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 of 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 at: `https://github.com/Road2Redemption/Awesome_Large_Models_In_Sports1`.

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). A pivotal pillar of this transformation is the ability to process and generate sports-related language, which serves as a vital bridge translating raw athletic data into actionable insights for participants and fans alike.

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). As shown in Figure 1, the transition to the era of large models—underpinned by the rapid evolution of Large Language Models (LLMs) and Multimodal Large Language Models (MLLMs) like GPT-4 (Achiam et al., 2023) and Gemini (Team et al., 2023)—has brought new opportunities and challenges to the sports domain. With linguistic intelligence at their core, 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), developing 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., 2024c). 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., 2024c), 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.

To ensure a comprehensive and rigorous survey, we adopted a systematic snowballing methodology (Wohlin, 2014), adhering to the PRISMA statement (Page et al., 2021). Starting from the aforementioned review papers, we performed iterative

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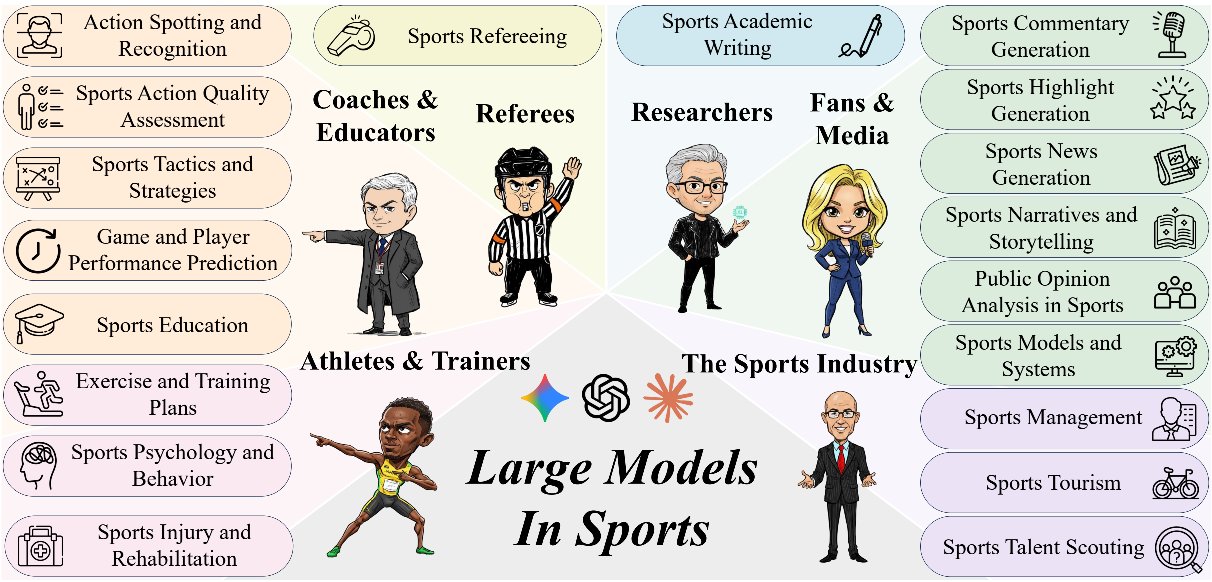


Figure 1: Large models have shown powerful applications across 6 sports stakeholder groups: athletes and trainers, coaches and educators, referees, researchers, fans and social media, and the sports industry, enabling diverse tasks.

forward and backward searches to capture the latest advancements in the era of large models (Jan 2020–July 2025). This process resulted in a final collection of **241** core academic papers addressing large models in sports. The detailed selection methodology is provided in the Appendix A.

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

2 Large Model Applications in Sports

The fast growth of large models has brought big chances for their use in sports. As shown in Figure 2, we categorize these applications into a taxonomy with **6 stakeholder groups** and **19 specific tasks**. In this section, beyond merely listing existing literature, we conduct **a detailed analysis** of the impact of large models on each task, focusing on defining the task, analyzing technical paradigms, and summarizing common evaluation metrics. For comprehensive reviews of specific works associated with each task, see Appendix B.

2.1 Applications for Athletes and Trainers

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 significantly facilitate the generation of personalized training plans across a wide spectrum of health conditions and fitness goals, ranging from general weight management (Saraç et al., 2025) to chronic disease guidance (Onan et al., 2025). As shown in Table 1, in the YourSkatingCoach dataset (Chen et al., 2024c), a fine-tuned T5 model (Raffel et al., 2020) achieves a BLEU-4 score of *0.27*, while a vanilla Transformer (Vaswani et al., 2017) trained from scratch only reaches 0.04 (Yeh et al., 2023). This highlights that LLMs leverage pre-trained knowledge to address sports data scarcity and excel at open-ended generation, outperforming traditional rule-based or smaller deep learning models. Additionally, strategies like Retrieval-Augmented Generation (RAG) (Zhang et al., 2025b) and agentic paradigms (Vahdati et al., 2025) have been explored to enhance reliability and personalization. Common evaluation metrics include BLEU-4, METEOR, and ROUGE-L.

Sports Injury and Rehabilitation. Large models assist athletes and trainers throughout the entire lifecycle of sports injury management, spanning prevention, diagnosis, and rehabilitation, with applications expanding from providing preventive advice (Zhu et al., 2025) to aiding clinical decision-making for surgical treatments (Saglam et al., 2025). While LLMs possess the interdisciplinary knowledge required for orthopedics and rehabilitation (McBee et al., 2024), most current applications rely on the direct deployment of pre-trained large models for Question Answering (QA)

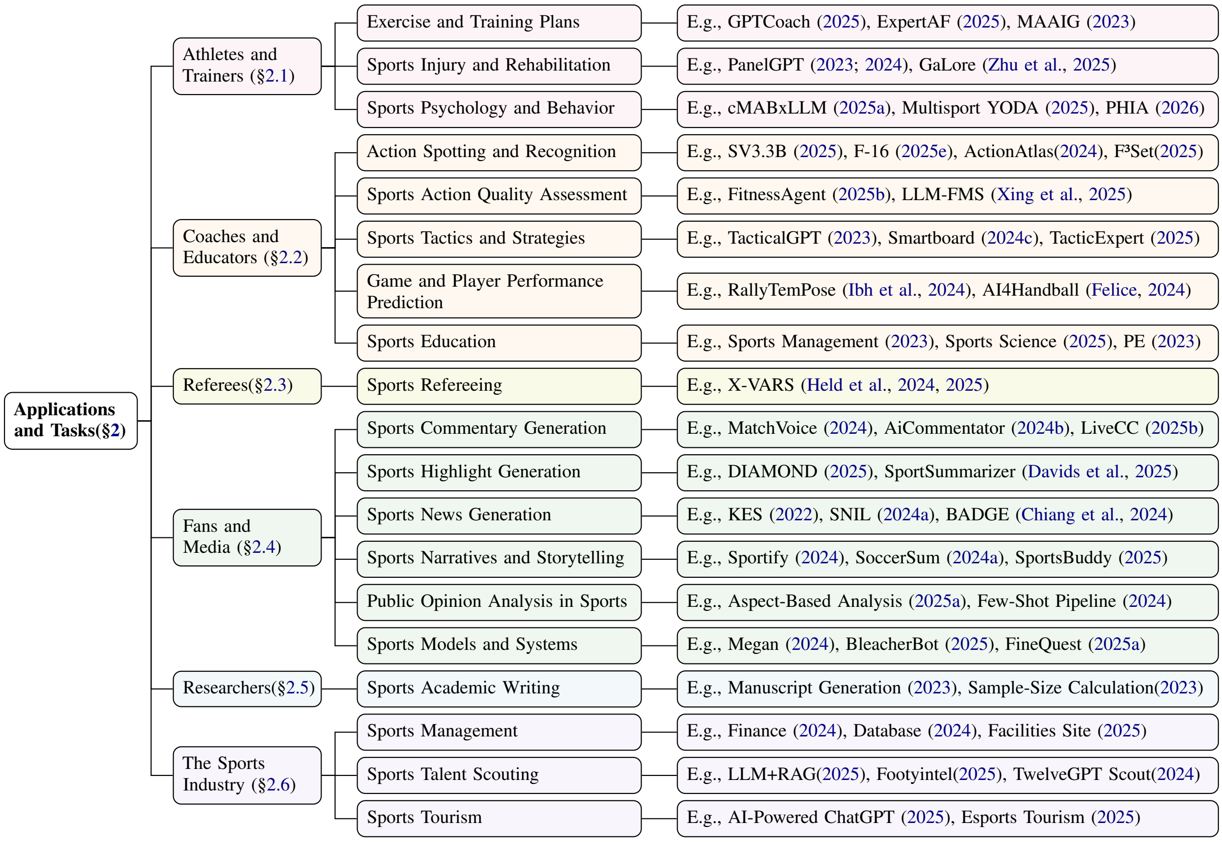


Figure 2: Taxonomy of applications, tasks, and approaches of large models in sports.

and classification. Deep technical integration remains limited, with only early exploration of efficient fine-tuning methods like GaLore (Zhao et al., 2024) to tailor models for sports medicine (Zhu et al., 2025). This indicates the field is in its infancy, lacking unified evaluation metrics.

Sports Psychology and Behavior. Sports psychology enhances athletes' training performance and mental well-being through behavioral interventions. Recent LLM applications range from general cognitive assessment (Zuccolotto, 2025) to targeted interventions for specific behavioral issues (Masur et al., 2025). Recent advances move beyond text generation by integrating multimodal physiological data from wearable sensors—such as heart rate and IMU signals—to deliver personalized interventions (Imran et al., 2024; Merrill et al., 2026). However, task definitions remain ambiguous, and the area lacks standardized benchmarks, requiring further exploration.

2.2 Applications for Coaches and Educators

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). Traditional methods relied on specific deep learning architectures trained from scratch, whereas recent MLLMs leverage pre-training alignment for enhanced semantic understanding. As shown in Table 1, on the SoccerNet-v2 action spotting benchmark (Deliege et al., 2021), fine-tuned Soccer-CLIP achieves a state-of-the-art *75.7%* t-AmAP (Shin et al., 2025), slightly surpassing specialized Transformers (73.1%) (Denize et al., 2024) and highlighting the importance of pre-training methods. In contrast, relying solely on language-centric LLMs through textual commentary prompts yields significantly lower results (60.8%) (Chakraborty et al., 2025), underscoring the necessity of fine-grained visual alignment rather than merely injecting textualized visual information. Common metrics include mAP, top-1 accuracy, and F1 score.

Sports Action Quality Assessment. Sports Action Quality Assessment (AQA) quantifies the execution of athletic movements for coaching and officiating (Zhou et al., 2024; Zhao et al., 2025). Methodologies have evolved from simple regression to fine-tuning MLLMs for personalized evaluation (Dibenedetto et al., 2025) and developing unified agents (Tang et al., 2025b). On the FineFS

Dataset	Model	Architecture	Paradigm	Metric	Performance
		Exercise and Training Plans			
YourSkatingCoach (2024c)	MAAIG (2023)	T5 (pretrained) (2020)	fine-tuning	BLEU-4	**0.27**
	Transformer (2017)	vanilla Transformer	train from scratch		0.04
		Action Spotting and Recognition			
SoccerNet-v2 (2021)	Soccer-CLIP (2025)	CLIP (2021)	fine-tuning	t-AmAP	**75.7**
	COMEDIAN (2024)	spatiotemporal Transformer	train from scratch		73.1
	Llama 3.1-8B (2024)	LLM w/ textual commentary (2025)	few-shot		60.8
		Sports Action Quality Assessment			
FineFS (2023)	Beats-to-Scores (2025a)	Video-Audio (V-A) fusion Transformer	train from scratch	Spearman's ρ	**0.88**
	InternVL2 (2024d)	InternViT + MLP + InternLM2	fine-tuning		0.86
	Qwen2-VL (2024a)	ViT + MLP + Qwen2	fine-tuning		0.75
		Sports Commentary Generation			
SoccerNet-Caption (2023)	MatchVoice (2024)	ViT + Aggregator & MLP + Llama 3	fine-tuning	CIDEr	**38.42**
	SoccerComment (2025d)	MLLM + memory unit	fine-tuning		36.58
	SN-Caption (2023)	encoder-decoder Transformer	train from scratch		23.74
	Video-LLaMA (2023)	V-A encoder + Q-Former + LLaMA	zero-shot		3.44

Table 1: Quantitative comparison of modeling paradigms across 4 representative sports tasks.

benchmark (Ji et al., 2023) (see Table 1), specialized small-scale Transformers currently outperform general MLLMs (*0.88* versus 0.86 Spearman's ρ) by explicitly aligning audio-visual features (Wang et al., 2025a). This indicates that high-precision scoring still depends on domain-specific traditional structural designs. Moreover, architectural choices within MLLMs remain pivotal, as seen in models like InternVL2 (Chen et al., 2024d) and Qwen2-VL (Wang et al., 2024a); model design and training details can lead to noticeably different performance on this task. Common metrics include Spearman's rank correlation, mean square error, and accuracy.

Sports Tactics and Strategies. Sports tactics and strategy analysis models on-field interactions to extract actionable strategic patterns using large models (Caron and Müller, 2023). Current methodologies employ large model-based frameworks for tactical analysis and visualization (processing structured and unstructured data) (Janssens et al., 2024; Michielssen et al., 2024), and tactical exploration and design (Liu et al., 2024c). Technically, current research mainly relies on prompt engineering with pre-trained large models, rather than extensive post-training, due to the scarcity of high-quality tactical datasets. This limits the depth of tactical discovery to the capabilities of the frozen base model, indicating that the field is still nascent and requires future exploration to address these data and methodological constraints.

Game and Player Performance Prediction. Game and player performance prediction utilizes historical, contextual, and multimodal data to forecast match outcomes and individual behaviors, thereby providing valuable insights for strategic planning and preparation (Xia et al., 2024b). Methodologies have advanced from BERT-based specific action forecasting (Ibh et al., 2024) to LLM-driven approaches that integrate diverse data sources for more holistic and interpretable predictions (Bhatnagar and Bhatnagar, 2025). Common metrics include accuracy and F1 score.

Sports Education. Recent applications of large models in sports education have demonstrated their versatility for educators and teachers. Current research primarily uses general-purpose LLMs to generate and analyze pedagogical data and content (Zhang and Liu, 2024; Gao et al., 2025b). However, a gap exists in high-level applications. Professional athlete guidance, in particular, demands deep domain-specific expertise that general models often lack, presenting a promising direction for exploration.

2.3 Applications for Referees

Sports Refereeing. Large models improve sports refereeing by supporting decision-making and enhancing fairness and transparency. Key tasks include QA, captioning, and action recognition. For example, X-VARS (Held et al., 2024) uses QLoRA (Dettmers et al., 2023) fine-tuning on MLLMs to accurately understand video content while following soccer rules, representing the first step toward explainable LLMs for refereeing.

2.4 Applications for Fans and Social Media

Sports Commentary Generation. Sports commentary generation creates natural-language narratives that integrate factual event descriptions, tactical analysis, and emotionally resonant insights, setting it apart from standard video captioning (Ge et al., 2024). Recent methods have advanced from end-to-end fine-tuning of MLLMs for better temporal alignment and coherence (Rao et al., 2024; Wang and Yoshinaga, 2024) to agentic frameworks that dynamically adapt by prompting LLMs with key events and tracking data (Andrews et al., 2024b; Vijayakumar et al., 2025). As shown in Table 1, in this semantic-rich task, adapted MLLM architectures like MatchVoice (CIDEr: *38.42*) (Rao et al., 2024) decisively outperform traditional encoder-decoder models (23.74) (Mkhallati et al., 2023) due to temporal aggregators that handle long-form narratives. Conversely, the near-failure of zero-shot Video-LLaMA (3.44) (Zhang et al., 2023) confirms that practical utility requires domain-specific fine-tuning or RAG (Li et al., 2025d) to bridge the linguistic gap between raw visual signals and professional terminology. Key metrics include METEOR, ROUGE-L, and CIDEr.

Sports Highlight Generation. Sports highlight generation aims to automatically identify and compile significant match moments into concise summaries for social media. Existing approaches typically employ hybrid frameworks combining computer vision and LLMs to perform sub-tasks like key frame extraction, event localization, video clipping, and captioning (Lee et al., 2020; Midoglu et al., 2024). However, the field faces ambiguous definitions and variance in practical applications, requiring future research to clarify task boundaries and standardize protocols.

Sports News Generation. Sports news generation automatically produces factual match reports in a standard journalistic style, summarizing key outcomes, events, and statistics. Existing techniques primarily rely on comprehensive frameworks powered by large models. Recent advances include knowledge retrieval (Wang et al., 2022), in-context learning (Cheng et al., 2024a), and Chain-of-Thought (CoT) prompting (Chiang et al., 2024) to enhance quality. Notably, specialized methods like Tree-of-Report address table-to-text challenges, ensuring accurate conversion of structured data into coherent narratives (Chiang et al., 2025). Common metrics include ROUGE-L, F1 score, and LLM-based metrics.

Sports Narratives and Storytelling. Sports narratives and storytelling aim to create long-form, multimodal stories that combine match events with contextual details to engage fans. Current work typically inputs keyframe information, commentator narration, and other relevant data into LLMs to generate engaging tactical analyses and personalized narratives for social media (Sarkhoosh et al., 2024a; Lin et al., 2025). While LLMs excel at crafting narratives, they often struggle with the intricacies of specific sports domains. To address this, meticulous prompt engineering is crucial to prevent factual inaccuracies and enhance personalization and engagement. Additionally, the field urgently needs unified evaluation metrics to effectively assess narrative quality.

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. However, achieving high accuracy in sports sentiment analysis is challenging due to the complexity of sport-specific contexts. Recent works have employed strategies such as fine-tuning on sports corpora (Qian et al., 2025a) and inference-time techniques like in-context learning and CoT prompting (Rauchegger et al., 2024). Yet, current research is mostly limited to small-scale analyses. Scaling these approaches to larger datasets is a crucial future direction to establish the generalizability and practical significance of the findings. Common evaluation metrics include accuracy and F1 score.

Sports Models and Systems. Unlike task-specific research, work on sports models and systems targets general-purpose infrastructures. These include: *(1) sports-related chatbots and models* that utilize dialogue state tracking (Song et al., 2025b), domain-specific fine-tuning (Rao et al., 2025b), and multi-agent frameworks to coordinate specialized reasoning (Rao et al., 2025a) and knowledge graph integration (Chen et al., 2025a); and *(2) search engines and retrieval systems* that employ RAG architectures and offline query understanding to ground LLM outputs in verified sports facts (Karat et al., 2025; Strand et al., 2024b) and facilitate fine-grained video retrieval (Gupta et al., 2025).

2.5 Applications for Researchers

Sports Academic Writing. Sports academic writing entails crafting and refining scholarly content in fields like sports science and medicine. The advent of LLMs like ChatGPT has revolutionized this area, shifting the writing process from traditional manual methods to AI-assisted collaboration. Current LLMs excel at generating structured text, such as research outlines and abstract summaries (Latzel and Glauner, 2024). However, their reliability for scientific accuracy is undermined by model hallucinations, which often compromise factual integrity and calculation precision (Methnani et al., 2023; Dergaa et al., 2023). Thus, while these models can be efficient writing partners, their outputs need thorough human verification and cautious use.

2.6 Applications for the Sports Industry

Sports Management. Large models are gaining traction in sports management, covering areas like financial, database, and facility management. Unlike traditional tools, large models excel at processing both structured and unstructured data, such as PDF reports and long interview transcripts (Merilehto, 2024; Haghparast et al., 2025). However, empirical research in this domain is still limited and requires further exploration.

Sports Talent Scouting. Sports talent scouting is vital for clubs to identify, evaluate, and predict player potential, thus building successful teams. Large models, capable of processing vast data, can make this process more objective and data-driven (Mateus et al., 2024). Recent research has used RAG to search unstructured data, speeding up football talent scouting (Raskar et al., 2025; Martire and Ragazzi, 2025). Yet, there is still much room to define and expand this task to other sports.

Sports Tourism. Sports tourism integrates travel services with athletic activities and major events, enriching the experiences of fans and participants. In this realm, large models play key roles, such as analyzing tourism trends and enhancing community engagement (Yenisoy and Silik, 2025). This shift transforms traditional, static travel planning into a dynamic, real-time interactive experience. Nevertheless, current models encounter several challenges, including privacy and data security concerns, as well as managing fan expectations and trust (Memon et al., 2025). Tackling these issues will be essential for future advancements.

3 Datasets for Large Models in Sports

In this section, we first categorize the landscape of sports datasets for large models into two main types based on their design objectives: **task-specific datasets** and **sports understanding datasets**. We then conduct a comprehensive multi-dimensional analysis of their **dataset distributions** across various facets to identify key trends and research gaps. More details are provided in the Appendix C.

3.1 Landscape and Categorization

Task-Specific Datasets. Task-specific datasets are created to support the practical applications of large models in various sports contexts, covering the 6 stakeholder groups and 19 tasks outlined in Section 2. These datasets offer detailed annotations and evaluation metrics, facilitating model training, fine-tuning, and performance assessment. They bridge the gap between the general capabilities of large models and real-world sports applications, enabling customized system development, reproducible evaluation, and advancing research on model deployment. Further details are provided in the Appendix C.1, and Tables 3 and 4.

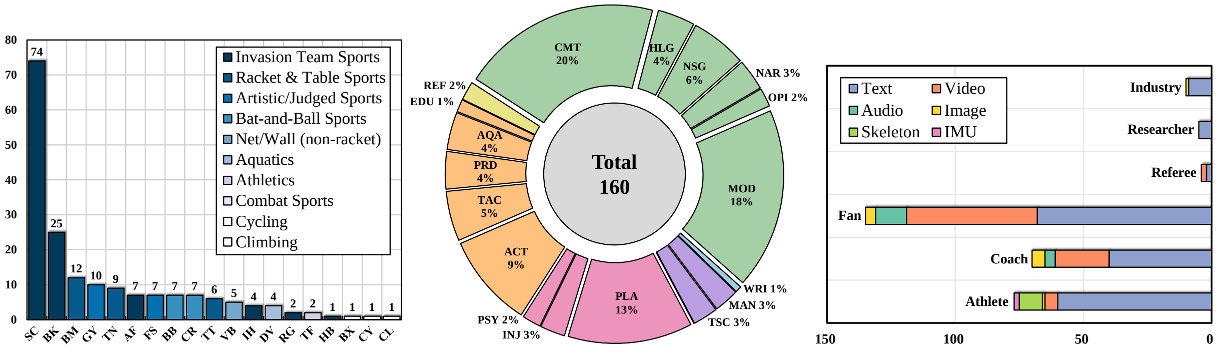
Benchmark	Sports	Modal	# Video	# QA
BIG-bench-SU (2023)	SC, BK, etc.	text	-	986
SportQA (2024a)	TN, AF, etc.	text	-	70592
SPORTU (2025)	BB, IH, etc.	video, text	1701	12948
Sports-3K-QA (2025b)	49 Sports	video, text	412	1174
FSBench (2025a)	FS	video, text	783	4000
FBBench (2025b)	BM	video, text	2563	2563
Gym-QA (2025a)	GY	video, text	6031	27469
Diving-QA (2025a)	DV	video, text	∼100	1055
Sports-QA (2026a)	GY, VB, etc.	video, text	5967	94073

Table 2: Overview of specialized sports understanding benchmarks related to large models. Sports abbreviations are listed in Table 6.

Sports Understanding Datasets. Sports are fast-paced, diverse, and strategically complex, presenting unique challenges for large models (Xia et al., 2024a). To enhance models' comprehension and reasoning in sports contexts, researchers have developed sports understanding datasets. These datasets fall into two main categories: *(1) datasets specifically for sports understanding*, with Table 2 providing an overview of relevant benchmarks; and *(2) general video understanding datasets containing sports content*, covering tasks like video captioning (Wang et al., 2024b), multi-view understanding (Grauman et al., 2024), and fine-grained analysis (Liu et al., 2024b). More details are in the Appendix C.2 and Table 5.

3.2 Comprehensive Analysis

Dataset Distribution by Sport Type. As illustrated in Figure 3a, the availability of datasets is notably skewed toward popular invasion team sports (e.g., soccer leading with 74 datasets), racket and table sports, and bat-and-ball sports. Conversely, individual disciplines such as cycling and boxing remain underrepresented with only a single dataset each, highlighting a significant coverage imbalance. Furthermore, the prevalence of fitness-related datasets (21) and the emergence of esports datasets (3) reflect the growing scholarly interest in these evolving domains.



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

Figure 3: Data analysis from 3 different perspectives. Sports and tasks abbreviations are listed in Table 6.

Dataset Distribution by Application. Analysis of the 6 stakeholder groups (Figure 3b) reveals that data representation is robust for athletes, coaches, and fans, aligning with the commercial popularity of these segments. Tasks such as sports commentary generation, exercise prescription, and action recognition have garnered substantial attention. In contrast, data for referees, sports researchers, and the sports industry remain scarce, with referee-relevant datasets accounting for a mere 2%. This disparity underscores an urgent need to develop specialized datasets to bridge these application gaps.

Dataset Distribution by Modality. In the era of large-scale models, video and text remain the dominant modalities (Figure 3c), while audio-centric studies are beginning to demonstrate their significance (Xie et al., 2025). However, specialized modalities such as IMU sensor data and skeletal poses are relatively rare and primarily confined to athlete-focused motion analysis. Expanding the diversity of these less common modalities is essential to strengthening the cross-modal reasoning capabilities of MLLMs in complex sports scenarios.

Dataset Distribution by Annotation Source. Based on Table 5, we categorized the datasets by their annotation origin (automatic, manual, and expert). While manual annotation remains the standard to minimize noise, a critical deficit exists in expert-level labels. This is particularly evident in general datasets, where expert annotation accounts for only 6%, compared to 41% in specialized sports understanding benchmarks. This lack of high-quality, professional-grade labels poses a key bottleneck for the fine-tuning and reliability of models intended for elite-level sports analysis.

Dataset Distribution by Modeling Paradigm. Sports datasets can be categorized based on their supported tasks, falling into two paradigms: discriminative and generative. *Discriminative-oriented datasets* (21.5%), such as action recognition and game prediction, benefit from large models' ability to capture spatio-temporal contexts—a notable improvement over traditional methods' handling of complex multimodal inputs. Conversely, *generative tasks* dominate the landscape (78.5%), spanning from descriptive applications like commentary generation to reasoning-intensive tactical synthesis. This transition underscores a paradigm shift in sports AI: moving beyond simple categorical labeling toward open-ended synthesis and logical reasoning facilitated by large models.

4 Discussion

In the preceding sections, we have examined the landscape of large models in sports and their emerging capabilities across a range of stakeholders. Building upon these insights, this discussion distills the key barriers to practical deployment and outlines promising directions for future research.

4.1 Challenges

Despite rapid progress, existing large models in sports still encounter 4 fundamental challenges that hinder robust and trustworthy real-world adoption.

Bias, Fairness, and Privacy. Current sports datasets are heavily skewed toward a small set of popular sports such as soccer and basketball (Deliege et al., 2021; Xi et al., 2025b), leaving many less popular sports largely underrepresented. Moreover, existing research disproportionately focuses on data from elite, mainstream competitions, while settings such as the Paralympics, youth development programs, and school sports remain underexplored. Current datasets and models also predominantly focus on men's sports, while women's leagues and competitions remain substantially underrepresented (Biester, 2025). These biases may lead to unfair model behaviors and limit generalization across diverse sporting contexts (Dergaa et al., 2023; Papini et al., 2025a).

Real-Time and High-FPS Understanding. Sports applications such as live officiating and broadcast commentary are highly latency-sensitive, yet current Video LLMs still incur substantial inference overhead (You et al., 2025), limiting their use in time-critical workflows. Moreover, long-video understanding remains difficult: sports broadcasts often last for hours and demand sustained temporal reasoning over extended contexts (Zou et al., 2024). Finally, most generic video pipelines are not designed for high-frame-rate inputs. In sports, decisive cues (e.g., ball contact, offside timing, foul initiation) can unfold within milliseconds; aggressive temporal downsampling removes these fine-grained dynamics, degrading event localization and rule-level judgments (Li et al., 2025e).

Hallucination and Interpretability. In practical sports workflows, stakeholders require explanations that directly support decisions, rather than descriptive summaries. For example, coaches and analysts need to identify actionable causes and detailed explanations, which remains challenging for current black-box models (Mersha et al., 2024). Meanwhile, hallucinations in sports often invent key events, actors, or causal links, producing plausible narratives that can directly mislead downstream decisions. Such errors are especially harmful in high-stakes settings as they can quickly erode user trust (Qiu, 2024; Held et al., 2024).

Practicability and Real-World Deployment. Recent research still falls short of real sports workflows in terms of ecological validity. Although models can perform well on curated clips, they often break down in the wild due to heavy occlusion, shifting camera viewpoints, and low-quality footage common in sports scenarios (Niu et al., 2025). At the same time, real-world deployment remains largely underexplored: practical setups such as deploying models on the sidelines or on edge devices like wearables and drone cameras remain challenging and are rarely validated in real-world settings (Koh et al., 2021; Bandraupalli et al., 2025).

4.2 Future Directions

Building on the challenges discussed above, we outline 4 future directions to advance large models in sports toward robust real-world use.

Trustworthy Sport AI. Future research should address these ethical and reliability challenges by integrating advanced technical safeguards into model development. Key directions include implementing rigorous data balancing and cleaning (Bai et al., 2022) alongside sport-specific alignment via Reinforcement Learning from Human Feedback (RLHF) to minimize bias (Yu et al., 2024; Gallegos et al., 2024).

Streaming and Long Video Mechanisms. Future work should better handle sports' temporal demands. For low latency, explore streaming inference with more efficient KV-cache and attention mechanisms (Chen et al., 2024a; Ding et al., 2025; Xu et al., 2026). For long matches, adapt long-video modeling via memory, parallelism, and token compression, or architectures like Mamba (Ren et al., 2024; You et al., 2025; Chen et al., 2025c; Wang et al., 2025d). For high-FPS events, develop vision backbones that support dense frames without losing fine-grained dynamics (Li et al., 2025e).

Knowledge Grounding and Tool Use. Future work should improve factual reliability via explicit retrieval from structured knowledge (e.g., RAG) (Strand et al., 2024a; Sepasdar et al., 2024b), grounding claims in visual evidence (Xia et al., 2026), and producing explicit rationales (Held et al., 2024). Tool-enabled models that query live databases, rule engines, or match-tracking APIs can further make outputs verifiable and logically consistent (Rao et al., 2025a).

In-the-Wild Evaluation and Edge Deployment. Future work should prioritize practical deployment by developing ecologically valid, workflow- and latency-aware in-the-wild benchmarks that stress-test models under real sports conditions (Wang et al., 2024d; Bandraupalli et al., 2025). In parallel, enabling on-device inference requires efficiency advances such as quantization (Zhu et al., 2024b; Lin et al., 2024b), knowledge distillation (Xu et al., 2024a), and mobile (M)LLMs (Lu et al., 2024; Van Nguyen et al., 2025) to support local analysis on wearables or mobile platforms.

5 Conclusion

This survey reviews the emerging landscape of large models in sports, establishing a structured taxonomy that spans 6 stakeholder groups. We provide a deep analysis of relevant datasets, and highlight fundamental challenges. By consolidating these disparate research efforts, we aim to establish a solid framework for future exploration. We hope this work serves as a foundation for advancing large-model-driven sports intelligence and provides a practical resource for research and development.

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, our literature selection primarily follows standard protocols focused on English-language publications. This may naturally limit the coverage of domestic research in other regions or studies published in other languages. Thirdly, our analysis objectively reflects the current research imbalance in the field, which is heavily skewed toward a few dominant sports. Consequently, this leads to a lack of in-depth coverage for underrepresented or niche sporting scenarios in our survey. Fourthly, 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. Finally, 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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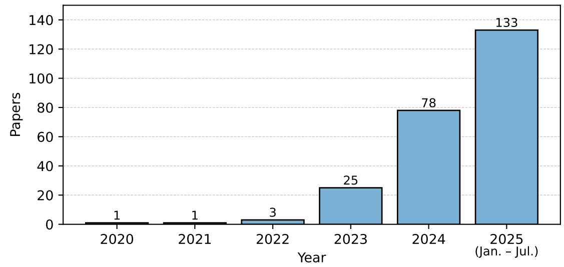

Figure 4: Papers on large models in sports over the years (data for 2025 is up to July).

A Methodology for Literature Selection

In this section, we detail the systematic methodology employed for literature identification, screening, and selection. To capture the fragmented and rapidly evolving landscape of large models in sports, we adopted a **systematic snowballing methodology** (Wohlin, 2014), adhering to the reporting standards of the **Preferred Reporting Items for Systematic Reviews and Meta-Analysis** (**PRISMA**) statement (Page et al., 2021). This dual-direction strategy (leveraging both reference lists and citation networks) is particularly effective for interdisciplinary fields such as large models in sports, ensuring high relevance by tracing semantic connections rather than relying solely on keyword indexing.

A.1 Construction of the Start Set

The effectiveness of snowballing relies heavily on the quality of the initial start set. Instead of a broad, potentially noisy keyword search, we established our foundation by identifying **3** highly relevant and comprehensive survey papers based on domain expertise (Xia et al., 2024b; Zhou et al., 2025a; Zhao et al., 2025). These papers serve as our "seeds" for initiating the iterative snowballing process. These papers were chosen for their:

Comprehensiveness. Collectively, they cover the entire spectrum from traditional deep learning to modern large models.

Recency. All selected seeds were published in 2024–2025, ensuring the survey is anchored in the most current research landscape.

Academic Standing. The set combines rigorous articles from premier journals with pioneering preprints that address the rapid evolution of large models before formal publication cycles.

Connectivity. They serve as central hubs in the citation network, linking to a wide range of task-specific studies.

A.2 Iterative Snowballing Procedure

Starting from these seed papers, we performed iterative forward and backward snowballing to expand our corpus. To manage the scale of the literature and ensure precision, we applied a specific Boolean query as a filtering mechanism during the forward pass.

Backward Snowballing. We scrutinized the reference lists of the included papers to uncover relevant prior studies and foundational works.

Forward Snowballing. We leveraged Google Scholar's "Cited by" feature to access the citation list of each paper. To efficiently filter out out-of-domain works from the large volume of citations, we enabled the "Search within citing articles" option and applied the following Boolean search string:

```
"Sports" AND ("Large Language Model" OR "LLM"
OR "GPT" OR "BERT" OR "T5")
```

This step allowed us to strictly identify studies that integrate large models within sports contexts, capturing the latest research developments up to July 2025.

Iteration & Saturation. Newly identified papers that met the inclusion criteria were added to the set and treated as new seeds. This cycle was repeated until theoretical saturation was reached (i.e., the filtered search yielded no new relevant papers).

A.3 Inclusion and Exclusion Criteria

To isolate relevant studies from the retrieved pool, we applied the following rigorous filters across four dimensions:

Research Topic. We included studies that target tasks within the sports domain or involve sports data analysis, provided that they utilize large models (e.g., LLMs, MLLMs) as a core methodological component. To maintain the survey's specific focus on the era of large models, we excluded studies that rely solely on traditional deep learning architectures (e.g., CNNs, LSTMs) without the integration of large models.

Publication Type. To ensure technical depth, scientific rigor, and mitigate the risk of low-quality evidence, we restricted our selection to full-length academic contributions. Included works comprise peer-reviewed conference and journal papers, as well as cutting-edge preprints that represent the latest advancements in the field. We excluded non-technical documents such as editorials, posters, extended abstracts, opinion pieces, and short papers that lacked sufficient implementation details or experimental validation.

Time Window. We defined a specific temporal scope to align with the emergence and proliferation of large models. The search and inclusion window was strictly defined from January 1, 2020, to July 31, 2025. Although the final search and screening process was executed on October 4, 2025, we enforced this cutoff date to ensure a consistent time-frame for data analysis.

Language. To ensure accessibility and consistent analysis, we included only articles written in English. Studies published in other languages were excluded.

A.4 Selection Results

Throughout the iterative forward and backward snowballing process, we examined a cumulative total of approximately **2,200** candidate records. After rigorously applying the inclusion and exclusion criteria to these candidates, a final set of **241** core academic papers was selected for this survey. The rapid growth trend and temporal distribution of these included works are illustrated in Figure 4.

B More Details on Large Model Applications in Sports

This section serves as a comprehensive supplement to Section 2, offering a detailed literature review of specific studies and methodologies. Given that task definitions, analyses of large model–related technologies, and common evaluation metrics have been elaborated in the main text, this section will focus on **systematically listing** the specific contributions and relevant content of each research work. The organization follows the taxonomy illustrated in Figure 2, detailing applications across the **6 stakeholder groups** and **19 specific tasks**.

B.1 Applications for Athletes and Trainers

Exercise and Training Plans. Recent AI coaches powered by LLMs have significantly streamlined the generation of effective training plans. 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., 2025b; 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., 2024b; 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 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., 2024a; Han, 2025), focus on acceptance, trust, and quality (Düking et al., 2024; Wachholz et al., 2025), and foster user self-reflection (Li et al., 2025f). In addition, some studies have designed AI coaches tailored to the specific requirements of individual sports, such as boxing (Bullard et al., 2025) and table tennis (Ma et al., 2025a,b). Within these sport-specific domains, two prominent tasks have emerged to provide professional-grade feedback. One is *expert commentary generation*, which utilizes MLLMs to provide evaluative insights and skill-level-aware feedback for basketball (Seino et al., 2025) and soccer (Ashutosh et al., 2025) based on video demonstrations. The other is *motion instruction generation*, where frameworks like MAAIG (Yeh et al., 2023) and the reference-based CoachMe (Yeh et al., 2025) automatically derive technical corrective guidance from 3D skeletal data to assist athletes in figure skating and boxing.

Sports Injury and Rehabilitation. Diagnosing and treating sports injuries necessitates extensive interdisciplinary knowledge, and LLMs have demonstrated a broad understanding of this domain (Hasnain et al., 2023; Lotfi and Madani, 2024), encompassing orthopedics (Fayed et al., 2023) and sports rehabilitation (McBee et al., 2023, 2024). Specifically, these models assist in providing preventive advice (Zhu et al., 2025), identifying and labeling medical information (Brogly et al., 2025), and supporting diagnostic imaging (Lotfi and Madani, 2024) and data processing (Musat et al., 2024). Furthermore, they play a crucial role in clinical decision-making (Saglam et al., 2025), surgical treatment planning (Cheng et al., 2023), and enabling patient outcome prediction (Ahsan, 2023) and medical oversight.

Sports Psychology and Behavior. LLMs have demonstrated initial potential in this field, capable of answering sports-related questions (Vandelanotte et al., 2023), assessing cognitive abilities (Zuccolotto, 2025), and summarizing psychological theories (Oliver and Guiller, 2025). A significant line of research integrates these models with wearable technology for real-time monitoring and behavioral modeling (Ferrara, 2024; Imran et al., 2024; Ji et al., 2024; Merrill et al., 2026). Furthermore, LLMs provide assistance in specialized areas such as managing exercise addiction (Szabo, 2023) and facilitate behavioral interventions by enhancing motivation for sports participation (Song et al., 2025a) and delivering sleep education (Masur et al., 2025).

B.2 Applications for Coaches and Educators

Action Spotting and Recognition. In this task, the majority of approaches employ MLLMs to facilitate direct action spotting and recognition. Specific methodologies include keyframe sampling (Kodathala et al., 2025), contrastive pretraining (Shin et al., 2025), and domain adaptation (Jiang et al., 2025b), primarily focusing on soccer. Applications extend to other sports, with studies fine-tuning MLLMs for rally-sequence recognition in tennis (Teo, 2025), utilizing high-framerate modeling for gymnastics and diving (Li et al., 2025e), and performing scene-level classification in rugby (Nonaka et al., 2024). Beyond visual-centric approaches, textual signals such as commentary have also been leveraged for spotting tasks (Chakraborty et al., 2025). Additionally, benchmarks like ActionAtlas (Salehi et al., 2024) and F³Set (Liu et al., 2025) provide platforms for evaluating fine-grained recognition capabilities.

Sports Action Quality Assessment. Recent endeavors in this domain focus on fine-tuning large multimodal models to facilitate personalized fitness evaluation (Dibenedetto et al., 2025). Researchers have also proposed unified agent frameworks tailored for open-set and user-specific assessments (Tang et al., 2025b), and established fine-grained datasets incorporating LLM-based evaluations for functional movement screening (Xing et al., 2025). In specific sports such as figure skating, MLLMs have been used to quantify technical and program scores, providing critical support for both athlete training and referee judging (Wang et al., 2025a).

Sports Tactics and Strategies. Early work in this field was largely text-centric, converting structured data into natural language for tactical modeling, such as fine-tuning LLMs on event sequences (Caron and Müller, 2023), transforming cycling commentary into graph representations (Janssens et al., 2024), or parsing play-by-play logs into spatial spray charts (Michielssen et al., 2024). Subsequent studies have examined the analytical reasoning of LLMs, including computing team scores from play-by-play data (Hu et al., 2024c) and aggregating narratives for score inference (Hu et al., 2024d). More recent approaches integrate diverse structural and spatial information for richer tactical reasoning, utilizing sketch-based LLM agents for interactive tactic design (Liu et al., 2024c), graph LLMs for zero-shot generalization (Lingrui et al., 2025), and multi-agent systems that combine video detection with statistical inference (Zhang et al., 2025a).

Game and Player Performance Prediction. Early research for this task predominantly utilized BERT-based models (Devlin et al., 2019) to predict specific player actions or traits, such as forecasting badminton strokes from skeleton poses (Ibh et al., 2024) and analyzing NBA players' performance deviations based on pre-game interview transcripts (Oved et al., 2020). More recent advancements leverage LLMs to synthesize diverse data sources for broader game outcome predictions. Specific applications include predicting basketball 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).

Sports Education. In this domain, LLMs are extensively applied to assist educators with lesson planning (Genç, 2023; Wang and Wang, 2024), designing interactive activities (Cui et al., 2025), providing formative feedback (Keiper et al., 2023), and automating assignment creation (Kauppinen, 2024). Research also emphasizes curricular support through automated visualization, synthetic dataset creation (Fazackerley et al., 2025), and sensing-driven feedback mechanisms (Gao et al., 2025b). Furthermore, student-centered applications focus on personalized exercise planning and mental health support (Zhang and Liu, 2024), while other studies investigate the inclusion, trust, and acceptance of tools like ChatGPT in educational practice (Chang et al., 2025).

B.3 Applications for Referees

Sports Refereeing. In this task, large models are leveraged to enhance fairness and transparency in decision-making. A prominent example is X-VARS (Held et al., 2024), which introduces an explainable Video Assistant Referee system. By fine-tuning MLLMs on expert-annotated foul data, this system provides textual rationales alongside decisions, thereby demonstrating clear benefits in improving decision accuracy, consistency, and trust among referees (Held et al., 2025).

B.4 Applications for Fans and Social Media

Sports Commentary Generation. Recent studies leverage LLMs to automatically produce commentary, offering fans an enhanced viewing experience. Most approaches adopt an agentic framework, where LLMs are prompted with extracted match information such as detected key events (Pavlovich et al., 2023; Andrews et al., 2024b,a; Sameer et al., 2025), player and ball tracking data (Andrews et al., 2024b,a; Vijayakumar et al., 2025), 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 explores end-to-end training to improve quality, either by fine-tuning MLLMs (Wang and Yoshinaga, 2024; Cook and Karakuş, 2024; Baughman et al., 2024; Jiang et al., 2025b) or designing novel architectures for better temporal alignment (Zhang et al., 2024a; Rao et al., 2024; You et al., 2025). Additionally, efforts target complementary directions like constructing 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 narratives (Andrews et al., 2024a), and advancing commercial applications (Baughman et al., 2024).

Sports Highlight Generation. Most research in this domain employs MLLMs to facilitate highlight generation via key event detection, incorporating techniques such as action spotting (Banu et al., 2025) and multimodal fusion with textual encoding (Davids et al., 2025). Some approaches explicitly leverage commentary transcripts or role-play prompting to enhance event classification accuracy (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).

Sports News Generation. Early work primarily focused on summarizing unstructured text commentary, utilizing LLMs to select and rewrite key segments (Wang et al., 2021, 2022) or to extract salient events (Sarkar et al., 2024). Recent advancements have extended these capabilities to process structured data, employing chain-of-thought prompting to interpret statistical tables (Chiang et al., 2025) or leveraging CSV inputs to generate comprehensive game reports (Chiang et al., 2024). Beyond summarization, Cheng et al. (2024a) propose an insight-driven approach where high-level user queries guide LLMs to construct narrative episodes enriched with data visualizations.

Sports Narratives and Storytelling. Recent research in this field focuses on generating factually consistent highlight narrations through advanced prompt engineering techniques (Sarfati et al., 2023). Significant advancements have also been made in leveraging multimodal embedded visualizations and personalized narratives to facilitate tactical understanding for general audiences (Lee et al., 2024; Lin et al., 2025). Furthermore, other works adapt narrative generation pipelines to platform-specific contexts, enabling the production of personalized reports and posts designed for large-scale fan interaction (Sarkhoosh et al., 2024a; Baughman et al., 2024).

Public Opinion Analysis in Sports. In this field, LLMs have been applied to identify key discussion themes within large-scale social media datasets (Qian et al., 2025b). Significant progress has been made in performing fine-grained sentiment and stance detection via aspect-based analysis (Qian et al., 2025a) and utilizing few-shot prompting to analyze controversial topics (Rauchegger et al., 2024). Additionally, researchers employ social science frameworks combined with LLMs to examine user acceptance and perceptions of emerging AI tools within the sports community (Argan and Dinç, 2025).

Sports Models and Systems. LLMs have been extensively applied to build sports chatbots for interactive dialogue (Priya et al., 2024) or co-viewing experiences (Kim et al., 2025), often incorporating dialogue state tracking for sports-specific contexts (Song et al., 2025b). General sports models, particularly for soccer, are developed using diverse techniques including fine-tuning (Unlu, 2023; Gautam et al., 2025; Rao et al., 2025b), knowledge graph integration (Chen et al., 2025a), and multi-agent LLM architectures (Rao et al., 2025a). In the area of search and retrieval, interactive agents combine LLMs with offline query understanding and online decision-making (Karat et al., 2025). Furthermore, RAG systems are utilized to query sports knowledge from natural language sources (Schilling et al., 2024; Strand et al., 2024a,b; Sepasdar et al., 2024a,b; Wang et al., 2025b). Extended applications also include online information retrieval for cricket (Wickramasinghe, 2025) and fine-grained video retrieval for sports such as gymnastics and diving (Gupta et al., 2025).

B.5 Applications for Researchers

Sports Academic Writing. In fields such as sports science and medicine, LLMs like ChatGPT are increasingly utilized to generate outlines, draft abstracts, and provide grammar and style suggestions (Latzel and Glauner, 2024; Hakam et al., 2024). However, the literature emphasizes the need for caution due to inherent risks in content accuracy (Dergaa et al., 2023), the reliability of generated references (Anderson et al., 2023), calculation precision (Methnani et al., 2023), and originality.

B.6 Applications for the Sports Industry

Sports Management. Large models are increasingly applied to streamline diverse functions within sports organizations. In financial management, research demonstrates their ability to conduct interviews, extract key themes, and develop tailored organizational strategies (Haghparast et al., 2024). For database management, LLMs are used to structure and analyze complex club data to enhance operational efficiency (Merilehto, 2024). In facility management, these models support human-computer dialogue to facilitate site selection and knowledge acquisition (Salimi Beni et al., 2025). Furthermore, they are employed to simulate future industry scenarios and provide robust support for data-driven strategic decisions (Haghparast et al., 2025).

Sports Talent Scouting. Large models enhance this domain by introducing more objective and data-driven methodologies for athlete evaluation (Mateus et al., 2024). Recent research has deployed LLMs to analyze complex player datasets (Raskar et al., 2025) and convert unstructured scouting reports into searchable, structured knowledge formats. Furthermore, some work combines large models with RAG strategies to optimize the integration of diverse information sources (Martire and Ragazzi, 2025).

Sports Tourism. Large models are increasingly leveraged in this domain to enhance intelligence and personalization, offering solutions for virtual guides, information assistants, and community building (Memon et al., 2025). Research also highlights the role of these models in improving operational efficiency and fan engagement during major events. Notably, LLMs also show strong potential in the specialized sector of esports tourism (Yenisoy and Silik, 2025).

C 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.

C.1 Task-Specific Datasets

This subsection echoes Section 3.1 of the paper and provides a further overview of these task-specific datasets. Table 3 and Table 4 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 results with their respective evaluation metrics, and the availability of open-source links, which can be directly accessed by clicking in the table.

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.

C.2 Sports Understanding Datasets

This subsection echoes Section 3.1 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 (§C.2.1), general video understanding datasets that include sports content (§C.2.2), and other general-purpose datasets containing sports-related data (§C.2.3). Table 5 presents a comprehensive summary of the first two categories of datasets from multiple perspectives, including dataset names, covered sports types, data sources, annotation methods, benchmark availability, input modalities, the number and average duration of videos, the number of QA pairs, and open-source links, which are directly accessible by clicking.

C.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., 2026a) 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 Fine-Diving (Xu et al., 2022), respectively, offer new benchmarks for sports video question answering in gymnastics and diving.

C.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., 2024b), 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., 2025c), 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., 2025), 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., 2024b), V-STaR (Cheng et al., 2025), MINERVA (Nagrani et al., 2025), VRBench (Yu et al., 2025), and CausalStep (Li et al., 2026b) 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., 2026), 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., 2026) 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.

C.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 (2024c)	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 / 5.00 (Likert)	✓
	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's ρ)	✗
PSY	Custom Dataset (2026)	Fitness	T	PHIA (2026)	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 (2024b)	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)	
	F^{3}Set (2025)	TN, BM, TT	V, T	F^{3}ED (2025)	GPT-4 (2023)	75.20 ($F1_{elm}$)	✓
	Video-MME (2025)	SC,BK,GY,DV	V, T	F-16 (2025e)	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 (2024d)	84.00 (Spearman's ρ)	✓
	FS1000 (2023)					90.00 (Spearman's ρ)	
	FineFS (2023)					76.00 (Spearman's ρ)	
	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 / 5.00 (Likert)	✓

Table 3: 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 (2024d)	5.44 (SCORES)	✗
	Custom Dataset (2015; 2023)	Soccer	T	LLM-Commentator (2024)	LLaMA 7B (2023a)	92.00 (F1)	✓
	Custom Dataset (2024)	Golf Tennis American Football	V, T	Baughman et al. (2024)	Llama 2 7B (2023b) Sandstone 3B (2020) Llama 2 7B (2023b)	99.12 (ROUGE-L) 86.80 (ROUGE-L) 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) WyScout (2024)	Soccer	V, T	Jiang et al. (2025b)	Claude 3.5 Sonnet (2025)	2.59 / 5.00 (Likert) 2.96 / 5.00 (Likert)	✗
	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) VC-NBA-2022 (2025a)	Basketball	V, T	LLM-IAVC (2025b)	Llama 3.2-3B (2024)	105.30 (CIDEr) 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 (2024b)	82.04 (ROUGE-L)	✓
	SoccerNet (2018)	Soccer	V, T	VLM-TSI (2025)	VideoLLM-Online (2024b)	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) SoccerNet (2018)	Cricket Soccer	V, A, T	SportSummarizer (2025)	DistilBERT (2019)	0.93 (HD) 0.92 (HD)	✗
NSG	SportsSum2.0 (2021) SportsSum (2020)	Soccer Soccer	T	Wang et al. (2021)	RoBERTa (2019), etc.	47.78 (ROUGE-L) 47.49 (ROUGE-L)	✓
	K-SportsSum (2022) SportsSum (2020)	Soccer Soccer	T	KES (2022)	mT5 (2021)	47.17 (ROUGE-L) 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 / 10.00 (LLM)	✓
	Custom Dataset (2024)	Cricket	T	Sarkar et al. (2024)	Google Gemini (2023)	9.20 / 10.00 (ACS)	✗
	RotoWire (2017) MLB (2019) ShuttleSet+ (2025)	Basketball Baseball Badminton	T	Tree-of-Report (2025)	GPT-4o mini (2024)	54.92 (CS F1) 62.99 (CS F1) 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 (2025a)	Soccer	T	ABSA (2025a)	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) SoccerNet-v2 (2021)	Soccer	V, T	SoccerChat (2025)	Qwen2-VL-7B (2024a)	6.81 / 10.00 (LLM) 6.42 / 10.00 (LLM)	✓
	SoccerBench (2025a)	Soccer	V, A, T	SoccerAgent (2025a)	DeepSeek-v3 (2024a)	60.90 (Acc)	✓
	SoccerNet-v2 (2021) SN-Caption-test-align (2024) MVFoul (2023)	Soccer	V, T	MatchVision (2025b)	Llama 3-8B (2024)	80.10 (Acc) 44.18 (CIDEr) 44.00 (Acc)	✓
	SoccerNet-V2 (2021) WyScout (2024)	Soccer	V, T	Jiang et al. (2025b)	LLaVA-NeXT-Video (2024a)	83.76 (Acc) 81.83 (Acc)	✗
	Gym-QA (2025a) Diving-QA (2025a) SPORTU (2025)	Gymnastics Diving 7 Sports	V, T V, T V, T	FineQuest (2025a)	Video-LLaVA (2024a), etc.	57.00 (Acc) 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 / 5.00 (Likert)	✗
	Custom Dataset (2025)	Soccer	I, T	Footyintel (2025)	-	-	✗

Table 4: 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	Annotation	Benchmark	Modal	# Video	Avg. Length	# QA	Link
Specialized Sports Understanding Datasets									
QASports (2023)	SC, BK, AF	Fandom	auto	✗	T	-	-	∼1500K	✓
BIG-bench-SU (2023)	SC, BK, AF, BB, IH	program	crowd	✓	T	-	-	986	✓
SportQA-Level-1 (2024a)	-	existing (dataset)	manual	✓	T	-	-	21385	
SportQA-Level-2 (2024a)	35 Sports	Wikipedia	expert	✓	T	-	-	45685	✓
SportQA-Level-3 (2024a)	SC, BK, TN, AF, TT, VB	expertise	expert	✓	T	-	-	3522	
SPORTU-text (2025)	SC, BK, TN, AF, VB	existing	expert	✓	T	-	-	900	✓
SPORTU-video (2025)	SC,BK,BM,TN,BB,VB,IH	competition	expert	✓	V, T	1701	-	12048	
Sports-3K-QA (2025b)	49 Sports	YouTube	manual	✓	V, T	412	-	1174	✓
FSAnno (2025a)				✗	V, A, T	783		-	
FSBench-Text (2025a)	FS	competition	expert	✓	T	-	∼3.5m	500	✗
FSBench-Motion (2025a)				✓	V, T	783		3500	
FineBadminton (2025b)	BM	YouTube	manual	✗	V, T	3215	12.4s	-	✓
FBBench (2025b)				✓	V, T	2563	-	2563	
Gym-QA (2025a)	GY	existing	manual	✓	V, T	6031	-	27469	✗
Diving-QA (2025a)	DV	existing	manual	✓	V, T	∼100	-	1055	✗
Sports-QA (2026a)	SC, BK, GY, VB	existing	manual	✓	V, T	5967	20.9s	94073	✓
General Video Understanding Datasets									
InternVid (2024b)	-	YouTube	auto	✗	V, A, T	7.1M	6.4m	N/A	✓
Ego-Exo4D (2024)	SC, BK, CL	field	expert	✗	V, A	5035	2.6m	N/A	✓
E.T. Bench (2024b)	SC, BK, TN, CR, etc.	existing	manual	✓	V, T	7002	129s	7289	✓
VideoVista (2024b)	SC, etc.	existing	auto	✓	V, A, T	894	131s	24906	✓
FIOVA (2024a)	BB, etc.	-	manual	✓	V	3002	33.6s	N/A	✓
Neptune (2024)	BK, etc.	existing	manual	✓	V, A, T	2405	2.5m	3268	✓
video-SALMONN2 (2025a)	BB, etc.	-	manual	✓	V, A, T	483	51s	N/A	✓
LVBench (2025c)	BK, etc.	YouTube	manual	✓	V, T	103	4101s	1549	✓
MMWorld (2025a)	SC, BK, GY, VB	existing	manual	✓	V, A, T	1910	∼105s	6627	✓
LongVILA_sft (2025c)	-	existing	manual	✗	V, T	15292	-	15292	✓
MLVU (2025b)	SC, BK, BM, TT, VB	-	manual	✓	V, T	3102	930s	3102	✓
Video-MME (2025)	SC, BK, etc.	YouTube	manual	✓	V, A, T	900	1017.9s	2700	✓
MotionBench (2025)	BB, etc.	existing, syn., web	manual	✓	V, T	5385	<10s	8052	✓
OVO-Bench (2025)	-	existing, YouTube	manual	✓	V, T	644	428.89s	2814	✓
VISTA-400K (2025)	-	existing	manual	✗	V, T	403994	48.6s	∼381K	✓
HRVideoBench (2025)	-	online	manual	✓	V, T	200	5.4s	200	✓
HarmonySet-train (2025c)	-	YouTube	manual	✗	V, A, T	44470	31.5s	44470	✓
HarmonySet-MC (2025c)				✓		3858		3858	
VideoA11y-40K (2025b)	-	online	auto	✗	V, A	40000	-	N/A	✓
TUNA (2025a)	SC, BK, etc.	existing	manual	✓	V, T	1000	14.5s	2000	✓
V-STaR (2025)	-	existing, YouTube	manual	✓	V, T	2094	110.23s	-	✓
MINERVA (2025)	BK, TN, etc.	YouTube	manual	✓	V, T	223	12m	1515	✓
MAVERIX (2025)	SC, BK, etc.	existing	manual	✓	V, A, T	700	5.7m	2556	✗
RTV-Bench (2025)	SC, BK, etc.	existing, online	manual	✓	V, T	552	18.2m	4631	✓
VidText (2025b)	SC, BK, BM, TT, SW	existing, YouTube	manual	✓	V, A, T	939	108.2s	2857	✓
SIV-Bench (2025b)	SC, etc.	YouTube, TikTok	manual	✓	V, A, T	2792	32.49s	8728	✓
ExAct (2025)	SC, BK, CL	existing	expert	✓	V, T	3521	105s	3521	✓
VRBench (2025)	SC, BK, VB, etc.	YouTube	manual	✓	V, A, T	960	1.6h	8243	✓
EgoExoBench (2025c)	BK, etc.	existing	manual	✓	V, T	-	-	7350	✓
WildVideo (2025a)	-	existing	manual	✓	V, T	1318	∼30s	17625	✗
WorldSense (2026)	-	existing	manual	✓	V, A, T	1662	141.1s	3172	✓
Trust-videoLLMs (2026)	-	existing, syn., YouTube	manual	✓	V, A, T	6955	-	-	✓
CausalStep (2026b)	-	existing	manual	✓	V, T	100	430.5s	1852	✗

Table 5: 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. Modal: V: video, A: audio, T: text.

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

Table 6: Abbreviations for sports and tasks mentioned in this paper (sorted alphabetically by abbreviation).