A Survey of Large Models in Sports

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Abstract

Sports have witnessed growing global enthusiasm in recent years, serving as a vital force for physical health, cultural exchange, social connection, and economic growth. The rapid advancement large models, particularly (multimodal) large language models (M)LLMs, has demonstrated transformative potential to reshape sports understanding, analysis, and interaction across diverse domains. This paper presents a comprehensive survey of large models in sports, including (i) an overview of tasks and applications across different participant groups; (ii) a detailed analysis of sports-related datasets and benchmarks; and (iii) a critical discussion of current challenges and future directions. Our goal is to establish a foundation for advancing research and practical development of large-model-driven sports intelligence. An open-source GitHub repository is maintained as a continuously updated resource: https://anonymous.4open.science/r/Anonym202B.

1 Introduction

In recent years, the global enthusiasm for sports has continued to rise, with more and more people actively participating in it, and the sports industry has also flourished. To further drive this development, modern sports increasingly rely on massive data support (Hutchins, 2016), while the introduction of Artificial Intelligence (AI) has greatly accelerated this trend (Zhou et al., 2025a).

Early interdisciplinary research in sports and AI focused on natural language processing and computer vision, with applications in tasks such as sports data processing (Cossich et al., 2023) and video analysis (Naik et al., 2022). Entering the era of large models, especially the rapid development of Large Language Models (LLMs) and Multimodal Large Language Models (MLLMs), such as GPT-4 (Achiam et al., 2023) and Google Gemini (Team et al., 2023), has brought new opportunities and challenges to the sports field, as shown in Figure 1. These models not only generate language effectively but also process multiple data modalities, enabling broader applications in sports. Tasks that were previously difficult–such as designing athlete training plans (Skerik et al., 2018), selecting coaching strategies (Bunker and Susnjak, 2022), and generating sports game summarization (Huang et al., 2020)–have been greatly enhanced by large models. Moreover, leveraging their vast knowledge bases, these models can generate more comprehensive and personalized content (Lin et al., 2024b). The number of papers on large models in sports has grown rapidly, from just 1 in 2020 to 78 in 2024, and continues to increase in 2025 (see Figure 4 in the Appendix).

A growing body of review literature has examined the use of AI and deep learning in sports (Zhou et al., 2025a; Zhao et al., 2025). The most relevant work on large models includes studies on their applications to exercise recommendations (Lai et al., 2025), sports science and medicine (Connor and O'Neill, 2023; Naughton et al., 2024), and the sports industry (Wang et al., 2024d), along with surveys of datasets for language and multimodal models (Xia et al., 2024b). However, these studies are still limited in scope, lacking comprehensive coverage of the diverse sports-related tasks and datasets where large models can be applied.

In this study, we used the aforementioned review papers as the starting point for multiple rounds of forward and backward snowballing on Google Scholar, using "sports" and the names of representative large models as keywords, and manually selected relevant studies. As a result, we collected more than **240** academic papers addressing large model applications in sports and provide here a comprehensive and in-depth survey.

We first systematically categorize and summarize existing applications of large models in sports across 6 key groups (§2). Then, we review and conduct an in-depth analysis of the relevant datasets

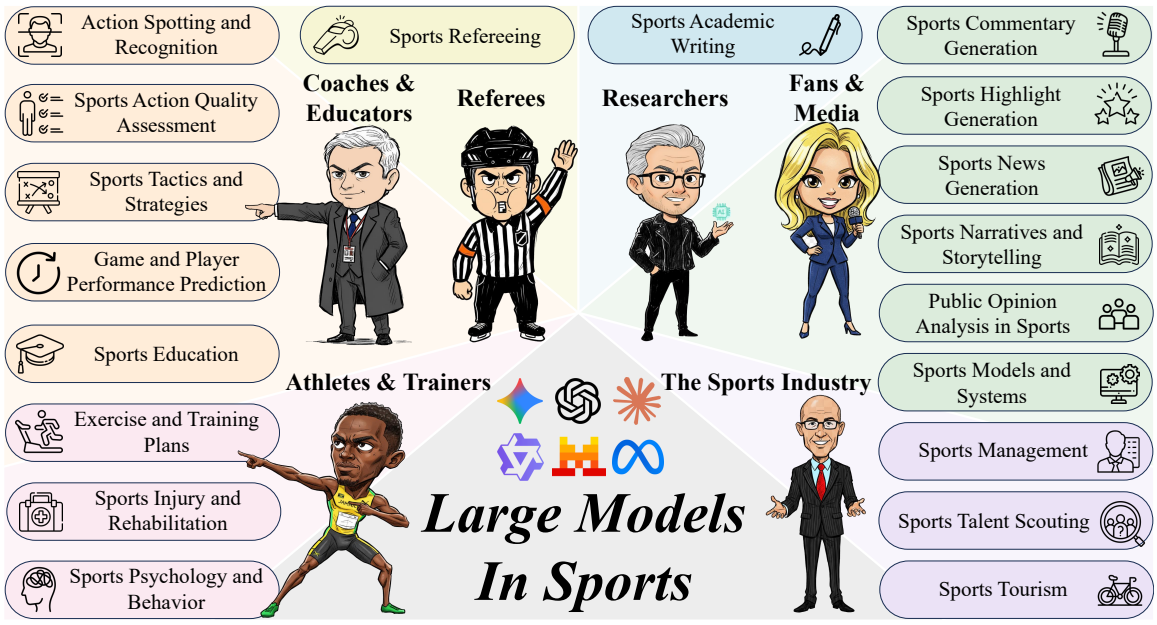


Figure 1: Large models have shown powerful applications across 6 sports stakeholder groups: athletes and trainers, coaches and educators, referees, researchers, fans and social media, and the sports industry, enabling diverse tasks.

and benchmarks (§3). Subsequently, we discuss the current challenges in this field and, finally, outline the potential opportunities and future directions (§4).

2 Large Model Applications in Sports

The fast growth of large models has brought big chances for their use in sports. This section categorizes and introduces large model applications in sports across 6 groups: athletes and trainers, coaches and educators, referees, fans and social media, researchers, and the sports industry. The taxonomy of the applications is shown in Figure 2.

2.1 Applications for Athletes and Trainers

2.1.1 Exercise and Training Plans

Large models help athletes and trainers create exercise prescriptions, translating sports science into practice to improve performance (Phillips and Kennedy, 2012; Wackerhage and Schoenfeld, 2021). Recent AI coaches powered by LLMs can make generating effective training plans easier. Many works have used LLMs to generate exercise prescriptions for various health conditions and fitness goals (Cavazzotto et al., 2024; Cosentino et al., 2024; Puce et al., 2025; Papini et al., 2025a; Masagca, 2025; Lederman et al., 2025), including weight management (Saraç et al., 2025), resistance and jump training (Washif et al., 2024; Havers et al., 2025; Pajo et al., 2025), upper body and core training (CANUZAKOV et al., 2025; Erol and Arıkan, 2024), and nutritional strategies for ultra-endurance sports (Puce et al., 2024; Solomon and Laye, 2025). LLMs can also help trainers develop fitness programs for specific patient populations, including obese people (Li et al., 2025c; Philuek et al., 2025), those with chronic diseases (Xu et al., 2024; Onan et al., 2025; Akrimi et al., 2025), and those with epilepsy (Rocha-Silva et al., 2024, 2025). In terms of methods, some studies employ digital twins with multimodal outputs (Vahdati et al., 2025), behavioral science theories (Hegde et al., 2024; Jörke et al., 2025; Dindorf et al., 2025), and Retrieval-Augmented Generation (RAG) technology (Zhang et al., 2025b; Ko et al., 2025); in terms of effectiveness, some emphasize the importance of personalization and contextual understanding (Dergaa et al., 2024; Zhu et al., 2024; Han, 2025), focus on acceptance, trust, and quality (Düking et al., 2024; Wachholz et al., 2025), and foster user self-reflection (Li et al., 2025g). In addition, some studies have designed AI coaches for specific sports such as boxing (Bullard et al., 2025) and table tennis (Ma et al., 2025a,b). Some of these require large models to provide expert-level evaluation and feedback on basketball (Seino et al., 2025) and football (Ashutosh et al., 2025) players (i.e., **Expert Commentary Generation**), while MAAIG (Yeh et al., 2023) in figure skating and CoachMe (Yeh et al., 2025) in boxing generate sports instructions automatically from 3D skeletal data (i.e., **Motion Instruction Generation**).

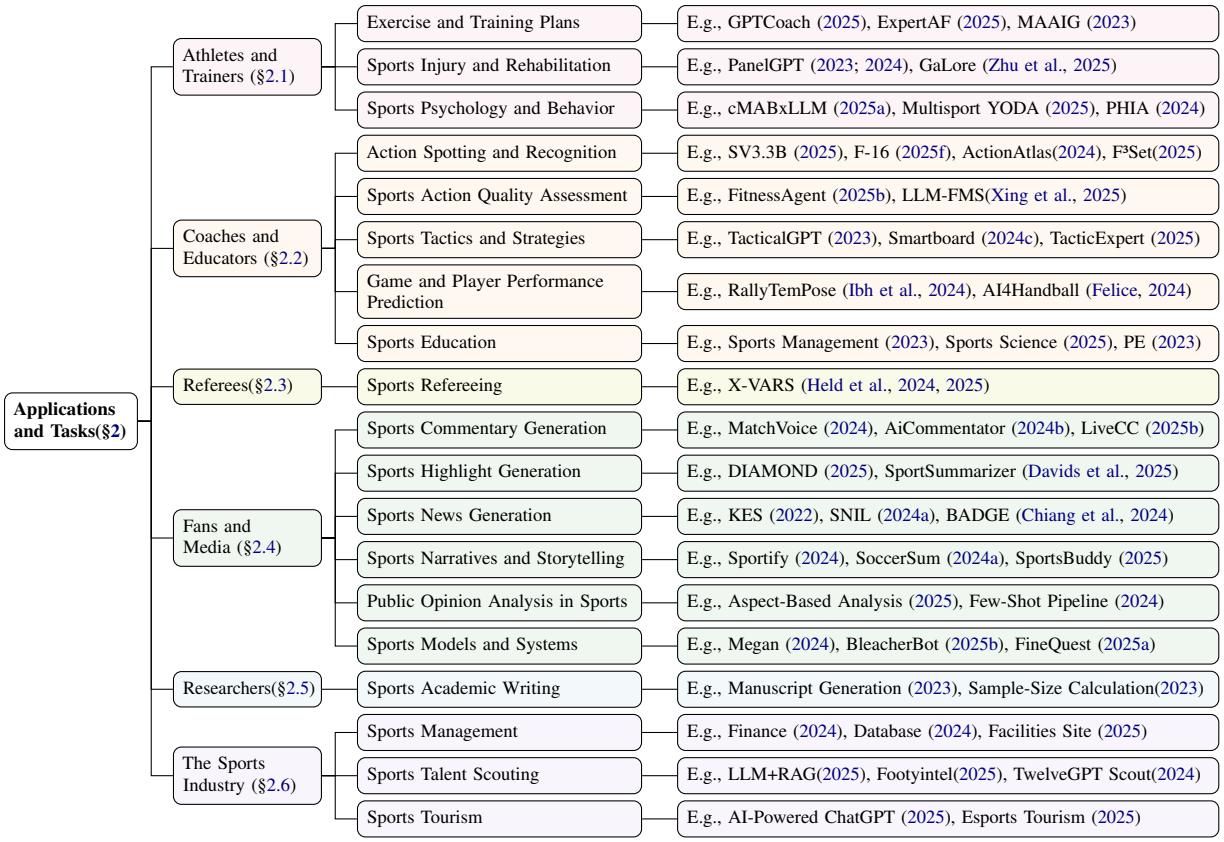


Figure 2: Taxonomy of applications, tasks, and approaches of large models in sports.

2.1.2 Sports Injury and Rehabilitation

Large models can assist athletes and trainers throughout the entire process of sports injury prevention, diagnosis, treatment, and rehabilitation. Diagnosing and treating sports injuries requires extensive interdisciplinary knowledge, and LLMs possess a broad understanding of sports injuries (Hasnain et al., 2023; Lotfi and Madani, 2024), including orthopedics (Fayed et al., 2023) and sports rehabilitation (McBee et al., 2023, 2024). Specifically, they can assist in providing preventive advice (Zhu et al., 2025), identifying and labeling information (Brogly et al., 2025), supporting diagnostic imaging (Lotfi and Madani, 2024) and data processing (Musat et al., 2024), assisting in clinical decision-making (Saglam et al., 2025) and surgical treatment (Cheng et al., 2023), and enabling patient outcome prediction (Ahsan, 2023) and medical oversight.

2.1.3 Sports Psychology and Behavior

Sports psychology, a key part of sports medicine, supports athletes through behavioral interventions to enhance training and performance. LLMs have demonstrated initial potential in this field, answering sports-related questions (Vandelanotte et al., 2023), assessing cognitive abilities (Zuccolotto, 2025), summarizing theories (Oliver and Guiller, 2025), and integrating with wearables for real-time monitoring and behavioral modeling (Merrill et al., 2024; Ferrara, 2024; Imran et al., 2024; Ji et al., 2024). LLMs can also provide assistance in specialized areas such as exercise addiction (Szabo, 2023) and sports and exercise psychology (Oliver and Guiller, 2025), and can play a role in behavioral interventions by increasing motivation to participate in sports activities (Song et al., 2025a) and providing sleep education (Masur et al., 2025).

2.2 Applications for Coaches and Educators

2.2.1 Action Spotting and Recognition

Action spotting and recognition in sports involves temporally localizing and classifying fine-grained player movements or events to provide reliable match facts for downstream analytics (Zhao et al., 2025). Most approaches employ MLLMs for direct action spotting or recognition. Some work leverage keyframe sampling (Kodathala et al., 2025), contrastive pretraining (Shin et al., 2025), or domain adaptation (Jiang et al., 2025b) for soccer. Others fine-tune MLLMs for single-action and rally-sequence recognition in tennis (Teo, 2025), while high-frame-rate modeling has been ex-

plored for gymnastics and diving (Li et al., 2025f). Scene-level classification has also been studied in rugby (Nonaka et al., 2024). Beyond multimodal inputs, textual signals such as commentary are also used for soccer action spotting (Chakraborty et al., 2025). Benchmarks like ActionAtlas (Salehi et al., 2024) and F³Set (Liu et al., 2025) evaluate MLLMs' fine-grained recognition capabilities.

2.2.2 Sports Action Quality Assessment

Sports action quality assessment evaluates the execution of athletic movements (Zhou et al., 2024), primarily to provide training feedback for coaches, and in some cases to support referees with objective scoring (Zhao et al., 2025). Recent work fine-tunes large multimodal models for personalized fitness evaluation (Dibenedetto et al., 2025), designs unified agent frameworks for open-set and user-specific assessments (Tang et al., 2025b), and builds fine-grained datasets with LLM-based evaluation for functional movement screening (Xing et al., 2025). In figure skating, assessment frameworks quantify technical and program scores, supporting both training feedback and referee judging (Wang et al., 2025a).

2.2.3 Sports Tactics and Strategies

Sports tactics and strategy analysis models and interprets on-field plays to uncover tactical structures and game dynamics, with large models automating data analysis and pattern discovery to provide coaches with strategic insights. Early work was text-centric, converting structured or non-linguistic data into natural language for tactical modeling, such as fine-tuning LLMs on event sequences (Caron and Müller, 2023), transforming cycling commentary into structured tactical variables with graph representations (Janssens et al., 2024), or parsing play-by-play logs into spatial spray charts (Michielssen et al., 2024). Other studies examine LLMs' analytical reasoning, including computing team scores from NBA/NFL play-by-play data (Hu et al., 2024c) and aggregating basketball narratives for score inference (Hu et al., 2024d). Recent approaches integrate diverse structural and spatial information for richer tactical reasoning, including sketch-based LLM agents for interactive tactic design (Liu et al., 2024c), graph LLMs for zero-shot basketball generalization (Lingrui et al., 2025), and multi-agent LLM systems combining video detection with statistical inference to support tactical decision-making (Zhang et al., 2025a).

2.2.4 Game and Player Performance Prediction

Game and player performance prediction leverages historical, contextual, or multimodal data to forecast match outcomes and individual behaviors, providing coaches with insights for strategy, preparation, and performance optimization (Xia et al., 2024b). Early studies used BERT-based (Devlin et al., 2019) models to predict player actions or traits, such as forecasting badminton strokes from skeleton poses (Ibh et al., 2024) or NBA players' performance deviations from pre-game interviews (Oved et al., 2020). More recent work leverages LLMs and diverse data sources for game outcomes prediction, including predicting basketball game results via in-context learning on social media data (Sprint, 2024), explaining handball match outcomes through feature attribution summarization (Felice, 2024), and fusing features from multimodal pre-match reports to enhance cricket score predictions (Bhatnagar and Bhatnagar, 2025).

2.2.5 Sports Education

Recent applications of large models in sports education demonstrate their diverse utility for educators and teachers. Some works apply LLMs to assist educators with lesson planning (Genç, 2023; Wang and Wang, 2024), interactive activities (Cui et al., 2025), formative feedback (Keiper et al., 2023), and autonomous assignment design (Kauppinen, 2024). Others emphasize curricular support through automated visualization, synthetic dataset creation (Fazackerley et al., 2025), and sensing-driven feedback reports (Gao et al., 2025b) . Meanwhile, student-centered applications address personalized exercise planning, engagement, and mental health support (Zhang and Liu, 2024), complemented by surveys examining inclusion, trust, and acceptance of ChatGPT in educational practice (Chang et al., 2025).

2.3 Applications for Referees

2.3.1 Sports Refereeing

Large models can also help sports refereeing by supporting decision-making and improving fairness and transparency. X-VARS (Held et al., 2024) introduces an explainable video assistant referee system by fine-tuning MLLMs on expert-annotated foul data and rationales, showing clear benefits for referees through improved decision accuracy, consistency, and trust (Held et al., 2025).

2.4 Applications for Fans and Social Media

2.4.1 Sports Commentary Generation

Sports commentary generation produces natural-language narratives that combine factual event descriptions with tactical analysis and contextual insights. Unlike video captioning, it delivers timely and emotionally resonant narration aligned with the flow of the game (Ge et al., 2024). Recent studies have leveraged LLMs to automatically produce sports commentary, offering fans an enhanced viewing experience. Most approaches adopt an agentic framework, where LLMs are prompted with extracted match information to generate commentary. Such information includes detected key events (Andrews et al., 2024b,a; Sameer et al., 2025; Pavlovich et al., 2023), player and ball tracking data (Vijayakumar et al., 2025; Andrews et al., 2024b,a), player background information (Mori et al., 2025; Xi et al., 2025b), audio signals (Gautam et al., 2022), and external knowledge (Li et al., 2025d). Beyond agentic frameworks, recent work has explored end-to-end training to improve commentary quality. Some studies fine-tune MLLMs (Wang and Yoshinaga, 2024; Jiang et al., 2025b; Cook and Karakuş, 2024; Baughman et al., 2024), while others design and train novel architectures for improved temporal alignment between videos and commentaries (Zhang et al., 2024a; Rao et al., 2024; You et al., 2025). In addition, several efforts target complementary directions, such as constructing sports commentary benchmarks (Chen et al., 2025b; Ge et al., 2024), enabling real-time streaming (Chen et al., 2025b; Ding et al., 2025; Yu and Chai, 2025), supporting multilingual commentary (Sameer et al., 2025), generating personalized commentary (Andrews et al., 2024a), and advancing commercial applications (Baughman et al., 2024).

2.4.2 Sports Highlight Generation

Sports highlight generation aims to automatically identify and compile the most significant moments from a full-length match into concise video or textual summaries. Most research employs MLLMs for highlight generation via key event detection, including action spotting (Banu et al., 2025), multimodal fusion with textual encoding (Davids et al., 2025), and event classification using commentary transcripts or role-play prompting (Sattar et al., 2023; Kang et al., 2025). Other works use MLLMs for summary and caption generation to support social media highlights (Midoglu et al., 2024), or for personalized highlight generation via simulated watch histories and preference descriptions (Lee et al., 2025).

2.4.3 Sports News Generation

Sports news generation automatically produces factual match reports suitable for publication, summarizing key outcomes, events, and statistics in a standard journalistic style. Early work focused on summarizing text commentary, either using LLMs to select and rewrite key segments (Wang et al., 2022, 2021) or to extract salient events (Sarkar et al., 2024). More recent studies extend this to structured data, employing chain-of-thought prompting for statistical tables (Chiang et al., 2025) or leveraging CSV inputs to generate game reports (Chiang et al., 2024). Beyond summarization, Cheng et al. (2024a) proposes an insight-driven approach where high-level user queries guide LLMs to construct narrative episodes enriched with data visualizations.

2.4.4 Sports Narrative and Storytelling

Sports narrative and storytelling creates long-form, multimodal stories about matches or players. It weaves together event sequences and contextual details to produce engaging narratives that captivate fans on social media. Recent research generates factually consistent highlight narrations through prompt-engineered LLMs (Sarfati et al., 2023), or leverages multimodal embedded visualizations and personalized narratives with LLMs to aid tactic understanding (Lee et al., 2024; Lin et al., 2025). Other works adapt narrative generation to platform-specific contexts, producing personalized reports and posts for large-scale fan interaction (Sarkhoosh et al., 2024a; Baughman et al., 2024).

2.4.5 Public Opinion Analysis in Sports

Public opinion and sentiment analysis in sports involves detecting, classifying, and measuring public attitudes toward sporting events or related issues. LLMs have been applied to identify key themes (Qian et al., 2024), perform fine-grained sentiment and stance detection via aspect-based analysis (Qian et al., 2025) and few-shot prompting (Rauchegger et al., 2024), and examine user acceptance of AI tools using social science frameworks (Argan and Dinç, 2025).

2.4.6 Sports Models and Systems

Unlike task-specific research, work on sports models and systems targets general-purpose capabilities and infrastructures to enhance users' overall sports experience, including (1) chatbots and models that enable interactive dialogue and general sport understanding, and (2) retrieval systems that provide precise and reliable access to sports knowledge.

Chatbots and Sports Models. LLMs have been applied to build sports chatbots for interactive dialogue (Priya et al., 2024) or co-viewing experiences (Kim et al., 2025b), with dialogue state tracking for sports-specific conversations (Song et al., 2025b). General sports models, especially in soccer, are developed via fine-tuning (Unlu, 2023; Gautam et al., 2025; Jiang et al., 2025b; Rao et al., 2025b), knowledge graphs (Chen et al., 2025a), or multi-agent LLM systems (Rao et al., 2025a).

Search Engines and Retrieval Systems. Interactive agents combine LLMs with retrieval, including search engines with offline query understanding and online decision-making (Karat et al., 2025), and RAG systems querying sports knowledge from natural language (Schilling et al., 2024; Strand et al., 2024a,b; Sepasdar et al., 2024a,b; Wang et al., 2025b). Extensions include online information retrieval for cricket (Wickramasinghe, 2025) and fine-grained sports video retrieval for gymnastics and diving (Gupta et al., 2025).

2.5 Applications for Researchers

2.5.1 Sports Academic Writing

Large models can aid sports researchers in academic writing, as shown in sports science (Latzel and Glauner, 2024) and sports medicine (Hakam et al., 2024). For instance, ChatGPT can generate outlines, abstracts, and provide grammar and style suggestions (Latzel and Glauner, 2024). However, caution is needed due to risks in content accuracy (Dergaa et al., 2023a), reference reliability (Anderson et al., 2023), calculation accuracy (Methnani et al., 2023), and originality.

2.6 Applications for the Sports Industry

2.6.1 Sports Management

Large models are increasingly applied in sports management. In financial management, they can conduct interviews, extract key themes, and develop tailored strategies (Haghparast et al., 2024); in database management, they structure and analyze club data to improve efficiency (Merilehto, 2024); and in facility management, they support human-computer dialogue to acquire site selection knowledge (Salimi Beni et al., 2025). They are also used to explore future industry scenarios and support data-driven decisions (Haghparast et al., 2025).

2.6.2 Sports Talent Scouting

Sports talent scouting helps clubs identify, evaluate, and predict player potential, and large models can make this process more objective and data-driven (Mateus et al., 2024). Recent research uses LLMs to analyze player data (Raskar et al., 2025), convert unstructured scouting reports into searchable knowledge, and combine them with RAG to optimize information integration (Martire and Ragazzi, 2025).

2.6.3 Sports Tourism

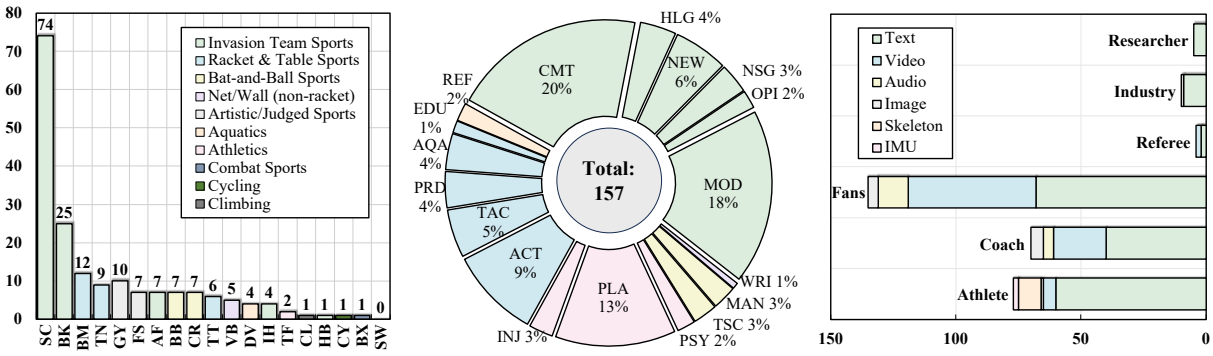
Sports and tourism are closely linked, and large models can enhance intelligence and personalization in sports tourism, offering virtual guides, information assistants, fan engagement, community building, and operational efficiency (Memon et al., 2025). They also show strong potential in esports tourism (Yenisoy and Silik, 2025).

3 Datasets for Large Models in Sports

In this section, we categorize existing datasets for large models in sports into two main types with distinct objectives and design orientations: **task-specific datasets** and **sports understanding datasets**. We will first introduce these two types of datasets and then analyze their characteristics from multiple perspectives, including sport type, task distribution, and modality composition. More details are provided in Appendix A.

3.1 Task-Specific Datasets

Task-specific datasets are developed to address concrete applications of large models across various sports contexts, corresponding to the 6 stakeholder groups and 19 tasks introduced in §2. They typically provide fine-grained annotations and evaluation metrics, supporting model training, fine-tuning, and task-specific performance assessment. Serving as a bridge between large models' general capabilities and practical sports applications, these datasets enable the development of customized systems, foster reproducible evaluation, and advance research on large model deployment in real-world sports scenarios.



(a) Analysis of sports types (b) Analysis of task distribution (c) Analysis of modality composition

Figure 3: Data analysis from 3 different perspectives. Sports and tasks abbreviations are listed in Table 5.

Benchmark	Sports	Input Modal	# Video	# QA
BIG-bench-SU (2023)	SC, BK, etc.	text	-	986
Sports-QA (2024b)	GY, VB, etc.	video, text	5967	94073
SportQA (2024a)	TN, AF, etc.	text	-	70592
SPORTU (2025)	BB, IH, etc.	video, text	1701	12948
Sports-3K-QA (2025b)	49 Sports	video, text	412	1174
FSBench (2025a)	FS	video, text	783	4000
FBBench (2025b)	BM	video, text	2563	2563
Gym-QA (2025a)	GY	video, text	6031	27469
Diving-QA (2025a)	DV	video, text	∼100	1055

Table 1: Overview of specialized sports understanding benchmarks related to large models. Sports abbreviations are listed in Table 5.

3.2 Sports Understanding Datasets

Sports are inherently fast-paced, diverse, and strategically complex, posing unique challenges to the sports understanding capabilities of large models (Xia et al., 2024a). Beyond task-specific datasets, numerous studies have developed sports understanding datasets to evaluate and improve models' general comprehension and reasoning in sports-related contexts. These datasets can be broadly classified into two categories: **(1) datasets specifically designed for sports understanding**, with Table 1 presenting an overview of relevant benchmarks; and **(2) general video understanding datasets that include sports content**, covering tasks such as video captioning (Wang et al., 2024c), multi-view understanding (Grauman et al., 2024), and fine-grained analysis (Liu et al., 2024b).

3.3 Comprehensive Analysis of Sports Datasets

We analyzed the datasets used in studies from sports-focused studies related to large models, across sport types, tasks, and modalities.

Dataset Distribution by Sport Type. Table 3a shows the number of datasets by major sport categories. The distribution is uneven, concentrated in popular sports such as invasion team sports, racket and table sports, and bat-and-ball Sports, with soccer leading at 74 datasets. Some sports, like cycling and boxing, have only one dataset, highlighting coverage imbalance. In addition, fitness-related datasets are relatively numerous (21), and esports datasets total 3, reflecting growing interest in esports.

Dataset Distribution by Task. Table 3b shows that among the 6 sports stakeholder groups, data are relatively abundant for athletes and trainers, coaches and educators, and fans and social media, reflecting stronger coverage of common sports participants. Academically, tasks such as sports commentary generation, training plan generation, and action recognition receive more attention. In contrast, data for referees, sports researchers, and the sports industry remain scarce, with researcher-relevant datasets accounting for only 1%, highlighting the need to address these gaps.

Dataset Distribution by Modality. Table 3c shows that in sports research with large-scale models, video and text are the most common modalities. Some studies also highlight the importance of audio (Xie et al., 2025). In contrast, sensor data such as IMUs and skeletal data are relatively rare, appearing only in athlete-focused studies. Exploring these less common modalities could potentially strengthen large models' understanding of sports.

4 Discussion

4.1 Challenges

Large models show great potential in sports by aiding various stakeholders. However, their adoption in sports faces challenges that need to be addressed to fully realize their benefits.

Data Coverage and Scarcity. Developing large models for sports faces significant challenges due

to data limitations. These include: *(1) narrow sports coverage*, with datasets focusing on a few major sports while others are neglected; *(2) shallow data depth*, as most data comes from elite competitions, underrepresenting Paralympics, secondary leagues, and amateur events; *(3) limited data modalities*, relying mainly on broadcast videos and textual data, while sensor-based and physiological data are rarely used; *(4) high data acquisition costs*, due to the need for expert annotations for detailed data like sports tactics, making large-scale data creation difficult; and *(5) lack of standardization*, with inconsistent annotation practices across sports, fragmenting resources and hindering fair benchmarking.

Limits of Current Modeling Capabilities. Current large models also face intrinsic limitations in sports applications. These include: *(1) hallucination and factual reliability*, with models generating inaccurate statistics (Huang et al., 2025) or misinterpreting match dynamics (Qiu, 2024; Oliver and Guiller, 2025; Hu et al., 2024d; Sepasdar et al., 2024a); *(2) insufficient long-video understanding*, as models struggle with reasoning over extended sequences (Zou et al., 2024; Wang et al., 2025c), making it hard to capture tactical developments across a match (You et al., 2025); *(3) weak generalization*, with models trained on professional leagues failing to transfer to amateur or youth sports (Qiu, 2024; Oliver and Guiller, 2025; Hu et al., 2024d; Sepasdar et al., 2024a).

Bias, Fairness, and Ethics. The deployment of large models in sports raises concerns about bias, fairness, and ethical responsibility, as flawed decisions in athlete selection, performance evaluation, medical support, and refereeing can have significant consequences. These challenges include: *(1) fairness and bias* due to imbalanced training data that can produce discriminatory outputs and amplify inequalities (Biester, 2025; Kim et al., 2025a); *(2) transparency and explainability* needed for high-stakes decisions to maintain trust (Dergaa et al., 2023b; Kim et al., 2025a); *(3) privacy and data ethics*, as sensitive data like biometric and health information lack adequate protection mechanisms (Papini et al., 2025b; Kim et al., 2025a); and *(4) accountability and responsibility*, with unclear liability among stakeholders (Kim et al., 2025a).

4.2 Future Directions

Large models have demonstrated strong capabilities in sports. Despite challenges, their deployment offers unique opportunities, and we outline future directions to address limitations and unlock their full potential.

Efficient Modeling. A key priority is developing models that provide real-time insights under strict latency constraints (Niu et al., 2025). Sports require responses during live play or halftime (Chen et al., 2025b), making lightweight edge-side LLMs/MLLMs with streaming I/O essential for fast, responsive analysis.

Expert-Level Modeling. Future models should deliver expert-level sports analysis. Tactical insights must go beyond shallow statistics, and commentary should be interactive and knowledge-rich, comparable to professional broadcasters. Achieving this requires domain priors and tool-using capabilities (Rao et al., 2025a).

Emerging Technologies and Modalities. Expanding beyond video–text pipelines, integrating sensors, wearables, and physiological data can enhance reasoning (Merrill et al., 2024; Ferrara, 2024). Robotics (Ma et al., 2025c) and mixed reality (Sawan et al., 2020; Cheng et al., 2024b) enable embodied training and immersive simulation.

Collaborative Human–AI Systems. Large models should augment human expertise, supporting interactive workflows where coaches, athletes, and fans refine tactics, prevent injuries, and enhance fan experiences (Zhu-Tian et al., 2022).

Practicability. Progress depends on deployable tools. For elite sports, collaboration with clubs, companies and media can deliver specialized analytics[1]. Extending applications to schools, community programs, and consumer fitness ensures impact from elite performance to grassroots participation (He et al., 2024; Ma and Tran-Nguyen, 2024).

5 Conclusion

This survey reviews the emerging landscape of large models in sports, summarizing applications across 6 participant groups, analyzing relevant datasets and benchmarks, and highlighting key challenges. Based on these findings, we outline future research directions and emphasize the vast opportunities in this rapidly evolving field. We hope this work serves as a foundation for advancing large-model-driven sports intelligence and provides a practical resource for research and development.

[1] https://www.hudl.com/en_gb/products/wyscout, https://www.statsperform.com/opta-analytics/

Limitations

Although this survey strives to provide a comprehensive overview of large models in sports, several limitations remain. Firstly, given the rapid development of this field, our survey may not be able to timely reflect the latest progress before and after the survey. Secondly, as some studies span multiple application domains, minor overlaps are inevitable; we categorize each work based on its primary research focus while cross-referencing related sections when appropriate. Thirdly, our analysis primarily centers on academic research, and the discussion of commercial systems or industrial applications remains limited. Despite these limitations, this survey provides a valuable and timely overview of the field, offering a solid reference for subsequent research and development.

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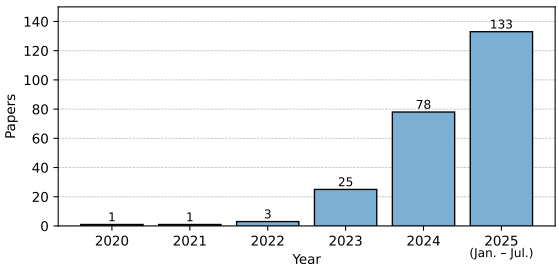

Figure 4: Papers on large models in sports over the years (data for 2025 is up to July).

A More Details on Datasets for Large Models in Sports

In this section, we further provide a comprehensive introduction to the datasets for large models in sports, as an extension of the main discussion in Section 3.

A.1 Task-Specific Datasets

This subsection echoes Section 3.1 of the paper and provides a further overview of these task-specific datasets. Table 2 and Table 3 present the datasets related to specific tasks for 5 sports stakeholder groups: athletes and trainers, coaches and educators, referees, fans and social media, and the sports industry. The information covers dataset names, involved sports types, data modalities, methods used in the papers, corresponding large models, best achieved performance, and links that can be accessed directly.

These datasets are unevenly distributed across tasks. From the perspective of target users, datasets for coaches and fans are relatively abundant, while those for referees, researchers, and the sports industry are relatively scarce. In terms of task types, early tasks in traditional computer vision and natural language processing, such as action spotting and recognition and sports commentary generation, have received more research attention and have richer datasets, whereas tasks like public opinion analysis in sports and sports talent scouting lack open-source data, reflecting an imbalance in scholarly focus across different tasks.

These datasets are unevenly distributed across sports. Popular sports such as soccer, basketball, and badminton receive more attention and have richer datasets, whereas niche sports like track and field, aquatics, and even esports are severely underrepresented. Nevertheless, these underexplored areas hold research value and warrant further expansion and investigation.

These datasets are unevenly distributed across modalities. Video and text are the most common modalities in sports datasets, while audio, sensor data (e.g., IMU), and skeletal data are relatively scarce. This reflects the current research focus on video in the sports domain and also highlights the untapped potential of other modalities.

These datasets are generally used with pre-existing models rather than being used to train or fine-tune models. Most researchers tend to rely on the inherent capabilities of large models, which explains the widespread use of powerful closed-source models such as GPT-4 (Achiam et al., 2023). This trend reflects both the scarcity of sports data and the significant value of constructing dedicated sports datasets and models, emphasizing the need for more attention to the field of large models in sports.

A.2 Sports Understanding Datasets

This subsection echoes Section 3.2 and provides a more detailed overview of datasets related to sports understanding tasks for large models. We cover datasets specifically designed for sports understanding with large models (§A.2.1), general video understanding datasets that include sports content (§A.2.2), and other general-purpose datasets containing sports-related data (§A.2.3). Table 4 presents a comprehensive summary of the first two categories of datasets from multiple perspectives, including dataset name, covered sports types, data source, benchmark availability, input modalities, number and average duration of videos, number of QA pairs, and the availability of open-source links, which can be directly accessed by clicking in the table.

A.2.1 Specialized Sports Understanding Datasets

Recently, numerous datasets have been developed to evaluate and enhance the general sports understanding capabilities of large models.

For LLMs, QASports (Jardim et al., 2023) introduced the first large-scale sports question-answering dataset with rich contextual information and diverse questions for model training and evaluation. The sports understanding subtask in BIG-bench (Srivastava et al., 2023) includes 986 binary-choice questions, primarily testing models' general

understanding of sports activities. SportQA (Xia et al., 2024a) comprises over 70,000 multiple-choice questions across three difficulty levels, enabling a comprehensive evaluation of LLMs' performance in sports understanding. SPORTU-text (Xia et al., 2025) and FSBench-Text (Gao et al., 2025a) assess models' understanding of rules, events, and scenarios in 5 major sports and figure skating, respectively.

For MLLMs, Sports-QA (Li et al., 2024b) is the first dataset specifically designed for sports video question answering, advancing the evaluation of multimodal models in sports video understanding. SPORTU-video (Xia et al., 2025) covers 7 sports and provides systematic video understanding tasks across three difficulty levels, while Sports-3K-QA (Chen et al., 2025b) includes a broader range of 49 different sports.. FSAnno (Gao et al., 2025a) constructs a large-scale, multi-task, multimodal figure skating dataset, while FSBench-Motion (Gao et al., 2025a) extends it by adding motion data and QA pairs, supporting tasks ranging from single-action analysis to full-performance commentary. FineBadminton (He et al., 2025b) is a large-scale badminton video dataset with fine-grained annotations, on which FBBench (He et al., 2025b) evaluates models' fine-grained sports video understanding. Gym-QA and Diving-QA (Chen et al., 2025a), built upon FineGym (Shao et al., 2020) and FineDiving (Xu et al., 2022), respectively, offer new benchmarks for sports video question answering in gymnastics and diving.

A.2.2 General Video Understanding Datasets Featuring Sports

In addition to datasets specifically designed for sports understanding, many general video understanding datasets also include sports content, in which sports constitute an important component.

In addition to large-scale, multi-task, and comprehensive video understanding datasets (Fu et al., 2025; He et al., 2025a; Yang et al., 2025a), some focus on specific capabilities. For example, InternVid (Wang et al., 2024c), FIOVA (Hu et al., 2024a), and VidText (Yang et al., 2025b) are primarily used for video description or subtitle generation, while Ego-Exo4D (Grauman et al., 2024) and EgoExoBench (He et al., 2025c) focus on video understanding from different viewpoints. LVBench (Wang et al., 2024b), MLVU (Zhou et al., 2025b), Neptune (Nagrani et al., 2024), LongVILA_sft (Chen et al., 2025c), and VR-Bench (Yu et al., 2025) are dedicated to long video understanding, while E.T. Bench (Liu et al., 2024b), MotionBench (Hong et al., 2025b), and ExAct (Yi et al., 2025) are used for fine-grained action, skill, or motion understanding. TUNA (Kong et al., 2025a) and VideoA11y-40K (Li et al., 2025b) emphasize temporal information and dynamic video understanding, while VideoVista (Li et al., 2024c), V-STaR (Cheng et al., 2025), MINERVA (Nagrani et al., 2025), VRBench (Yu et al., 2025), and CausalStep (Li et al., 2025e) target video reasoning tasks such as temporal-spatial, multi-step, and causal reasoning.

Furthermore, video-SALMONN-2 (Tang et al., 2024, 2025a), WorldSense (Hong et al., 2025a), HarmonySet (Zhou et al., 2025c), and MAVERIX (Xie et al., 2025) focus on joint understanding of audio and video, demonstrating multimodal capabilities; while OVO-Bench (Niu et al., 2025) and RTV-Bench (Xun et al., 2025) examine the real-time processing capabilities of models. In terms of model capability evaluation, Trust-videoLLMs (Wang et al., 2025d) is used to evaluate the credibility of video understanding, while SIV-Bench (Kong et al., 2025b) studies the understanding of social interaction behaviors in videos.

A.2.3 Other General Datasets Featuring Sports

Moreover, some other types of general datasets also contain sports content. To evaluate the image understanding capabilities of large models, MDI-Benchmark (Zhang et al., 2024b) collected 514 real images and 1,298 question-answer pairs to test basic perception and complex reasoning, and designed sports-related questions for different age groups. MIP-GAF (Madan et al., 2025) constructed a large dataset to examine the understanding of key figures in images, which also includes sports scenes. Furthermore, to assess the ability of large models as multimodal search engines, MMSearch (Jiang et al., 2025a) collected 300 unimodal and multimodal samples, and MomentSeeker (Yuan et al., 2025) constructed a dataset consisting of 268 long videos with an average length of over 1,200 seconds, all of which focus on sports scenes.

Task	Dataset	Sports	Modal	Method	Related Large Model	Performance	Link
				Athletes and Trainers			
PLA	YourSkatingCoach (2024b)	Figure Skating	V, T	MAAIG (2023)	T5 (2020)	22.08 (METEOR)	✗
	PACE (2022)	Fitness	T	Hegde et al. (2024)	LaMDA (2022)	3.78 ± 1.00 (Likert Scale)	✓
	NSCA-CSCS (2025)	Fitness	T	PH-LLM (2024)	Gemini Ultra 1.0 (2023)	88.00 (Acc)	✗
	T3Set (2025a)	Table Tennis	V, M, T	SenseCoach (2025a)	Llama 3.3-70B (2024)	51.64 (P@6-S1L)	✓
	SCD (2025)	Soccer	T	Han (2025)	BERT (2019)	85.64 (BERTScore)	✗
	Custom Dataset (2025b)	Table Tennis	V, I, S, T	Ma et al. (2025b)	GPT-4 (2023)	67.40 (Acc)	✓
	Ego-Exo4D (2024)	SC, BK, CL	V, T	ExpertAF (2025)	Llama 3-8B (2024)	49.60 (METEOR)	✓
	Ego-Exo4D (2024)	Basketball	V, T	Seino et al. (2025)	GPT-4o (2024)	25.60 (METEOR)	✗
	FS (2025)	Figure Skating	S, T	CoachMe (2025)	T5 (2020)	26.5 (BERTScore)	✓
	BX (2025)	Boxing				36.9 (BERTScore)	
INJ	cMedQA2 (2018)	-	T	Zhu et al. (2025)	Qwen2-0.5B (2024)	30.56 (BLEU-4)	✗
	Custom Dataset (2025)	-	T	Saglam et al. (2025)	GPT-4 (2023)	47.80 (Cronbach's α)	✗
	Custom Dataset (2025)	-	T	Brogly et al. (2025)	phi-3-mini (2024)	34.13 (Spearman)	✗
PSY	Custom Dataset (2024)	Fitness	T	PHIA (2024)	Gemini 1.0 Ultra (2023)	84.20 (Acc)	✓
	Capture24 (2021)	Fitness	M	HARGPT (2024)	GPT-4 (2023)	79.50 (F1)	✓
	In-the-Wild (2024)	Fitness	M, T	LLaSA (2024)	Vicuna-7B (2023)	79.95 (Acc)	✓
				Coaches and Educators			
ACT	Custom Dataset (2024)	Rugby	I, T	Nonaka et al. (2024)	LLaVA-7B (2023)	63.10 ± 2.20 (F1)	✗
	ActionAtlas v1.0 (2024)	56 Sports	V	Salehi et al. (2024)	GPT-4o (2024)	42.95 ± 2.91(Acc)	✓
	NSVA Subset (2025)	BK, AF	V, T	SV3.3B (2025)	Llama 3.2-3B (2024)	85.60 ± 5.20 (BERT F1)	✓
	FineTennis (2025)	Tennis	V	Teo (2025)	Video-LLaMA2-7B (2024c)	76.00 (Edit Score)	✓
	SoccerNet-v2 (2021)	Soccer	V	Soccer-CLIP (2025)	ViT-B/32 (2021)	75.70 (t-AmAP)	✗
	Tennis7 (2021)	Tennis	V			93.80 (Acc)	
	F³Set (2025)	TN, BM, TT	V, T	F³ED (2025)	GPT-4 (2023)	75.20 (F1elm)	✓
	Video-MME (2025)	SC,BK,GY,DV	V, T	F-16 (2025f)	LLaVA-OV (2025a)	65.00 (Acc)	✓
	SoccerNet-v2 (2021)	Soccer	T	Chakraborty et al. (2025)	Llama 3.1-8B (2024)	64.50 (mAP)	✗
	SoccerNet-v2 (2021)	Soccer	V, T	Jiang et al. (2025b)	LLaVA-NeXT-Video (2024a)	63.50 (Acc)	✗
	UCI-HAR (2013)	Fitness	M	Gao et al. (2025b)	GPT-4 (2023)	92.30 (Acc)	✗
	SoccerNet (2018)	Soccer	V, A, T	Banu et al. (2025)	Video-LLaMA (2023)	87.00 (F1)	✗
AQA	Fis-V (2019)	Figure Skating	V, A, T	Wang et al. (2025a)	InternVL2 (2024c)	84.00 (Spearman)	✓
	FS1000 (2023)					90.00 (Spearman)	
	FineFS (2023)					76.00 (Spearman)	
	Fitness-AQA (2022)	Fitness	V, T	Dibenedetto et al. (2025)	LLaVA-Video-7B (2025c)	22.82 (mAP)	✓
	FMS (2025b)	Fitness	V, T	FitnessAgent (2025b)	ChatGLM4 (2024)	39.34 (Acc)	✗
	LLM-FMS (2025)	Fitness	V, T	Xing et al. (2025)	-	91.00 (Acc)	
TAC	Custom Dataset (2023)	Soccer	T	TacticalGPT (2023)	GPT-NeoX-20B (2022)	50.00 (Acc)	✗
	STATS SportVU 2025	Basketball	I, T	Smartboard (2024c)	GPT-4V (2024)	-	✗
	Custom Dataset (2021)	Baseball	T	Michielssen et al. (2024)	Curie (2020)	97.00 (Acc)	✓
	SportsMetrics (2024c)	BK, AF	T	Hu et al. (2024b,c)	Gemini-Pro 2023	32.30 (ΔGScore)	✓
	Custom Dataset (2024)	Cycling	T	Janssens et al. (2024)	GPT-4o (2024)	-	✗
	Custom Dataset (2024d)	Basketball	T	SportsGen (2024d)	GPT-4o (2024)	98.41 (DnC-10)	✓
	Custom Dataset (2025a)	Badminton	V, T	ChatMatch (2025a)	GPT-3.5-turbo (2022)	98.84 (Acc)	✗
	Basketball-Instants 2024	Basketball	I, T	TacticExpert (2025)	Vicuna-7B-v1.5 (2023)	83.33 (Macro F1)	✗
PRD	Custom Dataset (2020)	Basketball	T	Oved et al. (2020)	BERT (2019)	58.50 (Acc)	✗
	ShuttleSet (2023)	Badminton	V, T	RallyTemPose (2024)	BERT (2019)	54.30 (Acc)	✓
	BadmintonDB (2022)					62.80 (Acc)	
	Custom Dataset (2024)	Basketball	T	Sprint (2024)	GPT-3.5-turbo (2022)	64.90 (Acc)	✓
	SportDevs (2025)	Handball	T	Felice (2024)	Mistral-7B (2023)	5.20 (RMSE)	✗
	Custom Dataset (2025)	Cricket	V, T	Bhatnagar and Bhatnagar (2025)	GPT-4o mini (2024), etc.	86.30 (F1)	✓
				Referees			
REF	SoccerNet-XFoul (2024)	Soccer	V, T	X-VARS (2024; 2025)	Video-ChatGPT (2024)	3.80 (Likert Scale)	✓

Table 2: Summary of task-specific sports datasets related to large models, including athletes and trainers, coaches and educators, and referees. Task: PLA: exercise and training plans, INJ: sports injury and rehabilitation, PSY: sports psychology and behavior, ACT: action spotting and recognition, AQA: sports action quality assessment, TAC: sports tactics and strategies, PRD: game and player performance prediction, REF: sports refereeing. Sports: SC: soccer, BK: basketball, CL: sports climbing, AF: American football, TN: tennis, BM: badminton, TT: table tennis, GY: gymnastics, DV: diving. Modal: V: video, I: image, A: audio, S: skeleton data, M: IMU data, T: text.

Task	Dataset	Sports	Modal	Method	Related Large Model	Performance	Link
				Fans and Social Media			
CMT	Custom Dataset (2022)	Soccer	V, A, T	Gautam et al. (2022)	GPT-3 (2020)	0.31 (ROUGE-L)	✓
	SN-Caption-test-align (2024)	Soccer	V, T	MatchVoice (2024)	Llama 3 (2024)	42.00 (CIDEr)	✓
	LoL19 (2024)	Esports	T	Wang and Yoshinaga (2024)	Llama 2 13B (2023b)	-4.61 (BARTScore)	✓
	Custom Dataset (2024b)	Soccer	V, T	AiCommentator (2024b)	GPT-3.5-turbo (2022)	0.56 (Cohen's d)	✗
	CommentarySet (2024)	TF,SC,BK,GY,TT,TN	V, T	Ge et al. (2024)	InternVL-Chat-2 (2024c)	5.44 (SCORES)	✗
	Custom Dataset (2015; 2023)	Soccer	T	LLM-Commentator (2024)	LLaMA 7B (2023a)	92.00 (F1)	✓
		Golf			Llama 2 7B (2023b)	99.12 (ROUGE-L)	
	Custom Dataset (2024)	Tennis	V, T	Baughman et al. (2024)	Sandstone 3B (2020)	86.80 (ROUGE-L)	✗
		American Football			Llama 2 7B (2023b)	86.80 (ROUGE-L)	
	BH-Commentary (2024a)	Basketball	V, T	Zhang et al. (2024a)	BERT (2019)	12.19 (CIDEr)	✓
	SoccerNet-Caption (2023)	Soccer	V, T	TimeSoccer (2025)	Llama 2 7B (2023b)	8.30 (CIDEr)	✓
	SoccerNet-V2 (2021)	Soccer	V, T	Jiang et al. (2025b)	Claude 3.5 Sonnet (2025)	2.59 (Likert Scale)	✗
	WyScout (2024)					2.96 (Likert Scale)	
	LFCBI (2025)	Soccer	V, T	Mori et al. (2025)	GPT-4o (2024)	15.50 (MSE)	✓
	SoccerTrack-Commentary (2025)	Soccer	V, I, T	Vijayakumar et al. (2025)	GPT-3 (2020)	33.84 (CIDEr)	✗
	LiveSports-3K-CC (2025b)	49 Sports	V, A, T	LiveCC (2025b)	Qwen2-VL-7B (2024a)	40.08 (Win Rate)	✓
	SoccerNet-v2 (2021)	Soccer	V, A, T	SoccerComment (2025d)	Vicuna-7B-v1.5 (2023)	36.58 (CIDEr)	✗
	NBA-Identity (2025b)	Basketball	V, T	LLM-IAVC (2025b)	Llama 3.2-3B (2024)	105.30 (CIDEr)	✓
	VC-NBA-2022 (2025a)					150.70 (CIDEr)	
	Custom Dataset (2025)	Cricket	V, T	Sameer et al. (2025)	GPT-4o mini (2024), etc.	83.00 (BERT F1)	✗
	SoccerNet-Caption (2023)	Soccer	V, T	StreamMind (2025)	Video-LLaMA2-7B (2024c)	82.04 (ROUGE-L)	✓
	SoccerNet (2018)	Soccer	V, T	VLM-TSI (2025)	VideoLLM-Online (2024a)	39.10 (TRACE)	✓
HLG	CricPulse (2023)	Cricket	V, T	Sattar et al. (2023)	BERT (2019)	97.00 (F1)	✗
	Custom Dataset (2024)	Soccer	V, A	SmartCrop (2024)	GPT-4 (2023)	-	✗
	Custom Dataset (2025)	Baseball	T	DIAMOND (2025)	Mistral-Large (2024)	76.50 (F1)	✗
	HIPPO-Video (2025)	-	V, T	HiPHer (2025)	GPT-4 (2023)	76.60 (mAP)	✓
	Custom Dataset (2025)	Cricket	V, A, T	SportSummarizer (2025)	DistilBERT (2019)	0.93 (HD)	✗
	SoccerNet (2018)	Soccer				0.92 (HD)	
NSG	SportsSum2.0 (2021)	Soccer	T	Wang et al. (2021)	RoBERTa (2019), etc.	47.78 (ROUGE-L)	✓
	SportsSum (2020)	Soccer				47.49 (ROUGE-L)	
	K-SportsSum (2022)	Soccer	T	KES (2022)	mT5 (2021)	47.17 (ROUGE-L)	✓
	SportsSum (2020)	Soccer				47.79 (ROUGE-L)	
	NBA API (2022)	Basketball	T	SNIL (2024a)	GPT-3.5 (2022)	63.00 (Acc)	✓
	ShuttleSet (2023)	Badminton	T	BADGE (2024)	GPT-4 (2023)	8.63/10 (LLM)	✓
	Custom Dataset (2024)	Cricket	T	Sarkar et al. (2024)	Google Gemini (2023)	9.20/10 (ACS)	✗
	RotoWire (2017)	Basketball	T	Tree-of-Report (2025)	GPT-4o mini (2024)	54.92 (CS F1)	✗
	MLB (2019)	Baseball				62.99 (CS F1)	
	ShuttleSet+ (2025)	Badminton				93.94 (CS F1)	
NAR	Custom Dataset (2023)	Soccer	T	Sarfati et al. (2023)	T5-large (2020)	49.04 (ROUGE-L)	✗
	SportsVU (2024)	Basketball	V, T	Sportify (2024)	-	72.22 (Acc)	✓
	SoccerSum (2024a; 2024b)	Soccer	V, A	SoccerSum (2024a)	GPT-4 Turbo (2023)	-	✓
	Custom Dataset (2025)	Basketball	V	SportsBuddy (2025)	GPT-4o (2024)	90.80 (Acc)	✗
OPI	Custom Dataset (2024)	Soccer	T	Rauchegger et al. (2024)	GPT-4-turbo (2023)	70.30 (F1)	✗
	Custom Dataset (2025)	Soccer	T	ABSA (2025)	RoBERTa (2019)	80.00 (F1)	✓
MOD	Custom Dataset (2024)	Soccer	T	Schilling et al. (2024)	GPT-3.5 (2022)	71.40 (Acc)	✗
	SoccerNet (2018)	Soccer	V, A, I	SoccerRAG (2024a; 2024b)	GPT-4 (2023), etc.	80.00 (Acc)	✓
	Custom Dataset (2025)	Soccer	T	Karat et al. (2025)	GPT-4o (2024)	88.25 (Precision)	✗
	Custom Dataset (2025)	Cricket	T	Wickramasinghe (2025)	Copilot (2021)	100.00 (Acc)	✗
	TF-CoVR (2025)	GY, DV	V, T	TF-CoVR-Base (2025)	BLIP (2022)	23.02 (mAP@10)	✓
	KICK (2025b)	Soccer	T	Song et al. (2025b)	GPT-4o (2024)	15.86 (JGA)	✓
	SoccerNet-XFoul (2024)	Soccer	V, T	SoccerChat (2025)	Qwen2-VL-7B (2024a)	6.81/10 (LLM)	✓
	SoccerNet-v2 (2021)					6.42/10 (LLM)	
	SoccerBench (2025a)	Soccer	V, A, T	SoccerAgent (2025a)	DeepSeek-v3 (2024a)	60.9 0(Acc)	✓
	SoccerNet-v2 (2021)					80.10 (Acc)	
	SN-Caption-test-align (2024)	Soccer	V, T	MatchVision (2025b)	Llama 3-8B (2024)	44.18 (CIDEr)	✓
	MVFoul (2023)					44.00 (Acc)	
	SoccerNet-V2 (2021)	Soccer	V, T	Jiang et al. (2025b)	LLaVA-NeXT-Video (2024a)	83.76 (Acc)	✗
	WyScout (2024)					81.83 (Acc)	
	Gym-QA (2025a)	Gymnastics	V, T	FineQuest (2025a)	Video-LLaVA (2024a), etc.	57.00 (Acc)	✗
	Diving-QA (2025a)	Diving	V, T				
	SPORTU (2025)	7 Sports	V, T			73.20 (Acc)	
				The Sports Industry			
MAN	Custom Dataset (2024)	-	T	Merilehto (2024)	Claude 3 Opus (2024)	90.28 (Acc)	✗
TSC	Custom Dataset (2025)	Soccer	T	Martire and Ragazzi (2025)	GPT-4o (2024)	3.80 (Likert Scale)	✗
	Custom Dataset (2025)	Soccer	I, T	Footyintel (2025)	-	-	✗

Table 3: Summary of task-specific sports datasets related to large models, including fans and social media, and the sports industry. Task: CMT: sports commentary generation, HLG: sports highlight generation, NSG: sports news generation, NAR: sports narratives and storytelling, OPI: public opinion analysis in sports, MOD: sports models and systems, MAN: sports management, TSC: sports talent scouting. Sports: TF: track and field, SC: soccer, BK: basketball, TN: tennis, TT: table tennis, GY: gymnastics, DV: diving. Modal: V: video, I: image, A: audio, T: text.

Dataset	Sports	Source	Benchmark	Input Modal	# Video	Avg. Length	# QA	Link
Specialized Sports Understanding Datasets								
QASports (2023)	SC, BK, AF	Fandom	✗	text	-	-	∼1500K	✓
BIG-bench-SU (2023)	SC, BK, AF, BB, IH	program	✓	text	-	-	986	✓
Sports-QA (2024b)	SC, BK, GY, VB	exist (dataset)	✓	video, text	5967	20.9s	94073	✓
SportQA-Level-1 (2024a)	-	exist	✓	text	-	-	21385	
SportQA-Level-2 (2024a)	35 Sports	Wikipedia	✓	text	-	-	45685	✓
SportQA-Level-3 (2024a)	SC, BK, TN, AF, TT, VB	expert	✓	text	-	-	3522	
SPORTU-text (2025)	SC, BK, TN, AF, VB	expert	✓	text	-	-	900	✓
SPORTU-video (2025)	SC,BK,BM,TN,BB,VB,IH	competition	✓	video, text	1701	-	12048	
Sports-3K-QA (2025b)	49 Sports	YouTube	✓	video, text	412	-	1174	✓
FSAnno (2025a)			✗	video, text, audio	783		-	
FSBench-Text (2025a)	FS	competition	✓	text	-	∼3.5m	500	✗
FSBench-Motion (2025a)			✓	video, text	783		3500	
FineBadminton (2025b)	BM	YouTube	✗	video, text	3215	12.4s	-	✓
FBBench (2025b)			✓	video, text	2563	-	2563	
Gym-QA (2025a)	GY	exist	✓	video, text	6031	-	27469	✗
Diving-QA (2025a)	DV	exist	✓	video, text	∼100	-	1055	✗
General Video Understanding Datasets								
InternVid (2024c)	-	YouTube	✗	video, text, audio	7.1M	6.4m	N/A	✓
Ego-Exo4D (2024)	SC, BK, CL	manual	✗	video, audio	5035	2.6m	N/A	✓
E.T. Bench (2024b)	SC, BK, TN, CR, etc.	exist	✓	video, text	7002	129s	7289	✓
LVBench (2024b)	BK, etc.	YouTube	✓	video, text	103	4101s	1549	✓
VideoVista (2024c)	SC, etc.	exist	✓	video, text, audio	894	131s	24906	✓
FIOVA (2024a)	BB, etc.	-	✓	video	3002	33.6s	N/A	✓
Neptune (2024)	BK, etc.	exist	✓	video, text, audio	2405	2.5m	3268	✓
videoSALMONN2 (2025a)	BB, etc.	-	✓	video, text, audio	483	51s	N/A	✓
MMWorld (2025a)	SC, BK, GY, VB	exist	✓	video, text, audio	1910	∼105s	6627	✓
LongVILA_sft (2025c)	-	exist	✗	video, text	15292	-	15292	✓
MLVU (2025b)	SC, BK, BM, TT, VB	-	✓	video, text	3102	930s	3102	✓
Video-MME (2025)	SC, BK, etc.	YouTube	✓	video, text, audio	900	1017.9s	2700	✓
MotionBench (2025b)	BB, etc.	exist, syn, web	✓	video, text	5385	<10s	8052	✓
OVO-Bench (2025)	-	exist, YouTube	✓	video, text	644	428.89s	2814	✓
VISTA-400K (2025)	-	exist	✗	video, text	403994	48.6s	∼381K	✓
HRVideoBench (2025)	-	manual	✓	video, text	200	5.4s	200	✓
HarmonySet-train (2025c)	-	YouTube	✗	video, text, audio	44470	31.5s	44470	✓
HarmonySet-MC (2025c)			✓		3858		3858	
VideoA11y-40K (2025b)	-	online	✗	video, audio	40000	-	N/A	✓
TUNA (2025a)	SC, BK, etc.	exist	✓	video, text	1000	14.5s	2000	✓
WorldSense (2025a)	-	exist	✓	video, text, audio	1662	141.1s	3172	✓
V-STaR (2025)	-	exist, YouTube	✓	video, text	2094	110.23s	-	✓
MINERVA (2025)	BK, TN, etc.	YouTube	✓	video, text	223	12m	1515	✓
MAVERIX (2025)	SC, BK, etc.	exist	✓	video, text, audio	700	5.7m	2556	✗
RTV-Bench (2025)	SC, BK, etc.	exist, online	✓	video, text	552	18.2m	4631	✓
VidText (2025b)	SC, BK, BM, TT, SW	exist, YouTube	✓	video, text, audio	939	108.2s	2857	✓
SIV-Bench (2025b)	SC, etc.	YouTube, TikTok	✓	video, text, audio	2792	32.49s	8728	✓
ExAct (2025)	SC, BK, CL	exist	✓	video, text	3521	105s	3521	✓
VRBench (2025)	SC, BK, VB, etc.	YouTube	✓	video, text, audio	960	1.6h	8243	✓
Trust-videoLLMs (2025d)	-	exist, syn, YouTube	✓	video, text, audio	6955	-	-	✓
CausalStep (2025e)	-	exist	✓	video, text	100	430.5s	1852	✗
EgoExoBench (2025c)	BK, etc.	exist	✓	video, text	-	-	7350	✓
WildVideo (2025a)	-	exist	✓	video, text	1318	∼30s	17625	✗

Table 4: Summary of large-model-related datasets specifically for sports understanding and general video understanding with sports content. Sports: SC: Soccer, BK: Basketball, BM: Badminton, TN: Tennis, GY: Gymnastics, FS: Figure skating, AF: American Football, BB: Baseball, CR: Cricket, TT: Table Tennis, VB: Volleyball, DV: Diving, IH: Ice Hockey, CL: Sports Climbing, SW: Swimming. Source: syn: synthesis.

Sports	**Abbr.**	**Task**	**Abbr.**
Soccer	SC	Exercise and Training Plans	PLA
Basketball	BK	Sports Injury and Rehabilitation	INJ
Badminton	BM	Sports Psychology and Behavior	PSY
Tennis	TN	Action Spotting and Recognition	ACT
Gymnastics	GY	Sports Tactics and Strategies	TAC
Figure Skating	FS	Game and Player Performance Prediction	PRD
Rugby & American Football	RG & AF	Sports Action Quality Assessment	AQA
Baseball	BB	Sports Education	EDU
Cricket	CR	Sports Refereeing	REF
Table Tennis	TT	Sports Commentary Generation	CMT
Volleyball	VB	Sports Highlight Generation	HLG
Diving	DV	Sports News Generation	NSG
Ice Hockey	IH	Sports Narratives and Storytelling	NAR
Track and Field	TF	Public Opinion Analysis in Sports	OPI
Sports Climbing	CL	Sports Models and Systems	MOD
Handball	HB	Sports Academic Writing	WRI
Cycling	CY	Sports Management	MAN
Boxing	BX	Sports Talent Scouting	TSC
Swimming	SW	Sports Tourism	TOU

Table 5: Abbreviations for sports and tasks mentioned in this paper.