Assembly Training?. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1––12. https://doi.org/10.1145/3313831.3376720

[15] Dan Cervone, Luke Bornn, and Kirk Goldsberry. 2016. NBA court realty. In *Proceedings of Sloan Sports Analytics Conference*.

[16] Fengxin Chen, Ye Yu, Liangliang Ni, Zhenya Zhang, and Qiang Lu. 2024. DSTVis: toward better interactive visual analysis of Drones' spatio-temporal data. *Journal of Visualization* 27, 4 (2024), 623–638. https://doi.org/10.1007/s12650-024-00982-2

[17] Zhutian Chen, Qisen Yang, Jiarui Shan, Tica Lin, Johanna Beyer, Haijun Xia, and Hanspeter Pfister. 2023. iBall: Augmenting Basketball Videos with Gaze-moderated Embedded Visualizations. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–18. https://doi.org/10.1145/3544548.3581266

[18] Zhutian Chen, Qisen Yang, Xiao Xie, Johanna Beyer, Haijun Xia, Yingnian Wu, and Hanspeter Pfister. 2023. Sporthesia: Augmenting Sports Videos Using Natural Language. *IEEE Transactions on Visualization and Computer Graphics* 29, 1 (2023), 918–928. https://doi.org/10.1109/TVCG.2022.3209497

[19] Gianmarco Ciocca and Harald Tschan. 2023. The Enjoyability of Physical Exercise: Exergames and Virtual Reality as New Ways to Boost Psychological and Psychosocial Health in Astronauts. A Prospective and Perspective View. *IEEE Open Journal of Engineering in Medicine and Biology* 4 (2023), 173–179. https://doi.org/10.1109/OJEMB.2023.3234014

[20] Junting Dong, Qi Fang, Wen Jiang, Yurou Yang, Hujun Bao, and Xiaowei Zhou. 2022. Fast and Robust Multi-Person 3D Pose Estimation and Tracking from Multiple Views. In *T-PAMI*. 6981–6992. https://doi.org/10.1109/TPAMI.2021.3098052

[21] Charles Faure, Annabelle Limballe, Benoît Bideau, and Richard Kulpa. 2020. Virtual reality to assess and train team ball sports performance: A scoping review. *Journal of Sports Sciences* 38, 2 (2020), 192–205. https://doi.org/10.1080/02640414.2019.1689807

[22] Félix Guillén and Julio Román Martínez-Alvarado. 2014. The Sport Engagement Scale: An Adaptation of the Utrecht Work Engagement Scale (UWES) for the Sports Environment. *Universitas Psychologica* 13, 3 (2014), 975–984. https://doi.org/10.11144/Javeriana.UPSY13'3.sesa

[23] David Hamilton, Jim McKechnie, Edward Edgerton, and Claire Wilson. 2021. Immersive virtual reality as a pedagogical tool in education: a systematic literature review of quantitative learning outcomes and experimental design. *Journal of Computers in Education* 8, 1 (2021), 1–32. https://doi.org/10.1007/s40692-020-00169-2

[24] Ramy Hammady and Minhua Ma. 2019. Designing Spatial UI as a Solution of the Narrow FOV of Microsoft HoloLens: Prototype of Virtual Museum Guide. *Augmented Reality and Virtual Reality* (2019), 217–231. https://doi.org/10.1007/978-3-030-06246-0_16

[25] Sebastian Hubenschmid, Jonathan Wieland, Daniel Immanuel Fink, Andrea Batch, Johannes Zagermann, Niklas Elmqvist, and Harald Reiterer. 2022. ReLive: Bridging In-Situ and Ex-Situ Visual Analytics for Analyzing Mixed Reality User Studies. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–20. https://doi.org/10.1145/3491102.3517550

[26] Yao-Fu Jan, Kuan-Wei Tseng, Peng-Yuan Kao, and Yi-Ping Hung. 2021. Augmented Tai-Chi Chuan Practice Tool with Pose Evaluation. In *2021 IEEE 4th International Conference on Multimedia Information Processing and Retrieval (MIPR)*. 35–41. https://doi.org/10.1109/MIPR51284.2021.00013

[27] Pascal Jansen, Julian Britten, Alexander Häusele, Thilo Segschneider, Mark Colley, and Enrico Rukzio. 2023. AutoVis: Enabling Mixed-Immersive Analysis of Automotive User Interface Interaction Studies. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–23. https://doi.org/10.1145/3544548.3580760

[28] Jihyung Kim, Jong Soon Ka, Yelin Lee, Younghak Lee, Sang rong Park, and Wooksung Kim. 2022. Mixed Reality-based Outdoor Training System to Improve Football Player Performance. In *2022 International Conference on Engineering and Emerging Technologies (ICEET)*. 1–3. https://doi.org/10.1109/ICEET56468.2022.10007354

[29] Seungwon Kim, Gun A. Lee, and Nobuchika Sakata. 2013. Comparing pointing and drawing for remote collaboration. In *2013 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. 1–6. https://doi.org/10.1109/ISMAR.2013.6671833

[30] You-Jin Kim, Joshua Lu, and Tobias Höllerer. 2023. Dynamic Theater: Location-Based Immersive Dance Theater, Investigating User Guidance and Experience. In *Proceedings of the 29th ACM Symposium on Virtual Reality Software and Technology*. 1–11. https://doi.org/10.1145/3611659.3615705

[31] Naohiro Kishishita, Kiyoshi Kiyokawa, Jason Orlosky, Tomohiro Mashita, Haruo Takemura, and Ernst Kruijff. 2014. Analysing the effects of a wide field of view augmented reality display on search performance in divided attention tasks. In *2014 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. 177–186. https://doi.org/10.1109/ISMAR.2014.6948425

[32] Karsten Klein, Björn Sommer, Hieu Tri Nim, Andrea Flack, Kamran Safi, Máté Nagy, Stefan P. Feyer, Ying Zhang, Kim Rehberg, Alexej Gluschkow, Michael Quetting, Wolfgang Fiedler, Martin Wikelski, and Falk Schreiber. 2019. Fly with the flock: immersive solutions for animal movement visualization and analytics. *Journal of the Royal Society Interface* 16, 153 (2019), 20180794. https://doi.org/10.1098/rsif.2018.0794

[33] J.V. Krause and C. Nelson. 2019. *Basketball Skills & Drills-4th Edition*. https://books.google.co.jp/books?id=WlFyDwAAQBAJ

[34] Leonardo Lamas, Junior Barrera, Guilherme Otranto, and Carlos Ugrinowitsch. 2014. Invasion team sports: strategy and match modeling. *International Journal of Performance Analysis in Sport* 14, 1 (2014), 307–329. https://doi.org/10.1080/24748668.2014.11868723

[35] Benjamin Lee, Michael Sedlmair, and Dieter Schmalstieg. 2024. Design Patterns for Situated Visualization in Augmented Reality. *IEEE Transactions on Visualization and Computer Graphics* 30, 1 (2024), 1324–1335. https://doi.org/10.1109/TVCG.2023.3327398

[36] Tiemeng Li, Songqian Wu, Yanning Jin, Haopai Shi, and Shiran Liu. 2023. X-Space: Interaction design of extending mixed reality space from Web2D visualization. *Visual Informatics* 7, 4 (2023), 73–83. https://doi.org/10.1016/j.visinf.2023.10.001

[37] Tica Lin, Zhutian Chen, Johanna Beyer, Yingcai Wu, Hanspeter Pfister, Yalong Yang, Melanie Tory, and Daniel F. Keefe. 2023. The Ball is in Our Court: Conducting Visualization Research With Sports Experts. *IEEE Computer Graphics and Applications* 43, 1 (2023), 84–90. https://doi.org/10.1109/MCG.2022.3222042

[38] Tica Lin, Zhutian Chen, Yalong Yang, Daniele Chiappalupi, Johanna Beyer, and Hanspeter Pfister. 2023. The Quest for Omnioculars: Embedded Visualization for Augmenting Basketball Game Viewing Experiences. *IEEE Transactions on Visualization and Computer Graphics* 29, 1 (2023), 962–971. https://doi.org/10.1109/TVCG.2022.3209353

[39] Tica Lin, Rishi Singh, Yalong Yang, Carolina Nobre, Johanna Beyer, Maurice A. Smith, and Hanspeter Pfister. 2021. Towards an Understanding of Situated AR Visualization for Basketball Free-Throw Training. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 13. https://doi.org/10.1145/3411764.3445649

[40] Pin-Xuan Liu, Tse-Yu Pan, Hsin-Shih Lin, Hung-Kuo Chu, and Min-Chun Hu. 2023. VisionCoach: Design and Effectiveness Study on VR Vision Training for Basketball Passing. *IEEE Transactions on Visualization and Computer Graphics* (2023), 1–14. https://doi.org/10.1109/TVCG.2023.3335312

[41] Weiquan Liu, Baiqi Lai, Cheng Wang, Xuesheng Bian, Wentao Yang, Yan Xia, Xiuhong Lin, Shang-Hong Lai, Dongdong Weng, and Jonathan Li. 2020. Learning

to Match 2D Images and 3D LiDAR Point Clouds for Outdoor Augmented Reality. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 655–656. https://doi.org/10.1109/VRW50115.2020.00178

[42] Patrick Lucey, Alina Bialkowski, Peter Carr, Yisong Yue, I. Matthews, and Peter Carr. 2014. " How to Get an Open Shot " : Analyzing Team Movement in Basketball using Tracking Data. In *Proceedings of the 8th annual MIT SLOAN sports analytics conference*.

[43] Weizhou Luo, Zhongyuan Yu, Rufat Rzayev, Marc Satkowski, Stefan Gumhold, Matthew McGinity, and Raimund Dachselt. 2023. Pearl: Physical Environment Based Augmented Reality Lenses for In-Situ Human Movement Analysis. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 15. https://doi.org/10.1145/3544548.3580715

[44] Chunyan Ma, Jizhuang Fan, Jing-Yue Yao, and Tao Zhang. 2021. NPU RGBD Dataset and a Feature-Enhanced LSTM-DGCN Method for Action Recognition of Basketball Players+. *Applied Sciences* 11, 10 (2021), 4426. https://doi.org/10.3390/app11104426

[45] Stefan C Michalski, Ancret Szpak, and Tobias Loetscher. 2019. Using virtual environments to improve real-world motor skills in sports: a systematic review. *Frontiers in psychology* 10 (2019), 2159. https://doi.org/10.3389/fpsyg.2019.02159

[46] Alessio Mocco, Lucia Valmaggia, Lara Bernardi, Margherita Alfieri, and Ilaria Tarricone. 2024. Enhancing Physical Activity with Immersive Virtual Reality: A Systematic Review. *Cyberpsychology, Behavior, and Social Networking* 27, 5 (2024), 303–317. https://doi.org/10.1089/cyber.2023.0394

[47] David L. Neumann, Robyn L. Moffitt, Patrick R. Thomas, Kylie Loveday, David P. Watling, Chantal L. Lombard, Simona Antonova, and Michael A. Tremeer. 2018. A systematic review of the application of interactive virtual reality to sport. *Virtual Reality* 22, 3 (2018), 183–198. https://doi.org/10.1007/s10055-017-0320-5

[48] Hermilo Nunes, Xavier Iglesias, Luca Del Giacco, and M. Teresa Anguera. 2022. The Pick-and-Roll in Basketball From Deep Interviews of Elite Coaches: A Mixed Method Approach From Polar Coordinate Analysis. *Frontiers in Psychology* 13 (2022), 801100. https://doi.org/10.3389/fpsyg.2022.801100

[49] Nelusa Pathmanathan, Seyda Öney, Michael Becher, Michael Sedlmair, Daniel Weiskopf, and Kuno Kurzhals. 2023. Been There, Seen That: Visualization of Movement and 3D Eye Tracking Data from Real-World Environments. *Computer Graphics Forum* 42, 3 (2023), 385–396. https://doi.org/10.1111/cgf.14838

[50] Donna Peuquet. 1994. It's About Time: A Conceptual Framework for the Representation of Temporal Dynamics in Geographic Information Systems. *Annals of The Association of American Geographers* 84, 3 (1994), 441–461. https://doi.org/10.1111/j.1467-8306.1994.tb01869.x

[51] Nimesha Ranasinghe, Pravar Jain, Shienny Karwita, David Tolley, and Ellen Yi-Luen Do. 2017. Ambiotherm: enhancing sense of presence in virtual reality by simulating real-world environmental conditions. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. 1731–1742. https://doi.org/10.1145/3025453.3025723

[52] Patrick Reipschläger, Frederik Brudy, Raimund Dachselt, Justin Matejka, George W. Fitzmaurice, and Fraser Anderson. 2022. AvatAR: An Immersive Analysis Environment for Human Motion Data Combining Interactive 3D Avatars and Trajectories. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–15. https://doi.org/10.1145/3491102.3517676

[53] Sadia Rubab, Lingyun Yu, Junxiu Tang, and Yingcai Wu. 2023. Exploring effective relationships between visual-audio channels in data visualization. *Journal of Visualization* 26, 4 (2023), 937–956. https://doi.org/10.1007/s12650-023-00909-3

[54] Sadia Rubab, Muhammad Wajeeh Uz Zaman, Umer Rashid, Lingyun Yu, and Yingcai Wu. 2024. Audio-visual training and feedback to learn touch-based gestures. *Journal of Visualization* (2024), 1–26. https://doi.org/10.1007/s12650-024-01012-x

[55] Rafael Sacks, Amotz Perlman, and Ronen Barak. 2013. Construction safety training using immersive virtual reality. *Construction Management and Economics* 31, 9 (2013), 1005–1017. https://doi.org/10.1080/01446193.2013.828844

[56] Jonas Schild, Guillermo Carbonell, Anna Tarrach, and Madeline Ebeling. 2022. ViTAWiN - Interprofessional Medical Mixed Reality Training for Paramedics and Emergency Nurses. In *2022 IEEE 10th International Conference on Serious Games and Applications for Health(SeGAH)*. 1–8. https://doi.org/10.1109/SEGAH54908.2022.9978566

[57] Sungbok Shin, Andrea Batch, Peter W. S. Butcher, Panagiotis D. Ritsos, and Niklas Elmqvist. 2024. The Reality of the Situation: A Survey of Situated Analytics. *IEEE transactions on visualization and computer graphics* 30, 8 (2024), 5147–5164. https://doi.org/10.1109/TVCG.2023.3285546

[58] Oto Takeuchi, Hidehiko Shishido, Yoshinari Kameda, Hansung Kim, and Itaru Kitahara. 2018. Generation Method for Immersive Bullet-Time Video Using an Omnidirectional Camera in VR Platform. In *Proceedings of the 2018 Workshop on Audio-Visual Scene Understanding for Immersive Multimedia*. 19–26. https://doi.org/10.1145/3264869.3264872

[59] Feng Tian, Shuting Ni, Xiaoyue Zhang, Fei Chen, Qiaolian Zhu, Chunyi Xu, and Yuzhi Li. 2024. Enhancing Tai Chi Training System: Towards Group-Based and Hyper-Realistic Training Experiences. *IEEE Transactions on Visualization and Computer Graphics* 30, 5 (2024), 1–11. https://doi.org/10.1109/TVCG.2024.3372099

[60] Feng Tian, Jiahui Zou, Keying Li, and Yuzhi Li. 2023. Kung Fu Metaverse: A Movement Guidance Training System. *IEEE Transactions on Learning Technologies* 16, 6 (2023), 1082–1095. https://doi.org/10.1109/TLT.2023.3317945

[61] Wan-Lun Tsai, Ming-Fen Chung, Tse-Yu Pan, and Min-Chun Hu. 2017. Train in Virtual Court: Basketball Tactic Training via Virtual Reality. In *Proceedings of the 2017 ACM Workshop on Multimedia-based Educational and Knowledge Technologies for Personalized and Social Online Training*. 3–10. https://doi.org/10.1145/3132390.3132394

[62] Wan-Lun Tsai, Tse-Yu Pan, and Min-Chun Hu. 2022. Feasibility Study on Virtual Reality Based Basketball Tactic Training. *IEEE Transactions on Visualization and Computer Graphics* 28, 8 (2022), 2970–2982. https://doi.org/10.1109/TVCG.2020.3046326

[63] Hanwen Wang, Bingyi Su, Lu Lu, Sehee Jung, Liwei Qing, Ziyang Xie, and Xu Xu. 2024. Markerless gait analysis through a single camera and computer vision. *Journal of Biomechanics* 165 (2024), 112027. https://doi.org/10.1016/j.jbiomech.2024.112027

[64] Zhe Wang, Petar Veličković, Daniel Hennes, Nenad Tomašev, Laurel Prince, Michael Kaisers, Yoram Bachrach, Romuald Elie, Li Kevin Wenliang, Federico Piccinini, et al. 2024. TacticAI: an AI assistant for football tactics. *Nature Communications* 15, 1 (2024), 1906.

[65] Zhen Wen, Wei Zeng, Luoxuan Weng, Yihan Liu, Mingliang Xu, and Wei Chen. 2023. Effects of View Layout on Situated Analytics for Multiple-View Representations in Immersive Visualization. *IEEE Transactions on Visualization and Computer Graphics* 29, 1 (2023), 440–450. https://doi.org/10.1109/TVCG.2022.3209475

[66] Wikipedia. 2024. Basketball court — Wikipedia, The Free Encyclopedia. http://en.wikipedia.org/w/index.php?title=Basketball%20court&oldid=1196544947. [Online; accessed 24-March-2024].

[67] Wikipedia. 2024. Tactic (method) — Wikipedia, The Free Encyclopedia. http://en.wikipedia.org/w/index.php?title=Tactic%20(method)&oldid=1210782077. [Online; accessed 24-March-2024].

[68] Wesley Willett, Yvonne Jansen, and Pierre Dragicevic. 2017. Embedded Data Representations. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (2017), 461–470. https://doi.org/10.1109/TVCG.2016.2598608

[69] Yihong Wu, Dazhen Deng, Xiao Xie, Moqi He, Jie Xu, Hongzeng Zhang, Hui Zhang, and Yingcai Wu. 2023. OBTracker: Visual Analytics of Off-ball Movements in Basketball. *IEEE Transactions on Visualization and Computer Graphics* 29, 1 (2023), 929–939. https://doi.org/10.1109/TVCG.2022.3209373

[70] Yihong Wu, Lingyun Yu, Jie Xu, Dazhen Deng, Jiachen Wang, Xiao Xie, Hui Zhang, and Yingcai Wu. 2023. AR-Enhanced Workouts: Exploring Visual Cues for At-Home Workout Videos in AR Environment. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–15. https://doi.org/10.1145/3586183.3606796

[71] Zhijie Xia, Kyzyl Monteiro, Kevin Van, and Ryo Suzuki. 2023. RealityCanvas: Augmented Reality Sketching for Embedded and Responsive Scribble Animation Effects. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–16. https://doi.org/10.1145/3586183.3606716

[72] L. Yao, Anastasia Bezerianos, Romain Vuillemot, and Petra Isenberg. 2022. Visualization in Motion: A Research Agenda and Two Evaluations. *IEEE Transactions on Visualization and Computer Graphics* 28, 10 (2022), 3546–3562. https://doi.org/10.1109/TVCG.2022.3184993

[73] L. Yao, Anastasia Bezerianos, Romain Vuillemot, and Petra Isenberg. 2023. Situated Visualization in Motion for Swimming. In *Journée Visu 2022*. 1–19.

[74] Lijie Yao, Romain Vuillemot, Anastasia Bezerianos, and Petra Isenberg. 2024. Designing for Visualization in Motion: Embedding Visualizations in Swimming Videos. *IEEE Transactions on Visualization and Computer Graphics* 30, 3 (2024), 1821–1836. https://doi.org/10.1109/TVCG.2023.3341990

[75] Yue Zhang, Zhenyuan Wang, Jinhui Zhang, Guihua Shan, and Dong Tian. 2023. A survey of immersive visualization: Focus on perception and interaction. *Visual Informatics* 7, 4 (2023), 22–35. https://doi.org/10.1016/j.visinf.2023.10.003

[76] Mengya Zheng, David Lillis, and Abraham G. Campbell. 2024. Current state of the art and future directions: Augmented reality data visualization to support decision-making. *Visual Informatics* 8, 2 (2024), 80–105. https://doi.org/10.1016/j.visinf.2024.05.001

[77] Chen Zhu-Tian, Shuainan Ye, Xiangtong Chu, Haijun Xia, Hui Zhang, Huamin Qu, and Yingcai Wu. 2022. Augmenting Sports Videos with VisCommentator. *IEEE Transactions on Visualization and Computer Graphics* 28, 1 (2022), 824–834. https://doi.org/10.1109/TVCG.2021.3114806

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009