Smartboard: Visual Exploration of Team Tactics with LLM Agent

Ziao Liu, Xiao Xie, Moqi He, Wenshuo Zhao, Yihong Wu, Liqi Cheng, Hui Zhang, and Yingcai Wu

Abstract—Tactics play an important role in team sports by guiding how players interact on the field. Both sports fans and experts have a demand for analyzing sports tactics. Existing approaches allow users to visually perceive the multivariate tactical effects. However, these approaches require users to experience a complex reasoning process to connect the multiple interactions within each tactic to the final tactical effect. In this work, we collaborate with basketball experts and propose a progressive approach to help users gain a deeper understanding of how each tactic works and customize tactics on demand. Users can progressively sketch on a tactic board, and a coach agent will simulate the possible actions in each step and present the simulation to users with facet visualizations. We develop an extensible framework that integrates large language models (LLMs) and visualizations to help users communicate with the coach agent with multimodal inputs. Based on the framework, we design and develop Smartboard, an agent-based interactive visualization system for fine-grained tactical analysis, especially for play design. Smartboard provides users with a structured process of setup, simulation, and evolution, allowing for iterative exploration of tactics based on specific personalized scenarios. We conduct case studies based on real-world basketball datasets to demonstrate the effectiveness and usefulness of our system.

Index Terms—Sports visualization, tactic board, tactical analysis

1 Introduction

Tactics can be defined as a series of planned actions of multiple players. Both experts and sports fans have a strong need to understand and analyze tactics. Specifically, for sports fans, analyzing tactics can help them gain insights into the intricacies of the sport, such as how teams strategize, adapt, and compete against each other, thereby improving their own skills and performance in the sport and their engagement when watching games. Despite the great demand, analyzing tactics is challenging since it requires significant efforts to process the data and substantial domain knowledge to obtain insights from the data.

Advanced techniques have been successfully employed to reduce the efforts of data processing, such as extracting data from videos [24, 35] and detecting data patterns [32, 34, 48], etc. Consequently, the bottleneck in tactical analysis, especially for play design, lies in making sense of the data [57]. Visualization-based approaches [2, 55] are therefore introduced to address this problem. These approaches usually design statistical models based on sports domain knowledge and use these models to evaluate the effectiveness of tactics quantitatively. Different forms of visualizations are further designed and utilized to help users better understand the model results. While these approaches are valuable, it is still difficult for users to obtain insights from the data [53]. This requires a complex reasoning process to connect the multiple interactions within each tactic to the final tactical effect.

We propose to utilize Large Language Models (LLMs) and visualizations to address this problem. LLMs have demonstrated powerful capabilities in understanding complex text descriptions [33] and reasoning with spatio-temporal data [22]. This suggests that LLMs have great potential not only to comprehend complex tactical text descriptions but also to provide prospective insights through tactical reasoning [6], which is beyond the ability of traditional models. In this work, we choose basketball, one of the most representative sports, as our scenario. By collaborating with basketball experts, we propose an LLM-based interactive visualization system, Smartboard. Users can sketch on a tactic board to define the tactic of interest. They can further specify the scenario of tactics, e.g., the score difference or the specific players and teams, through visualizations. An LLM-based coach agent will receive the multi-modal input and can simulate the following situations on the court using its knowledge of basketball tactics. The output of the coach agent will be transformed into visualizations and users can progressively interact with the agent to understand the formulation of a tactic and its possible variants. Smartboard significantly reduces the required knowledge for users since the coach agent can help users conduct complex reasoning tasks in tactical play design and analysis.

However, we encountered two main challenges during the development. The first challenge is to propose a method to use LLMs for tactical analysis in play design. The diversity in basketball experts' tactical understanding makes customized input requirements necessary. Moreover, to enhance the realism of the simulation environment, the outcomes should present a coherent and comprehensible sequence of decision-making steps. However, the limited domain knowledge of LLMs substantially affects the quality of the simulation results, making this task challenging. The second challenge is to provide effective exploration, recommendation, and explanation for tactical play design. Experts aim to explore the simulation scenarios as thoroughly as possible. However, anticipating every conceivable scenario within the simulation process is difficult [20]. It is necessary to provide recommendations based on the current context [52]. Moreover, since LLMs' output modality is limited to natural language [68], it is difficult for users to extract key information from a large amount of output text quickly. Therefore, transforming text information into visualizations and providing explanations are particularly important. Designing an agent-based interactive visualization system for exploration, recommendation, and explanation in tactical play design is highly challenging.

Therefore, we propose an interaction framework to address the first challenge. We use prompt engineering to enhance the knowledge, integrate controllable external information to meet experts' personalized needs and leverage the chain-of-thought (CoT) [58] approach to guide results. Based on the framework, we design an interactive system to tackle the second challenge. Users can freely sketch tactics and convey tactical intentions through this system. Then, they can analyze the recommended results for comparison and select them to advance the next steps in the tactical simulation. At any stage of the analysis, users can explain the results. Through this iterative process, users can continuously explore until they obtain a satisfactory complete tactic.

In summary, our main contributions are as follows:

- ◇ An **extensible framework** supports complex interactions with LLM agents for basketball tactical analysis.
- ◇ An **agent-based interactive visualization system** that supports users in iteratively conducting tactical analysis for play design through exploration, recommendation, and explanation.
- ◇ Two **case studies** that demonstrate the effectiveness and usefulness of our system.

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2 RELATED WORK

This section presents related studies from two perspectives, namely, sports visualization and LLM application in visualization.

2.1 Sports Visualization

Visualization techniques have been widely used in the analysis of different sports such as soccer [2,3,49,65,67], baseball [7,26,37], racket sports [44, 45, 54, 60, 61, 64], ice hockey [43], ski [47] and rugby [19]. Numerous specialized visualization systems have emerged, tailored to specific data types and analytical needs [9]. For example, SoccerStories [41] provided a series of coordinated visualizations for the analysis of soccer data. VIRD [28] introduced an end-to-end immersive tool for analyzing match videos, enabling coaches to interactively analyze spatio-temporal and pose information from various perspectives in badminton match video analysis. Perin et al. [42] have provided a comprehensive overview of the most effective visualization techniques and analytical methods suitable for each kind of sports data.

In basketball, most works focused on designing visualization systems to facilitate the analysis task. GameViews [71] and GameFlow [4] designed visualizations to present various levels of basketball gameplay. In analyzing player performance, Buckets [1] and HoopInSight [11] provided insightful visualizations for shooting performance, enabling comparative analyses in varied contexts. In team analysis, PluMP [51] enhanced plus-minus values to a team-wide perspective, providing a visualization interface for in-depth exploration. OBTracker [63] introduced an interpretable off-ball movement model that assesses individual contributions, aggregated to summarize team-wide movement patterns, and employed an interactive visual analytics system for result explanation. For training purposes, VisionCoach [30] introduced an immersive virtual reality system focused on visual training for passing from the player's perspective. In addition to analysis, a set of works focused on creating storytelling visualizations for basketball data. For example, Chen et al. [5, 73, 74] improved the sports video viewing experience by enabling users to edit special visual effects, generating augmented videos based on user actions. Lin et al. [29] explored the design space of embedded visualizations to augment basketball viewers' experience. Fu et al. [10] developed a visualization system that aids writers and journalists in crafting compelling, data-driven basketball stories. These works provide guidance for our visualization design. However, the main challenge, i.e., coordinating with LLMs using visualizations for conducting basketball tactic analysis, has not been addressed.

Simulation tools like BasketballGAN [16] and Basketball Flow [25] are also closely related to this work. They modeled defensive strategies based on offensive plays sketched by users, yet they lacked detailed visualizations for thorough analysis and explanation of simulations. Furthermore, simulations based solely on players' trajectory data failed to replicate the complexity of actual game scenarios.

2.2 LLM Application in Visualization

Large language models (LLMs) have shown great performance in various domain tasks by combining various types of data [14]. Despite its usefulness, it is hard for users to accurately convey their intentions to LLMs using only natural language when tackling complex tasks. Hence, creating efficient visualization interfaces and interactions to help users better understand, control, and improve LLMs' outputs is urgently needed [12]. For example, ChartSpark [66] proposed a visualization system to help users obtain high-quality data charts by interactively optimizing prompts. To ensure that LLMs can accomplish certain tasks based on predefined knowledge, C2Idea [15] integrates design principles to prompts, allowing LLMs to create color schemes that follow these principles. To help users better understand LLM outputs and how they work, CommonSenseVis [56] developed an interactive visualization system to explain and explore the common sense reasoning abilities of natural language models. A set of research further treats LLMs as agents to support the co-analysis and show that LLM agents can assist in processing complex information [62] and facilitating the decision-making process [70]. However, the application in facilitating sports analysis, particularly in basketball tactical analysis, is less explored. Despite the capability of LLMs in interpreting spatial-temporal data [21], enabling experts to effectively explore and analyze tactics with the aid of LLMs poses a challenge. To bridge this gap, we proposed an extensible framework that allows users to fully express their tactical intentions, including complex spatio-temporal context information, to the agent with visualizations.

3 BACKGROUND

In this section, we first introduce the relevant concepts, followed by a detailed description of the interviews and a summary of the requirements. Finally, we introduce the dataset. Additionally, we provide a glossary to explain the basketball terms and tactics presented in our paper. Please refer to our supplemental material for more details.

3.1 Background and Concepts

Basketball is a competitive sport between two teams, each composed of five players, battling on a rectangular court to score points. Basketball tactics define a series of actions for players that can create opportunities to win the game. Related concepts are defined as follows.

- **A tactic board** is a tool for drawing and displaying basketball tactics. It facilitates understanding tactical execution between coaches and players, serving as a key to tactical communication.
- **Player roles** refer to the responsibilities of each player in a tactic, including point guard, shooting guard, small forward, power forward, and center. Each role carries distinct contributions to the tactical execution. Players may switch roles as tactics demand.
- **Game contexts** are external factors that influence tactical effects, such as game period, score gap, remaining time, etc.
- **A situation** is a specific scenario within tactical execution. In this paper, the situation is used to retrieve similar ones from datasets.

3.2 Interviews

We collaborated with six basketball experts for a year to develop an interactive system for tactical play design. These experts included two basketball coaches (E1 and E2, both with years of coaching experience), two basketball analysts (E3 and E4, both with extensive experience in tactical analysis), and two PhDs majoring in sports science (E5 and E6, both with distinguished backgrounds as players in elite teams).

Interview 1. To gain a deep understanding of the workflow involved in tactical analysis, especially for play design, we engaged in an hour-long semi-structured interview with our experts. According to our experts, tactical play design unfolds in an iterative loop. First, they analyze real game videos and sketch tactical setups on the tactic board. These setups are then applied in training sessions to evaluate the effectiveness and usefulness of the tactical execution. After analyzing the results, they refine or advance the tactic as needed. This process is repeated until the experts achieve a satisfactory tactic.

Experts encounter numerous challenges during the tactical play design process. They usually need to analyze videos to refine tactics setups, which is a time-consuming task. Moreover, frequent changes in training can lead to confusion and frustration, which may decrease players' motivation and persistence. While experts have attempted to use AI models to predict tactical execution outcomes, it remains challenging for them to express their specific tactical intentions to these models. For instance, E1 mentioned that it's difficult to specify the opponent's particular defensive tactic during the tactical simulation. Furthermore, E2 and E3 stated that the iterative analysis process requires frequent and effective interactions with the model. However, they identified gaps in their ability to adjust the model's parameters effectively [13]. Experts tried to use ChatGPT [38] to optimize the tactical analysis experience but also encountered issues. These prompted us to design an LLM-based interactive system to address these challenges.

Interview 2. Based on the domain challenges, we developed a system prototype and conducted a follow-up interview with each expert. We focus on their expectations about utilizing LLMs to assist with tactical analysis. E1 and E4 mentioned that integrating more information can help them in deploying the details of tactics. For example, they can better tailor the tactic to the players' habitual movements. E3 and E5 pointed out that displaying the reasoning process of tactics could assist them in analyzing changes in different situations such as *how tactics evolve in the current context?* and *why such changes are necessary?* E2 and E6 emphasized the significance of using natural language for interaction with the agent. They believed that it would be effective to convey their specific requirements precisely during the analysis.

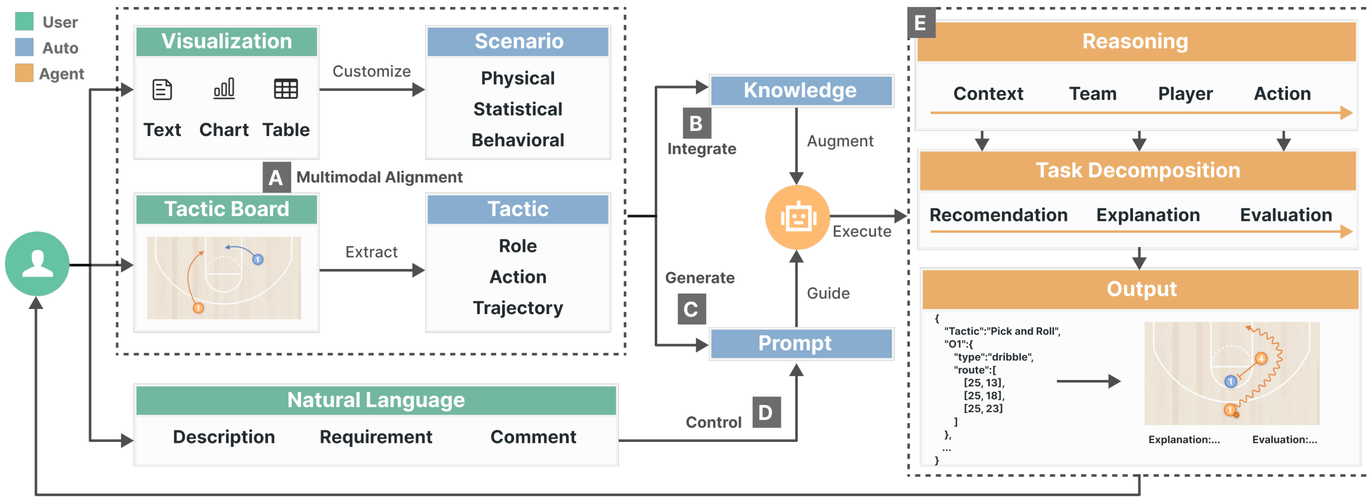

Fig. 1: System framework. (A) Multi-modal input to represent tactical intentions. (B) Integration of specific domain knowledge to augment LLM agent execution. (C) Prompt generation based on multi-modal input to guide LLM agent execution. (D) Additional fine-grained requirements to control the reasoning process. (E) The step-by-step reasoning process of the LLM agent.

3.3 Requirement Analysis

Based on the interviews, we summarized six requirements that follow the workflow of tactical analysis for play design, including three perspectives: tactical setup, simulation, and evolution.

- **Comprehensive Tactical Setup.**
  - **R1 Enhance sketching with guidance.** The setup on the tactic board requires guidance, such as tactical decisions and suggestions. This guidance streamlines the sketching process, enabling experts to explore strategic options more effectively.
  - **R2 Integrate contextual information.** The success of a tactic is influenced by various factors, such as physical conditions, historical performance, and behavioral patterns. Integrating broader contextual information can provide experts with a detailed background for tactical setups.
- **Reasonable Tactical Simulation.**
  - **R3 Display various options and variants.** Tactics vary by situation. For example, a pick-and-roll can transform into a pick-and-pop based on different choices. Therefore, experts need to understand a broader range of variations to grasp the applicability and potential outcomes of tactics in specific contexts.
  - **R4 Present the reasoning process.** Tactics are shaped by many factors. For instance, a tactic may change in the final minutes. Thus, experts should explore the thought process behind tactics for a better understanding of their pros and cons.
- **Controllable Tactical Evolution.**
  - **R5 Control with natural language.** Experts often use natural language to communicate and share ideas in tactics analysis. For example, they specify a tactical goal of creating space for a three-pointer. Thus, utilizing natural language for control should encompass the whole process, facilitating experts to simplify and refine the expression of their requirements.
  - **R6 Adjust based on user feedback.** Experts have unique insights and often need to modify or optimize tactics. Therefore, the system's ability to adjust based on user feedback helps experts efficiently refine and evolve their tactics.

3.4 Data Description

We use an open-source dataset furnished by STATS SportVU [31], which documents 631 NBA regular season games of the 2015-16 season. Each game is recorded with both event and tracking data. The event data encompass critical moments such as shots, fouls, and assists, along with their contextual information. The tracking data reveal the precise spatial locations of both players and the ball, captured at a rate of 25 frames per second. These data specifics are presented in Table 1. Additionally, we collect the height and weight of each player via the NBA api, enhancing our analysis with the physical attributes of the players involved.

Table 1: Basketball Data Description

Data	Description
Event Type	Events such as pass, dribble, shot, etc.
Off / Def Team	Offensive and defensive teams in the event.
Score	Score difference between Off and Def team.
Period	Every twelve minutes of the game.
Time	Remaining time in the current period.
Player	All Players on the court.
Player Trajectory	Player spatial locations $\{(X_i, Y_i), \ldots\}$.
Ball Trajectory	Ball spatial locations $\{(X_i, Y_i), \ldots\}$.

4 Framework

Based on the requirements, we propose a framework (Fig. 1) to enhance users' interaction with LLMs in basketball tactical play design. This framework is structured into three key parts: First, the user input allows users to provide detailed information (**R1, R2, R5**). Next, the model output enables the LLM agent to generate outcomes based on user needs (**R3, R4**). Finally, the iterative exploration ensures users control every stage using feedback in the analysis process (**R6**).

4.1 User Input

Contextual information provides essential support for fine-grained tactical analysis. To help users comprehensively convey information and intentions to the LLM agent, we introduce the sketching stage, further facilitating information integration (Fig. 1(A, D)). This creates a flexible interactive environment for basketball tactical play design.

Visualization improves user input from a data perspective. Text, charts, and tables are basic forms of visualization. They can represent various types of data, making it easier for users to understand. Users can customize the scenario for tactical analysis by interacting with the visual elements. Visualizations provide solid data support by integrating broader contextual information into the tactical setup (**R2**).

Tactic board offers users an intuitive platform for tactical setup. It enables the visual communication of key tactical information, such as player roles, trajectories, and actions. Sketching aligns with users' preferences (**R1**), providing a method of expressing tactical information.

Natural language provides a user-friendly interaction method (**R5**). We categorize natural language into three types, which serve as additional input to enrich background descriptions, specify tactical requirements, and provide feedback comments. Natural language enhances the flexibility of interaction between users and the model, ensuring that the analysis process aligns more closely with the users' intentions.

4.2 Model Output

Requirement-driven outputs (Fig. 1(E)) are essential throughout the tactical exploration process. We enable the LLM agent to reason step by step to understand the intricate factors provided by users. Furthermore, We summarize agent's task categories based on various needs.

Reasoning requires the LLM agent to conduct a top-down analysis across four levels: starting with the context level, which focuses on game contexts and specific scenarios; followed by the team level, considering the team's overarching strategies and styles; the player level for considering individual players' technical abilities and performances; and lastly, the action level for the details of tactical actions and their execution. This step-by-step thinking of Chain-of-Thought allows the agent to consider diverse factors and perspectives of complex tactics.

Task decomposition helps the LLM agent to break down complex tasks into more focused components. The tasks are decomposed into three types: recommendation, explanation, and evaluation. The recommendation task enables the model to present various options and variants (**R3**), offering tailored tactical suggestions for setups. The explanation provides insights into the agent's decision-making process (**R4**), significantly enhancing the transparency and understanding of tactics. The evaluation involves a thorough analysis of simulation outcomes to help users assess the potential and suitability of each setup.

4.3 Iterative Exploration

Our framework allows iterative interactions for tactical exploration. User input serves as the tactical setup, guiding the model towards customized scenarios. Model outputs offer insights and alternatives for tactical simulation, effectively turning analysis into a cyclical process that iterates between setup and simulation, which represents tactical evolution (**R6**). Through this structured yet flexible approach, users and the LLM agent work in a collaborative way to explore, simulate, and explain tactics, driving toward understanding and optimizing tactics.

5 Implementation

This section details our framework's implementation. First, we introduce multimodal alignment for handling inputs. Next, we integrate knowledge and generate prompts for the LLM agent. Finally, we provide user-customized control. We use GPT-4V [40] as the backend.

5.1 Multimodal Alignment

Recent studies show that multimodal alignment can effectively enhance LLMs' vision understanding by forming image-text pairs [18]. For aligning tactic images with scenario text from different modalities, we extract visual elements from user sketches and integrate them with semantic descriptions to achieve effective multimodal alignment (Fig. 2).

Visual extraction. The tactic board is rich in visual elements, including glyphs for players, lines for trajectories, and arrows for actions. To meticulously extract visual information from the tactic board, we process it from both spatial and temporal aspects.

- Spatial location: We establish a coordinate system to precisely locate players on the field and use continuous coordinate points to represent trajectories for better spatial expression.
- Temporal description: Based on the order of sketches, we describe the sequence of actions to present the logic of tactical execution.

Semantic integration. We use predetermined templates to organize the extracted visual elements. To enhance the overall description's understandability, the template includes the interactions between players, integrating semantic information to complete the alignment.

5.2 Knowledge Integration

Domain knowledge is a crucial factor influencing the performance of LLM agents. Although LLMs have demonstrated exceptional knowledge in some domain-specific tasks, they may lack sufficient expertise for tactical analysis in particular scenarios. To mitigate this limitation, we transform tactic and scenario knowledge into knowledge documents and utilize retrieval-augmented generation (RAG) [27] to improve the LLM agent's response by retrieving relevant information (Fig. 3).

Knowledge document. The knowledge document is composed of tactic-based and scenario-based knowledge organized as text data. This provides comprehensive information to enhance the LLM agent's understanding and response generation in tactical scenarios.

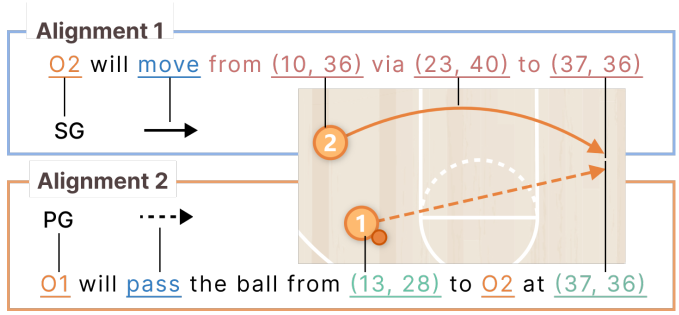

Fig. 2: Two templates of multimodal alignment. We use colors to characterize the information after visual extraction: orange for player role, blue for action, green for location, and red for trajectory.

Tactic-based knowledge (Fig. 3(A)) is derived from tactic image-text pairs after multimodal alignment, including the visual depiction and coordinate system. The visual depiction describes the visual encoding of the tactic board, including glyphs, lines, and arrows. The coordinate system includes the mapping of data relationships on the tactic board. This knowledge helps the LLM agent to understand the tactical details.

Scenario-based knowledge (Fig. 3(B)) is designed for users to convey customized scenarios to the LLM agent. This type of knowledge covers various aspects of tactical scenarios, including physical, statistical, and behavioral information, to provide a comprehensive understanding of tactical scenarios. The details are as follows.

- The physical information includes the collected height and weight data of each player within the current scenario. In addition, we calculate the average speed of each player through the selected scenario, which is treated as physical information to evaluate the physical capabilities of the player in the tactic.
- The statistical information is shown for the interactive selection of the team and player matchup in the current tactic. We calculate on/off-court statistics for every selected player matchup. On/off-court information measures the difference in performance of the offensive player with the defensive player on or off the court. It helps users to understand the impact of the matchup on the tactic. We calculate five metrics, including field goals, three-point field goals, assists, turnovers, and personal fouls, and normalize them.
- The behavioral information is reflected in the situation. Referring to the existing research [49], we allow users to perform similar situation retrieval, which can make users associate similar tactical execution in real games with the current situation. The behavioral information helps users customize the tactic's scenario, enabling the LLM agent to understand and generate similar situations.

Retrieval-augmented generation. We utilize the text-embedding-3-large model [39] provided by OpenAI to embed the knowledge documents. The resulting vectors are stored in a FAISS vector store [8], enabling efficient retrieval by the LLM agent. This approach enhances the LLM's ability to access and incorporate relevant external knowledge, thereby improving the quality of its responses.

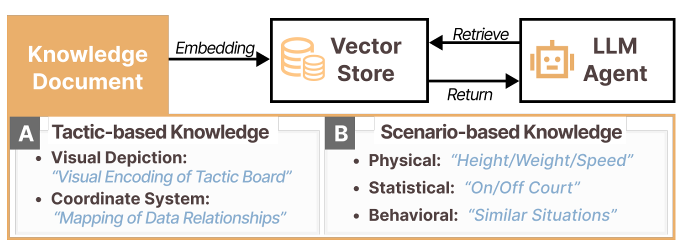

Fig. 3: Knowledge integration of our framework. (A) Tactic-based knowledge. (B) Scenario-based knowledge.

5.3 Prompt Generation

Prompt engineering has proved to effectively enhance the performance of LLMs in solving domain-specific tasks [59]. Therefore, we design a dynamic prompt template (Fig. 4) to leverage LLMs generating based on user demands, consisting of six components.

Prompt	Prompt Details		
Role	*"You are a basketball coach with years of experience strategizing and reading the game."*		
Knowledge	*"Use your knowledge to best respond to user queries."*		
Task	**Recommendation**	**Explanation**	**Evaluation**
	"Recommend three suitable tactical setups."	*"Explain tactical setups in both overview and detail."*	*"Evaluate tactical setups in both overview and detail."*
	Requirement (optional)		
Output Format	*"For each tactical setup, provide the following details:"* →	*O#*: offensive player number. *D#*: defensive player number. *Start Position*: [*(x, y)* for the initial location]. *Middle Position*: [*(x, y)* for the key location during execution]. *End Position*: [*(x, y)* for the final location post-execution].	
	Recommendation	**Explanation**	**Evaluation**
	Action Type: choose type from ["screen","move","dribble","pass","shot"]	*Overview*: explain in one sentence. *Detail*: [*action*][*counter*][*objective*]	*Overview*: evaluate in one sentence. *Detail*: [*objective alignment*][*reaction*]
Inputs	Knowledge + Image-Text Pair	Knowledge + Image-Text Pair + Recommendation	Knowledge + Image-Text Pair + Recommendation + Explanation
	Description (optional) or Comment (optional)		
Reasoning	*"Let's think step by step in context, team, player, and action level."*		

Fig. 4: The multi-step prompt generation for the tactical play design (From top to down). (1) Specify the role of the LLM agent. (2) Specify the knowledge document that the LLM agent should consider for the analysis. (3) Specify the task for the LLM agent. (4) Define the output format for the LLM agent. (5) Provide multi-modal input to the LLM agent. (6) Ask the LLM agent to conduct reasoning following chain-of-thought prompting.

- **The role** involves the context description related to the agent (Fig. 4(Role)). We clearly define the role played by the LLM and specify the necessary capabilities for this role.
- **Knowledge** augments the LLM agent's response by enabling the agent to retrieve from the external knowledge documents we provided (Fig. 4(Knowledge)).
- **The task** includes the requirements for each task. For example, the recommendation task requires recommending tactical setups, the explanation task delves into the logic behind tactical decisions, and the evaluation task focuses on analyzing the ability required to execute the tactics and the possible outcomes (Fig. 4(Task)).
- **The output format** describes the specific outputs for each task. We define a set of public variables and task-specific variables for all three kinds of tasks (Fig. 4(Output Format)). For instance, the recommendation task necessitates an additional output of the action type. Both explanation and evaluation tasks demand outputs with both overview and detail. The overview considers the overall tactic, while the detail focuses on individual players. For explanations, the agent details the actions of each player, including how these actions counter tactics and their objectives. The evaluation detail probes whether the evaluated player's ability aligns with the objectives of the current action and assesses potential opponent reactions.
- **The inputs** are the trigger of communicating with the LLM agent. Basic input requires knowledge and an image-text pair. Considering the task relation, the explanation has an external input of the recommendation's output, and the evaluation has both the recommendation and explanation's input (Fig. 4(Inputs)).
- **Reasoning** is to guide the logical reasoning process. The chain-of-thought prompting allows the LLM agent to think and solve problems comprehensively. We use the CoT method to guide the LLM along a specific logical path and require the model to reason in four levels, including context, team, player, and action level (Fig. 4(Reasoning)).

To manage context sessions, each prompt and its response are saved as a history node and used as part of the input for the LLM agent in subsequent interactions. This ensures the LLM agent can utilize historical information to generate coherent and relevant responses.

5.4 Customization Control

To flexibly control the generation of the LLM agent, we design structured tags to embed users' natural language inputs. These tags are categorized into three aspects according to different objectives, namely, description, requirement, and comment.

- **Description.** Users' descriptions primarily serve to supplement inputs. We add these into the inputs component of the prompt, enriching the LLM agent's understanding of the current situation.
- **Requirement.** We incorporate users' requirements into the task component. This allows users to add semantic requirements for the expected response, ensuring that the LLM agent's output more closely matches users' specific requirements.
- **Comment.** Users' comments are served as feedback to the responses. We add comments along with the current response to guide the agent in refining its response. Considering the previous context, the agent is directed to complete the task after integrating these comments.

6 Visual Design

Smartboard consists of four views. The chat view (Fig. 5(A)) allows users to type text to control the exploration process with the LLM agent. The setup view (Fig. 5(B)) helps users define the initial tactics of interest. Users can select one of the alternatives to iterate the tactical simulation. The simulation view (Fig. 5(C)) shows the simulation alternatives returned by the LLM agent. The history view records (Fig. 5(D)) the simulation path and users' interactions.

6.1 Chat View

To enhance natural language interactions between users and the system, the chat view (Fig. 5(A)) presents system feedback and allows users to control outputs (**R5, R6**). From the outset, the chat view offers clear textual guidance through the operational process and various functionalities of the system (**R1**). We introduce tags representing different input types, including the description, requirement, and comment (Fig. 5(A1)). This approach significantly enhances users' ability to steer the results generated, ensuring a more tailored and controlled interaction experience. Throughout the interaction, the chat view delivers real-time feedback, including confirming the reception of user commands, indicating the current status of operations, and suggesting the next steps (Fig. 5(A3)). Moreover, users can conduct free-form conversations with the LLM agent (Fig. 5(A2)).

Interaction. The interactions of the chat view are as follows.

- *Input natural language.* Users can type directly into the chat box or utilize voice input by clicking the microphone button, enabling fluent natural language input.
- *Select tags.* Users can refine their input for targeted outcomes by selecting from a range of predefined tags, thus exercising precise control over the generated results.

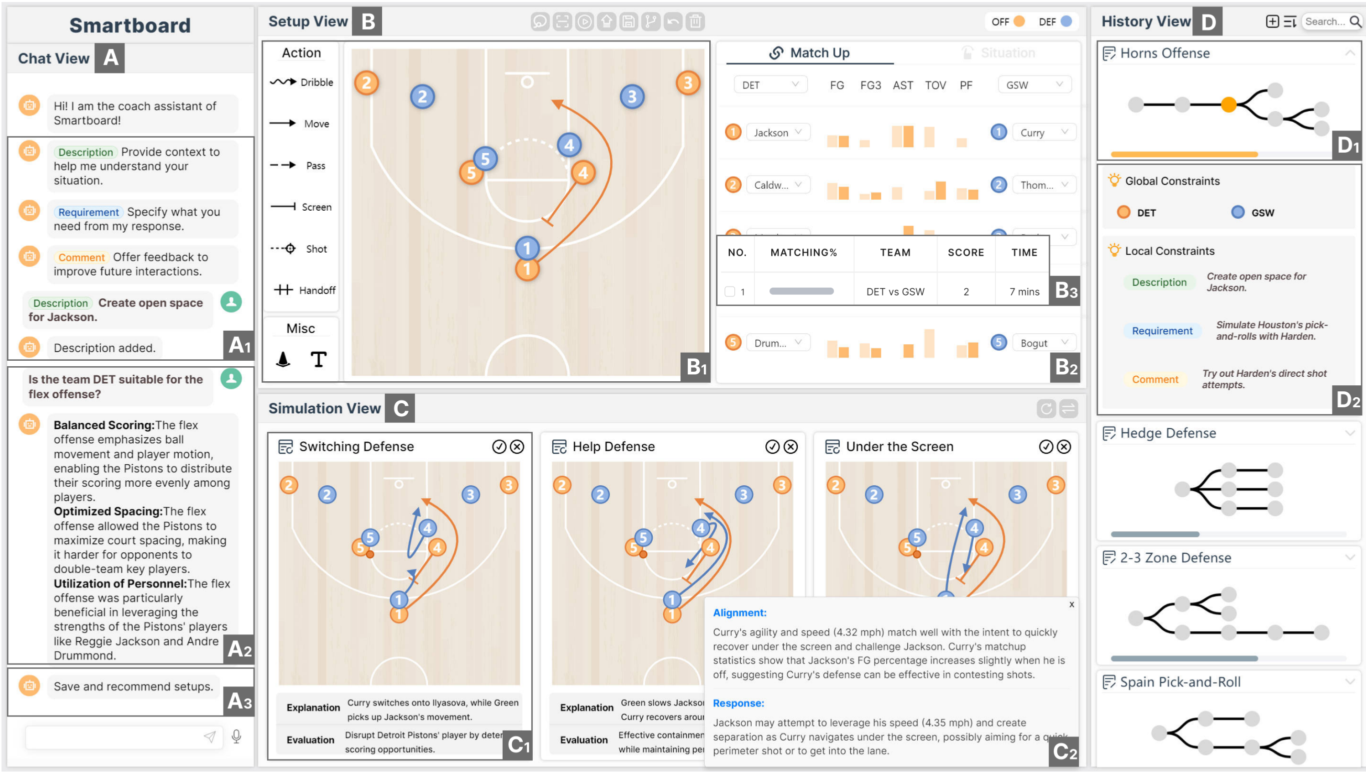

Fig. 5: The system interface of Smartboard. (A) The chat view provides system feedback and enhances communication between users and the system through tag selections and open-question answering. (B) The setup view provides interactions during tactical setup with tactics sketching, matchup analysis, and situation retrieval. (C) The simulation view presents the recommended tactics of the coach agent with an explanation and evaluation in both overview and detail. (D) The history view records the users' tactics and provides the classic tactics for starting exploration.

6.2 Setup View

The setup view (Fig. 5(B)) consists of the tactic view, matchup view, and situation view. The tactic view enables users to sketch basketball tactics (**R1**). The matchup view provides matchup references (**R2**). The situation view allows users to retrieve similar tactical situations(**R2**).

The tactic view (Fig. 5(B1)) allows users convey specific tactical content through sketching (**R1**). Referring to the existing design [46], we use circles with different colors to represent offensive and defensive players, respectively, with numbers indicating player roles and different line types denoting player actions. Users can specify player locations and roles on the tactic board by clicking the corresponding player icons and assign actions to players by selecting different line types.

The matchup view (Fig. 5(B2)) is designed to offer a detailed customization of the tactical scenarios. It allows users to set up player matchups and analyze them using historical statistical data (**R2**). Users can choose two teams from a dropdown menu, assigning specific roles to players based on a list. These role assignments are then integrated with the LLM agent as scenario-based knowledge. The on/off-court statistics are visualized using bar charts, with different colors indicating on-court or off-court performance. The charts display metrics such as field goal percentage, three-point field goal percentage, assists, turnovers, and fouls, normalized for comparative analysis. Moreover, we design a tooltip to present the physical information of each player.

The situation view (Fig. 5(B3)) enables users to retrieve the current tactic's situation from the tactic view, examine historical real-game data for similar situations, providing insights into player behavior (**R2**). By mapping retrieval errors to the matching rate, we provide a list of retrieved situations, including sequence number, matching rate, teams, score difference, and remaining time, allowing users to integrate selected behavioral information into the LLM agent.

Interaction. The interactions of the setup view are as follows.

- *Switch matchups.* Users can select offensive and defensive teams and players in the matchup view to analyze detailed matchups.
- *Sketch tactics.* Users can specify players in the matchup view and draw movements from the action list in the tactic view.
- *Save setups.* Users can click the save button to record the setup and generate recommendations.
- *Lasso situations.* Users can click the Lasso button to filter specific players and actions in the tactic view with a Lasso tool, updating the retrieval results in the situation view.

6.3 Simulation View

After completing the current tactical setup, users can conduct a simulative analysis in the simulation view, including up to three tactic boxes and the narration view (Fig. 5(C)). The tactic box provides recommendation tactics (**R3**). The narration view allows users to explore the detailed explanation and evaluation results of these tactics (**R4**).

The tactic box (Fig. 5(C1)) presents the recommended tactical option. Three tactic boxes correspond to different tactical variants (**R3**). In each box, the tactic's name is displayed at the top, followed by a tactic board that details specific tactical information, mirroring the style and visual mapping of the setup view for consistency. Below the tactic board, a textual description provides an overview and evaluation of the tactic, ensuring users have a clear and quick understanding of the recommended options. This layout helps users compare and contrast the different tactical variants effectively.

The narration view (Fig. 5(C2)) presents the detailed explanation and evaluation of each player in the tactic, incorporating visual elements directly within the narrative reasoning content (**R4**). The detailed explanation includes actions, counters, and objectives, while the evaluation covers objective alignment and potential reactions. We use bold blue titles to highlight distinct aspects of these details to streamline the user's understanding of the insights in the narrative words.

Interaction. The interactions of the simulation view are as follows.

- *Accept recommendations.* Users can click the button to accept the recommended simulation result. The result is updated in the setup view for users to perform a new round of tactic setup.
- *Switch modes.* Users can click the toggle to switch between explanation and evaluation.
- *Select players.* Users can click on the player to present the tooltip displaying narrative information according to the current mode.

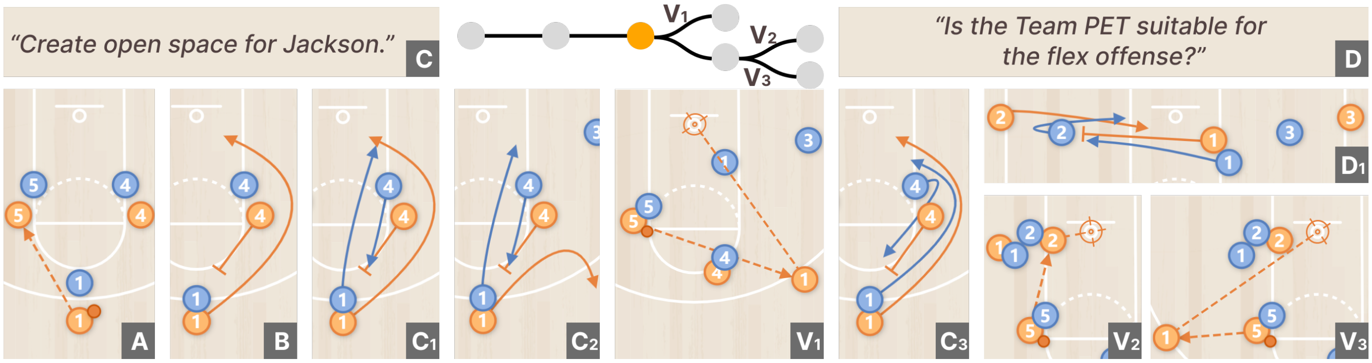

Fig. 6: Case 1. (A) O1 passes to O5. (B) O1's off-ball cut using the screen set by O4. (C) The description added by the expert. (C1) Under the screen defense. (C2) Route adjustment of O1. (V1) The first tactical variant. (C3) Help defense. (D) The question asked by the expert. (D1) O1's flex screen for O2. (V2) The second tactical variant. (V3) The third tactical variant.

6.4 History View

The history view (Fig. 5(D)) is designed to record users' tactics (**R3**) and provides classic tactical setups for exploration (**R6**).

The tactic card (Fig. 5(D1)) is designed to record the users' simulation path of tactics, with the title displaying the user-customized name. Each card contains a tree diagram representing a complete tactic. Each circle in the diagram denotes a tactic state saved as a history node. Following the order from left to right, several states constitute a variant of the tactic (**R3**). Below the tree diagram, a time slider allows users to customize the required execution time for the current tactic. The time bar follows the overall color theme, with orange for presenting and blue for collapsing. The slider spans from 0s (start) to 24s (full offensive round). This time slider method effectively records the user's perception of time when analyzing tactics.

The constraint list (Fig. 5(D2)) records users' operation histories while exploring tactics (**R6**). Global constraints capture scenario information customized to the entire tactic, such as the selected teams. Local constraints are attached to each tactic state, documenting the natural language input. The types of constraints correspond to the tags in the chat view for consistency, with text detailing the specific contents.

Interaction. The interactions of the history view are as follows.

- *Unfold details.* Users can click the button in the top right corner of the tactic card to expand the constraint list.
- *Select tactic states.* Users can click nodes in the tree diagram to select a specific tactic state and view the corresponding constraint list. Simultaneously, information in the setup view and the simulation view will roll back to that state.
- *Search tactics.* Users can type the tactic name and search for the matched tactics in the top right corner of the history view.

7 System Evaluation

We invited E1 and E2, both with years of coaching experience, to conduct case studies using our system. The studies are based on NBA 2015-16 data, detailed in Sec. 3.4. We first introduced the interaction and visualization features of Smartboard and then allowed the experts to freely explore interesting tactics and scenarios within an hour. We recorded their actions and comments throughout the process and conducted interviews to collect their feedback for further improvement.

Each tactic presented in our case studies was evaluated through a user study. We re-invited six experts (E1-E6) and recruited two additional certified basketball coaches (E7 and E8). The LLM-generated outcomes were evaluated from three perspectives: individual tactics, tactical variants, and overall outcomes. The experts rated them on several metrics, including correctness, practicality, diversity, efficiency, insightfulness, and consistency, using a 5-point Likert scale [23]. The results analysis demonstrated that the outcomes performed well on these metrics. Please refer to our supplemental material for more details.

7.1 Case 1

This case is an in-depth exploration and analysis of the horns offense conducted by E1. Starting from the horns formation, the horns offense aims to use screens and cuts to create scoring opportunities.

Insight 1: Creating open space through team movement is crucial for team DET against team GSW. In the beginning, E1 conducted an initial tactical setup. To confirm the specifics of the horns offense, E1 typed a question in the chat view. After receiving the required details, E1 focused on the specific team matchup for further setup. E1 selected the Detroit Pistons (DET) from the 2015-16 NBA season, noting their achievement of making the playoffs for the first time since the 2008-09 season. E1 then chose the Golden State Warriors (GSW) as the defensive team, as GSW's strong defense would provide a challenging scenario for analysis. The information displayed in the matchup view caught the experts' attention. By switching several different player matchups, E1 observed that all DET players in the matchup view had a slightly lower FG percentage against GSW players (Fig. 5(B2)). E1 concluded that since the DET players' shooting percentage slightly decreased, it was crucial to create more open shooting opportunities through increased team movement to maintain effective offense. E1 selected the horns offense as the base setup in the history view and clicked the save button in the setup view for the first simulation. Based on the recommendations, E1 selected *man-to-man defense* as the base defense setup for further analysis of the horns defense.

Insight 2: Jackson's off-ball cut remains challenging against Curry's *under the screen* defense unless adjusting routes. Commencing with the standard horns offense setup, E1 sketched a pass from O1 (offensive player 1) to O5 (Fig. 6(A)) in the setup view. Then E1 continued the simulation with *man-to-man defense* and sketched O1's cut following an off-ball screen by O4 in the next state (Fig. 6(B)). To provide clarity, E1 added a description in the chat view explaining that the tactic was designed to create space for O1 (Jackson) (Fig. 6(C)). After clicking the save button, E1 reviewed three potential defensive setups and their respective overview information in the simulation view. E1 considered *switch on screen* overly reliant on individual prowess, which diverged from his exploration objective. Therefore, E1 focused on the setup of *under the screen*. Considering D1's fast speed mentioned in the detailed explanation (Fig. 5(C2)) and O1's decreased FG percentage shown in the matchup view, E1 noted that D1's action made it difficult for O1 to receive the pass and make a layup. However, given the initiative of the offense, E1 mentioned that O1 had the opportunity to change the route when encountered *under the screen*, potentially leading to an open shot instead of a layup. Hence, E1 proceeded with *under the screen* setup, adjusting the route of O1 (Fig. 6(C2)) and sketching a scoring method as a conclusion to the horns offense (Fig. 6(V1)). The tactic information was recorded in the history view.

Insight 3: Flex screen optimizes scoring opportunities for team DET players with similar field goal percentages. E1 aimed to explore an alternate scenario and selected a prior state in the history view. After reviewing the recommendations, E1 discovered that D4's help defense (Fig. 6(C3)) could effectively decelerate O1's cutting, prompting further exploration. Accepting this recommendation, E1 revisited the matchup view (Fig. 5(B2)) and found that DET players have similar FG percentages, indicating comparable scoring abilities. E1 noted that the flex offense provides adaptable opportunities for all players. Consequently, E1 inquired through the chat view to validate the applicability of the flex screen in the current scenario (Fig. 5(A2)). After receiving positive feedback, E1 sketched O1's flex screen for O2 and chose a defense (Fig. 6(D1)). E1 quickly discovered a scoring opportunity for O2 and recorded it in the history view (Fig. 6(V2)).

To further explore with real game data, E1 used the lasso tool to filter the four players involved in the screen in the tactic view and examined the retrieval results in the situation view (Fig. 5(B4)). Notably, in a game between DET and GSW, the outcome showed that GSW executed a *switch on screen* defense similar to the recommended setup against DET's flex screen. In this specific situation, O5 chose to make a layup that resulted in a foul. Inspired by the outcomes of situation retrieval, the expert sketched an alternative tactical variant and recorded it in the history view (Fig. 6(V3)). E1 concluded, *"the flex screen optimizes the scoring opportunities for especially DET players."* Thus, the expert finished the exploration with three tactical variants, combining the horns offense with the flex screen. Additionally, the expert mentioned that the time slider in the history view served as an effective cue that aided in preventing the endless extension of tactics.

7.2 Case 2

The second case focuses on the hedge defense [36]. The hedge is a defensive tactic where the defender guarding the screener temporarily leaves to pressure the ball-handler, aiming to delay or disrupt the play.

We invited expert E2 to conduct this case study. Due to the defensive prowess and teamwork of the San Antonio Spurs (SAS) during the 2015-16 NBA season, E2 selected it as the defensive team and matched it against the Houston Rockets (HOU), known for its strong offense. In the matchup view, E2 found O2 (Harden) has decent three-point shooting ability facing the D2's (Green) defense. In order to examine his three-point shooting situations, E2 sketched several scenarios in the tactic view and used the lasso tool for retrieval. In the situation view, E2 reviewed several situations and discovered that team HOU frequently used pick-and-rolls around O2 outside the three-point line. These related situations were chosen to integrate behavioral knowledge.

Insight 1: Team SAS requires monitoring Harden's actions to minimize fouls when executing the hedge defense. E2 selected the requirement tag and detailed his intention to simulate defending pick-and-rolls (Fig. 7(A)). After clicking the save button, the recommendation view showcased three variants of pick-and-rolls (Fig. 7(A1, A2, A3)). E2 noted, *"It's clear to find that the main difference here is the screen setter."* Upon reviewing the explanation of every screen setter, E2 found that *high pick-and-roll* involving O5 (Howard) and D2 presented a significant size mismatch, making O5's screen a substantial threat (Fig. 7(A1)). Considering this threat, E2 accepted this recommendation and focused on the potential next move of D5 (Duncan), O5's defender. In the setup view, E2 sketched a hedge defense (Fig. 7(B)) to prevent O2's easy shot through D5's pressure. The results showcased that O2 passes the ball to circumvent challenges instead of opting for a direct shot (Fig. 7(B1)). Checking the situation view again, E2 noticed situations where O2 could still score through quick reactions and his three-point ability. This prompted E2 to add a comment to simulate O2 taking direct shots (Fig. 7(B2)). After clicking the refresh button, the results (Fig. 7(B3)) were shown in the tactic box. The detailed explanation highlighted that the tactic's objective is to score or draw a foul by leveraging defensive pressure. While O2 may possess the ability to shoot under pressure, shots against a hedge are risky but could lead to beneficial fouls and free throws. E2 emphasized, *"The LLM agent considers Harden's characteristics well. SAS should monitor Harden's actions to minimize fouls when executing the hedge."*

Insight 2: Effective hedge defense of team SAS requires adaptive help and recover to manage mismatches caused by Howard. E2 reviewed the recommendations for O5's off-ball cut (Fig. 7(B1)) and noticed that O5 was left unguarded because of D5's involvement in the hedge. Thus, E2 accepted this recommendation and aimed to further evolve the defensive tactic in the setup view. To quickly pressure O5 after receiving O2's pass, E2 devised a layout for other players to move toward the cutting route of O5 for help defense (Fig. 7(C)). After reviewing the detailed explanation, E2 noticed the potential defensive response to O5's cut, "The defense might rotate to block Howard's path, but his strength can mitigate this effort." E2 remarked, *"The LLM agent has already considered this countermeasure, showing how thoroughly it evaluates the situation."* To block O5's cut, E2 highlighted

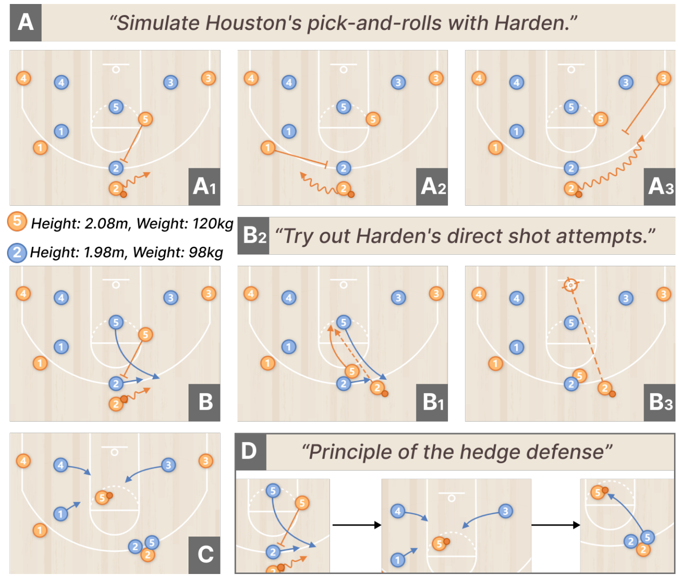

Fig. 7: Case 2. (A) The requirement added by the expert. (A1) High pick-and-roll. (A2) Wing pick-and-roll. (A3) Corner pick-and-roll. (B) D5 and D2 hedge defense. (B1) O2 passes to O5. (B2) The comment added by the expert. (B3) O2's direct shot. (C) Help defense. (D) Principle of the hedge defense.

the importance of avoiding a size mismatch and then sketched D5 recovering to defend O5. To validate the generalizability of this tactic, E2 explored other pick-and-roll setups, focusing on the screen setter's cut post-hedge. Using a similar defensive approach, E2 achieved favorable outcomes and noted that the help and recover allowed D5 to limit O2's perimeter shooting and mitigate interior score opportunities caused by mismatches, showcasing a comprehensive hedge defense. Therefore, E2 concluded the hedge defense with an insightful principle centered around "hedge, help, and recover" (Fig. 7(D)).

7.3 Expert Interview

After the case studies, we conducted interviews with experts to collect their feedback. We engaged in open discussions about the system's usability and suggestions. Their insights were summarized as follows.

Usablity. The overall response was positive, with all experts confirming that the Smartboard is a highly effective tool for analyzing tactics in basketball games. First, the fine-grained tactical analysis enabled users to gain deeper insights and consider more tactic variants in different situations. E1 mentioned: *"Smartboard's step-by-step sketching makes me dive deep into each part of a tactic."* E2 also stated, *"This provides a clear understanding of the complex interactions between players at each step, with complex variants of the play possible."* Moreover, E2 mentioned: *"Using the Smartboard to explore isn't just for top-level coaches. It also provides an effective way for players and fans to get a better understanding of complex tactics."* Second, the interaction with the LLM agent for exploring tactics offers advantages over the traditional analysis process. E1 mentioned, *"Analyzing with the coach agent saves a lot of time compared to analyzing videos and even highlights important situations I might have overlooked."* E2 added, *"In real training, we need to simulate many scenarios for tactics. Using the LLM agent can supplement many variations and details."* E2 also commented, *"During my exploration of tactics, the Smartboard gets what I expressed just like a real coach would. But unlike a real coach, it's ready to give me all the related information and reasoning I need."*

Suggestions. The experts provided several suggestions. First, E2 wanted to use our system to analyze tactics in ongoing games, *"Players' conditions influence the effect of tactical execution in real games. It would be beneficial if the LLM agent could consider the impact of player conditions during ongoing games."* Second, E2 focused on the history view and highlighted the importance of collaboration and sharing tactics, *"Sometimes, I need to share tactics with my players and analysts. It's meaningful to export and import tactics in Smartboard."*

8 Discussion

In this section, we discuss our work from three perspectives, namely, visual exploration of team tactics, integration of LLM agent, and future work of sports LLM agent.

8.1 Visual Exploration of Team Tactics

Significance—exploring tactics with LLM agent visually. Fine-grained tactical analysis revisedfor play design remains pivotal in team sports. Existing studies [69] have proposed various visualization systems for tactical analysis. However, the integration of experts' most familiar interaction method—sketching with verbal discussion—has not been adequately considered. We introduce an LLM agent in Smartboard that supports users in visually analyzing tactics by merging sketching with natural language inputs. This approach streamlines communication and fosters dynamic interaction between users and the LLM agent, leading to personalized and deeper insights into tactics.

Extensibility—modular framework. Our framework is designed to be modular and extensible, facilitating interaction with LLM agents through components that can be extended and customized. The interactive sketching of tactics invites evolution into immersive environments for lifelike simulations. Information integration can adapt to encompass domain-specific data, enhancing depth and relevance. LLM agent tasks and reasoning processes are designed to scale with diverse requirements and various outputs. Human control can be broadened, incorporating interactions such as gestures or facial expressions. These extensions are closely aligned with the task's demands and the model's capabilities. While the components of the framework are adaptable, the core strategy of interaction with the LLM agent remains constant and effective.

Generalizability—beyond sports tactics. While Smartboard is primarily designed for basketball scenarios, its whiteboard-based tactical representation can be applied across various team sports such as soccer, rugby, and hockey. Moreover, the principles underpinning Smartboard's visual exploration, iterative interactions, and personalized scenarios have the potential to transcend the realm of sports. These methodologies can be adapted to other tactical domains, such as military, choreography, and finance. However, generalizing to these fields poses significant challenges in acquiring domain-specific knowledge and data, as deep tactics are often closely guarded due to competitive reasons. Forming in-depth collaborations with professional teams offers a practical solution.

Applicability—extending broader scenarios. Through interviews, experts recognized the potential of Smartboard to apply to tactical training. As E1 observed, *"The detailed tactics stored in a history view can be transformed into interactive guidance for training."* This functionality enriches the training process, allowing for an interactive review and refinement of past and present tactics. Players and fans also stand to benefit from engaging with stored tactics on Smartboard, delving into an interactive learning experience that deepens their understanding of the tactics' diversity and complexity. Moreover, developing a tactic-based community is a potential application for Smartboard. Utilizing its interactive features, we can collect tactics and usage logs to fine-tune a tactical LLM. This could create a collaborative environment where tactics are not just discussed but also actively improved upon, leveraging Smartboard to explore and share tactics. These applications are the system engineering aspects that we intend to pursue in the future.

8.2 Integration of LLM Agent

LLM's performance. During the development and testing, several issues impacting the LLM agent's performance were identified, some caused by user inputs. One notable problem is unexpected inputs, such as paths or coordinates outside court boundaries. When such inputs are given, the LLM generates responses based on these unrealistic scenarios without recognizing the error. Although adding comments to prevent out-of-bound outputs resulted in reasonable responses, the agent itself cannot detect this problem or alert the user. To address this, we restricted the sketching area and implemented boundary validation mechanisms. If the LLM's response includes out-of-bound coordinates, the system prompts the user to correct the input in the chat view. Another issue is the LLM's handling of rare or non-existent scenarios, particularly specific player matchups and tactics. The LLM often struggles with these scenarios due to the knowledge boundary [17], potentially leading to hallucinations or inaccurate outputs. While providing additional relevant descriptions or enhancing the knowledge base can help mitigate these edge cases, the LLM still faces challenges with fundamentally non-existent knowledge or scenarios. A potential solution is validating these non-existent inputs with a verified database.

On the model side, although the LLM's variability in recommended tactics showcases its creativity, it also presents challenges. Inconsistent terminology for the same concepts, such as "pick-and-roll" and "screen and roll", can confuse users. This issue can be mitigated by standardizing terminology through post-processing. Despite specifying the response format, the agent sometimes deviates by adding unnecessary commentary and outputting overlapping coordinates for tightly guarded players. We address these issues using regular expressions and an overlap detection algorithm. Hallucinations are another significant issue, with the agent generating nonexistent tactics or overstating player abilities, such as recommending three-point shots for centers with low goal percentages. While we use CoT prompting [72] and RAG [50] to mitigate these hallucinations, further improvements may lie in expanding the tactical knowledge base and designing a targeted RAG system to enhance the accuracy and reliability of the LLM's outputs. Moreover, the LLM may exhibit bias by over-relying on star players rather than role players, stemming from imbalanced training data. We suggest fine-tuning an LLM with diverse players represented data and implementing fairness checks to balance tactical recommendations.

Multi-agent. We integrated LLM as a coach agent to support varied interactions and tasks throughout the tactical exploration process. Multi-agent, which allows for autonomous interactions among agents, could be a potential enhancement. On one hand, the multifunctional coach agent can be decomposed into several agents, each focusing on a single task. Users can thus interact with the task-specific agent in parallel. On the other hand, different user groups have distinct priorities. For example, coaches focus more on the overall tactical adaptability across various scenarios, whereas players concentrate on how these tactics affect their detailed actions and roles. While our system addresses these requirements by task decomposition, the multi-agent could offer a more nuanced approach by assigning role-specific agents to streamline complex tactical play design.

8.3 Future Work of Sports LLM Agent

The future directions of our work can be summarized into two aspects. First, Smartboard currently lacks real-time technique integration. Experts express their interest in exploring tactics that consider ongoing match factors. Real-time data extraction and player condition evaluation present significant challenges due to the dynamic nature of team sports. While LLMs can produce streaming outputs, effectively mapping these outputs to visual representations remains difficult. Thus, we plan to integrate advanced real-time techniques and develop a dynamic visualization system to enable tactical exploration considering real-time factors. Second, quantitatively evaluating the quality of generated tactics is challenging. While our case studies have demonstrated the effectiveness and usefulness of our system, more rigorous evaluation is needed. Therefore, we will focus on establishing metrics from both real games and experts' perceptions. This involves developing a comprehensive framework to assess the accuracy, practicality, and insightful value of generated tactics for enhanced analysis.

9 Conclusion

In this work, we propose a method for visually exploring team tactics using an LLM agent. At first, we collaborate with basketball experts and propose an extensible framework that allows users to communicate with the coach agents. leveraging this framework, we develop Smartboard, an agent-based interactive visualization system designed for fine-grained tactical analysis. Smartboard enables users to customize scenarios and iteratively explore tactics in setup, simulation, and evolution. Our approach's effectiveness is validated through case studies based on real-world basketball datasets and expert interviews, demonstrating the usability of our system in analyzing team tactics.

In the future, we plan to generalize our framework to other team sports and explore its feasibility in other tactical domain applications. Furthermore, we plan to use our system to collect a dataset of complex team tactics and fine-tune an open-source tactical LLM.

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