The University of Tennessee Knoxville

Journal of Applied Sport Management

Volume 17 | Issue 4 Article 1

12-1-2025

An Introduction to the AI Special Issue and a Modern Framework for AI in Sport Management

Jun Woo Kim
Arcadia University, kimjw@arcadia.edu

Vitaly Ford
Arcadia University, fordv@arcadia.edu

Journal of Applied Sport Management
https://doi.org/10.7290/jasm17LDQV
Vol. 17, No. 4
https://trace.tennessee.edu/jasm/vol17/iss4/1

An Introduction to the AI Special Issue and a Modern Framework for AI in Sport Management

Jun Woo Kim

Vitaly Ford

Arcadia University

Please send correspondence to Jun Woo Kim, kimjw@arcadia.edu

Abstract

This paper introduces the special issue while also exploring the theoretical foundations and practical applications of AI in sport management, guided by Artificial Intelligence: A Modern Approach (Russell & Norvig, 2021). The manuscript examines AI's evolution from rule-based systems to large language models (LLM)–driven intelligent agents and classifies the technology into five major subfields—machine learning, natural language processing, computer vision, reinforcement learning, and AI agency. Using real-world sport industry examples and recent academic research, this paper presents a modern taxonomy of AI's role in sport management, articulates managerial implications, and outlines future research directions necessary for sustainable and ethical integration of AI in sport organizations
.

Keywords: artificial intelligence (AI), large language models (LLMs), AI agent

Introduction to the Special Issue

Artificial intelligence (AI) is the scientific field dedicated to designing systems that can perceive their environment, reason under uncertainty, and act effectively to achieve defined goals. Rather than merely replicating human behavior, AI seeks to create rational agents capable of learning, adapting, and making informed decisions in complex and dynamic settings (Russell & Norvig, 2021). These agents integrate perception, reasoning, learning, and action to operate autonomously within complex, dynamic environments. As such, AI encompasses a wide range of subfields, including machine learning, natural language processing, robotics, and computer vision, all contributing to the overarching goal of developing machines that can function intelligently in real-world contexts (Rudowsky, 2004; Russell & Norvig, 2021).

What does this hold for the realm of sports? The next phase of AI in sport management may be led by the rise of AI agents: LLM-driven autonomous systems that can gather information, reason under uncertainty, and carry out multi-step tasks with little human involvement. Sport organizations are already using machine learning and analytics, but the move toward these more autonomous, agent-based systems is still just beginning. A central technical direction involves developing multimodal agent architectures that unify text, video, biomechanical sensors, physiological metrics, and player tracking information into a single decision system. Recent advances in multimodal foundation models (Fei et al., 2022), for example, suggest that future sport systems will be able to interpret complex game environments holistically rather than through isolated data streams.

Sport organizations may also integrate LLM-based automation tools into their day-to-day operations. Platforms such as n8n, Zapier, Make, AutoGPT, OpenAI's Assistants API, CrewAI, and LangGraph already allow sport organizations to automate portions of their workflows. These platforms connect databases, communication channels, tracking systems, and analytical tools into unified pipelines that can take actions based on predefined conditions or learned patterns. Newer LLM-driven agents would extend these capabilities by making workflows conversational and context-aware. For example, a scouting agent can ingest raw video, classify player actions through computer vision, generate comparative reports, and alert decision-makers when a prospect meets organizational thresholds. A contract-analysis agent could read complex compensation clauses, identify unusual patterns, and draft contract structures aligned with cap constraints. A fan-engagement agent can monitor real-time sentiment during games, generate multilingual messaging, and tailor outreach to individual supporters.

Ultimately, AI represents more than a technological upgrade. It is changing the way sport organizations think, make decisions, and operate daily. The rise of agentic systems marks a transition from predictive analytics to operational autonomy, where AI systems can understand context, combine information from multiple sources, and carry out meaningful tasks across entire departments. As Russell and Norvig (2021) emphasize, AI is ultimately about building rational agents that can perceive, reason, and act in pursuit of goals. In sport management, those goals range from winning games to sustaining revenue, strengthening community relationships, and upholding responsibility to athletes and fans. As AI continues to advance in autonomy, multimodal perception, and real-time reasoning, sport organizations must not only deploy these capabilities but also actively shape their development, evaluation, and governance. The real challenge moving forward is not whether AI agents will change sport (they will), but how the sport industry will design, regulate, and collaborate with these systems in ways that strengthen both organizational performance and the human spirit at the core of sport. Accordingly, the purpose of this special issue is to provide perspectives on AI in sports to facilitate conversation and provide recommendations for future research as the AI revolution advances.

The first paper from Arbieu et al. focuses on systemic sport ecology. They look to address common challenges facing contemporary applied sport ecology such as limited resources and biases toward climate action. The next two think pieces tackle recruiting, but through differing lenses. The piece from Corr focuses on the relational aspects of recruiting and how, though AI is valuable, it should not (and cannot) replace an essential aspect of recruiting: relationships. In comparison, Judge and Magnusen focus on riding the AI wave rather than swimming against it. Together they discuss AI, the displacement of human judgement, and how AI can be used ethically when evaluating athletes. Next, Lee et al. look to emotions, collective participation, and virtual and digital experiences. The authors propose and discuss a four-level framework that positions sport organizations as comprehensive emotional development centers that can harness AI-powered technologies. Finally, in the piece by Morgan and Stamatis, the authors propose and explore a provocative question: under what conditions might simulation move from enhancement to substitution? With that question in mind, they discuss why human physical performance may not be the only future for sport as a business and entertainment enterprise.

AI and Sport Management

In recent years, the sport industry has transformed into a data-driven ecosystem defined by complexity, uncertainty, and constant change (Chmait & Westerbeek, 2021). Even before the emergence of AI, data analytics had already begun to influence decision-making across areas such as athlete performance, fan engagement, sponsorship valuation, and media distribution. Today, AI technologies are already integrated across multiple facets of sport, enabling organizations to predict injury risks, optimize training schedules, and track player movements with unprecedented precision (Li et al., 2025). Yet despite its growing influence, the rapid evolution of AI has outpaced conceptual understanding in the sport management discipline. This paper seeks to bridge that gap by proposing a modern taxonomy of AI applications in sport management that compares the pre-Large Language Model (LLM) era with the emergence of LLMs, and explores what this shift means for intelligent agents, workforce transformation, and future research.

Theoretical Foundations

Defining Artificial Intelligence

The foundational architecture of AI can be traced to Alan Turing's seminal work on machine intelligence. The Turing Test, proposed in 1950, established a behavioral criterion for intelligence: if a machine could engage in conversation indistinguishably from a human, it could be considered intelligent (Russell & Norvig, 2021). This test implicitly identified core capabilities that remain central to AI development. To pass the Turing Test, a system requires natural language processing to communicate successfully, knowledge representation to store information, automated reasoning to answer questions and draw conclusions, and machine learning to adapt to new circumstances and detect patterns. Turing viewed physical simulation as unnecessary for demonstrating intelligence. However, subsequent researchers proposed a total Turing Test, which requires interaction with objects and people in the real world (Huang, 2024; Russell & Norvig, 2021). This view of AI requires abilities like computer vision and speech recognition to understand the world, and robotics to interact with and move through it. Together, these capabilities offer a useful way to think about how AI operates across different application areas, many of which connect directly to sport management. In our field, these same elements map onto core organizational processes such as market sensing, strategic analysis, operational learning, and managerial execution. This theoretical lens reframes sport organizations as intelligent agents that, while dealing with uncertainty, seek to maximize multiple objectives: winning games, financial sustainability, and community engagement. AI, then, is not just a technical toolkit; it represents a fundamental shift in how managers understand and define rational decision-making.

The Evolution of AI: From Rule-Based Systems to Large Language Models

The modern history of AI can be divided into two eras: the pre-LLM era, characterized by rule-based and narrowly focused systems, and the LLM era, defined by the emergence of LLMs capable of general-purpose reasoning and generation (Huang, 2024; Wang et al., 2024). This transition represents one of the most significant paradigm shifts in the history of computing, with profound implications for how sport organizations leverage intelligent systems (see Table 1).

The Evolution of AI: From Rule-Based Systems to Large Language Models

Before large language models emerged, AI was built on rule-based systems, statistical learning, small-scale neural networks, and early pretrained language models (PLMs), all of which depended on logic that humans explicitly programmed (Naveed et al., 2025). Expert systems and symbolic reasoning dominated the field, with computers programmed to follow explicit "if-then" rules (Russell & Norvig, 2021). In sport management, this early generation of AI mostly took the form of basic statistical models and decision support tools. Teams used statistical analyses to forecast player performance, applied simple classification techniques to understand fan segments, and relied on optimization models to allocate resources. These tools were useful, but they relied heavily on human judgment. Analysts had to decide which variables mattered, how to prepare the data, and how to interpret the results. Because these systems learned only within the narrow boundaries defined by their designers, they could not apply insights from one problem to another (Tuyls et al., 2021).

As AI evolved into the machine learning phase, models began learning patterns directly from data rather than relying entirely on hand-crafted rules. Algorithms such as logistic regression, support vector machines, and early artificial neural networks improved the ability to detect patterns, classify images, and make predictions. Still, these models remained task-specific and relied heavily on supervised learning with carefully labeled datasets (Russell & Norvig, 2021). In sport analytics, this meant that injury prediction models, talent identification tools, and fan engagement tools all had to be developed separately, each demanding extensive data preparation and ongoing human supervision (Li et al., 2025).

As such, the limitations of pre-LLM AI were structural. Systems were highly specialized and performed well only within tightly defined domains. They needed substantial human involvement in their design, rule-setting, and iterative tuning. Even though the data requirements were modest compared to today's standards, collecting high-quality datasets was still a major challenge. Early technologies of this era, such as IBM Watson's first applications and rule-based conversational agents, demonstrated the promise of AI but also revealed clear limitations in flexibility, adaptability, and generalization (Naveed et al., 2025; Russell & Norvig, 2021). The same constraints were evident in early sports technologies as well. Tools like the first version of LongoMatch platform enabled coaches to tag events such as passes, shots, and turnovers, providing useful descriptive insights. However, they could not read the game the way a coach can. They could not recognize tactical intent, uncover broader strategic patterns, or apply what they learned from one context to another.

Table 1. ***Comparison of Pre-LLM AI vs. LLM-Era AI Across Key Dimensions***

Aspect	Pre-LLM AI	LLM Era AI
Architecture	Predominantly rule-based, statistical, or composed of relatively shallow neural networks designed for narrowly defined tasks. System logic and decision pathways were explicitly programmed or or linearly parameterized.	Grounded in transformer-based architectures comprising large-scale, deeply layered neural networks capable of contextual attention and parallelized learning across extensive token sequences.
Learning Paradigm	Reliant on task-specific, fully supervised learning approaches that required substantial human annotation and domain expertise to construct labeled datasets.	Employs self-supervised and few-shot learning paradigms, allowing models to infer structure and semantics from unannotated data and to generalize to new tasks via prompting without retraining.
Data Scale	Trained on small, domain-restricted datasets, often curated for particular organizational or research objectives, limiting generalization capacity.	Trained on massive, heterogeneous corpora encompassing trillions of tokens from diverse textual, visual, and multimodal sources, enabling broad linguistic and conceptual gen eralization.
Adaptability	Exhibited narrow functional specialization, performing effectively only within the specific domains or tasks for which the system was designed.	Demonstrates general-purpose adaptability, executing multiple, diverse tasks through natural-language prompting and contextual learning without structural modification.

Feature Engineering	Required manual and expert-driven feature extraction, with human analysts defining relevant variables, rules, or linguistic patterns for each application.	Performs automatic representation learning, internally discovering high-dimensional features and latent structures without human intervention, thus minimizing the need for explicit feature design.
Reasoning Capacity	Characterized by deterministic or domain-bound logical reasoning, constrained to symbolic manipulation or pre-specified statistical inference mechanisms.	Exhibits emergent probabilistic reasoning, whereby contextual understanding and inference arise organically from large-scale exposure to language and multimodal data patterns.
Human Involvement	Entailed high levels of human participation in system design, rule specification, feature engineering, and iterative parameter tuning.	Involves reduced direct human intervention, with practitioners acting as high-level supervisors who guide models through prompt construction, fine-tuning, and alignment oversight.
Representative Systems	Examples include IBM Watson, expert systems, and rule-based conversational agents, which dominated early commercial and academic AI deployments.	Representative systems include GPT-5, Claude, Gemini, and LLaMA, which exemplify the scalability and generative versatility of transformer-based large language models.

LLM-Era AI: The Age of Generalization and Scale

The introduction of LLMs in the late 2010s revolutionized the landscape of AI (Naveed et al., 2025). The introduction of the Transformer model by Vaswani et al. (2017) marked a turning point in AI. What makes it revolutionary is that it completely eliminates recurrence: it does not read text one step at a time like Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM). Instead, it uses a mechanism called self-attention, which allows the model to look at all input tokens simultaneously (Vaswani et al., 2017; Wang et al., 2024). This breakthrough established the foundation for modern LLMs.

This era marks a major shift from narrow, task-specific AI to models with general-purpose adaptability. LLMs can translate text, summarize documents, answer questions, generate code, and even reason through problems (Wang et al., 2024). Instead of depending on features handcrafted by experts, these models learn their own understanding of language, including its meaning, structure, and logic. This is what allows them to make inferences, generate original text, and bring together information based on context. Their power comes from the Transformer architecture, which uses attention mechanisms to focus on the most relevant parts of the input when generating a response (Russell & Norvig, 2021; Vaswani et al., 2017).

Rather than relying on hand-crafted features built by experts, LLMs learn their own internal understanding of language, including its meaning, structure, and logic. This, in turn, allows them to make inferences, create original text, and pull together information based on context. For sport management, the implications are substantial. A single LLM can now analyze player contracts, generate scouting reports, respond to fan inquiries, summarize game footage transcripts, and even support strategic planning. These are tasks that once required multiple specialized tools and significant human effort with different backgrounds and expertise. Another defining feature of the LLM era is how little direct human intervention is now required (Naveed et al., 2025). Instead of building complicated rules or hand-labeling huge datasets, practitioners can simply guide LLM models through natural language prompts. This shift has opened the door for non-technical sport managers to use machine learning in ways that were once out of reach. A general manager with no programming background can now ask an LLM about comparable player contracts, injury risks, or sponsorship market trends and receive detailed, data-driven analysis within seconds.

However, this new flexibility also brings challenges. LLMs can exhibit hallucination, generating plausible but factually incorrect information. They can reproduce biases from their training data, which raises ethical concerns in areas like hiring and player evaluation. As sport organizations begin using LLM-powered tools, they now need clear governance frameworks that balance innovation with responsibility and ensure that AI-generated insights are verifiable (coming from trusted, verified sources), interpretable, and aligned with ethical standards.

AI Taxonomy for Sport Management: Five Core Domains

AI in sport management can be understood through five major domains that represent different forms of computational reasoning: (a) machine learning, (b) natural language processing, (c) computer vision, (d) reinforcement learning, and (e) AI agency. Adapted from the taxonomy proposed by Russell and Norvig (2021), this framework helps explain how sport organizations apply AI across a wide range of functions (see Table 2).

Domain 1: Machine Learning in Sport Analytics

Machine learning is the most widely used area of artificial intelligence in sport management, covering supervised, unsupervised, and deep learning approaches. In supervised learning, sport organizations rely on historical datasets with known outcomes to forecast player performance, assess injury risk, and understand fan behavior (Kim et al., 2023; Li et al., 2025). These models detect subtle patterns in early career indicators, biomechanical movement, training loads, recovery patterns, and consumer activity. These insights help teams make more informed decisions about scouting, contract negotiations, and fan engagement.

Unsupervised learning adds another layer of insight by revealing structure in unlabeled data. It can group players into performance archetypes, simplify large and complex datasets into more interpretable components, or flag unusual patterns that may indicate anti-doping issues or concerns about match integrity. Deep learning expands these capabilities by automatically extracting features from large sets of spatial and temporal data. This makes it possible to recognize tactical patterns, track player movements, and analyze evolving game states that traditional methods often struggle to capture (Chmait & Westerbeek, 2021).

Machine learning methods such as random forests, gradient boosting machines, and neural networks are also increasingly used to predict injury risk. These systems identify early warning signs in workload and biomechanical data, allowing medical and performance teams to intervene before issues escalate (Weirich et al., 2025). Organizations using these tools often report fewer injuries and longer careers for their athletes, creating both competitive and financial advantages (Claudino et al., 2019; Mateus et al., 2024).

Machine learning also plays a major role in understanding fan behavior. Classification models help segment audiences, predict which fans are likely to stop engaging, and identify which demographic groups respond best to particular marketing messages. By tailoring outreach to fan preferences, organizations can increase engagement, improve retention, and strengthen lifetime value. This trend is already shaping league-level strategies. For example, the National Football League formed an expanded partnership with Adobe in 2025 that uses tools such as the Adobe Experience Platform to personalize content for millions of fans and enhance live event experiences at scale (Business Wire, 2025).

Domain 2: Natural Language Processing (NLP) and Communication

Natural language processing (NLP) refers to the set of computational techniques allowing machines to understand, interpret, and generate human language (Russell & Norvig, 2021). In sport management, NLP has quickly expanded into everyday operations, supporting tasks such as automated content creation, sentiment tracking, contract analysis, and conversational fan services (Ortu & Mola, 2025). Sport organizations generate an enormous amount of written material, including game recaps, player profiles, social media updates, press releases, and scouting reports. Today, systems powered by LLMs, such as Stats Perform's OptaAI Studio, can produce much of this content at scale and with quality that comes close to human writing. By combining structured data like box scores and play-by-play logs with broader contextual information, these systems create narratives that are both informative and engaging. Their flexibility also allows them to adjust tone and style for different platforms, translate content for global audiences, and personalize messages based on individual fan preferences.

NLP also plays a crucial role in helping organizations understand how fans, media, and the general public respond to events in real time. By analyzing millions of social media posts, news stories, and comments, NLP systems can assess sentiment, identify emerging topics, and track mentions of specific players, teams, or sponsors. These insights are valuable for managing brand reputation, supporting player welfare, and strengthening commercial partnerships. When a controversial call is made, for instance, sentiment analysis can reveal how fans are reacting across different regions or demographic groups, helping organizations craft targeted responses. Similarly, when assessing sponsorship performance, NLP metrics go beyond simple reach and engagement numbers by providing a clearer picture of how audiences perceive the brand and how those perceptions change over time.

Domain 3: Computer Vision and Visual Intelligence

Computer vision allows machines to interpret and make sense of visual information much like humans do (Russell & Norvig, 2021). In sport, this is especially powerful because so much of what happens on the field or court is captured through video, broadcast feeds, and tracking systems. AI-driven computer vision turns these visual streams into meaningful insights that support performance analysis, officiating, and the fan experience (Tuyls et al., 2021). These systems can follow player movements, track the ball, and map out spatial patterns throughout a game. With deep learning models such as convolutional neural networks, they can recognize players, classify actions, and calculate performance metrics without requiring analysts to manually tag every moment. Coaches gain real-time feedback on positioning, spacing, and tactical execution, helping them make quick adjustments. By comparing an athlete's movement to their own baseline or an ideal model, these tools can flag small changes that may suggest fatigue, compensation, or rising injury risk. They can also automatically detect passes, shots, tackles, and other sport-specific events, speeding up video analysis and revealing long-term patterns across entire seasons or leagues.

Computer vision is also reshaping officiating (Li et al., 2025). Technologies like goal-line systems, Hawk-Eye, and Video Assistant Referee (VAR) rely on computer vision to determine scoring plays and rule violations with greater accuracy than the human eye alone. These tools reduce controversial decisions and support fair competition. A major recent example is MLB's decision to implement the Automated Ball Strike System (ABS) league-wide in the 2026 season (MLB.com, 2025). Beyond straightforward yes-or-no calls, computer vision can help evaluate more complex or subjective rules. In judged sports such as gymnastics, diving, or figure skating, AI systems offer consistent reference points that help reduce bias. While human judgment remains an important part of these sports, computer vision adds a layer of transparency and accountability that strengthens trust in officiating.

Finally, computer vision is also pushing fan experience beyond traditional broadcasting. It enables features such as augmented reality overlays, automated highlight reels, and personalized viewing angles that help fans better understand the game. Live broadcasts now incorporate real-time graphics on player statistics, formations, and predictive analytics, much of which depends on computer vision models that track players and interpret spatial patterns. Alongside these advancements, the NBA has expanded its use of immersive media technologies like Virtual Reality (VR) to give fans new ways to experience games, such as courtside VR viewing and interactive 360-degree replays. Although these VR experiences are not computer vision technologies themselves, they rely on computer vision pipelines and AI-driven media processing (NBA.com, 2023). As these technologies evolve, the line between in-person attendance and digital viewing will continue to blur, opening new revenue opportunities and broader access to premium experiences.

Domain 4: Reinforcement Learning and Strategic Optimization

Reinforcement learning (RL) focuses on how an agent learns to make good decisions by interacting with its environment and receiving feedback in the form of rewards or penalties (Russell & Norvig, 2021). Unlike supervised learning, which depends on labeled data, RL systems learn through experience by experimenting, making mistakes, and gradually discovering what works, based on pre-defined rewards and penalties. This approach fits sport particularly well. Games are filled with strategic choices, shifting conditions, and constant adjustments, and each decision can influence how opponents respond. RL models capture this dynamic, allowing systems to learn effective tactics by simulating thousands of competitive scenarios (Tuyls et al., 2021). When agents train by playing against themselves or against learned models of their opponents, they can uncover strategies that maximize the chances of winning.

We have already seen how powerful this can be. AlphaGo's landmark wins over world champion Go players revealed that RL can achieve strategic understanding beyond human capability, even in highly complex environments (Russell & Norvig, 2021). In sport, similar ideas are now being put into practice. Teams use RL-based tools to analyze opponent tendencies, test alternative game plans, and recommend tactics that exploit weaknesses. These insights give coaches another layer of evidence to support in-game decisions. The collaboration between Google DeepMind and Liverpool FC is a strong example. Their system, TacticAI, uses geometric deep learning to evaluate corner-kick strategies and suggest optimal player positioning. Expert raters preferred its recommendations over existing tactics 90 percent of the time (Wang et al., 2024).

Beyond tactics, reinforcement learning also supports broader organizational decisions. Many sport operations involve optimization problems, such as setting schedules, allocating budgets, adjusting ticket prices, or managing rosters. RL models are uniquely suited to these challenges because they can balance short-term rewards with long-term goals under uncertainty. Dynamic ticket pricing systems, for instance, use RL to respond to real-time demand and maximize revenue while maintaining attendance. Roster-building models apply RL to weigh immediate performance needs against long-term potential and salary-cap constraints. Through this lens, RL becomes not just a tool for strategy on the field, but a decision framework that can support competitive and financial success across the entire organization.

Table 2. ***The Five Core AI Domains in Sport Management***

Domain	Core Definition	Key Techniques	Primary Sport Management Applications	Real-world Examples in Sport
Machine Learning	Algorithms that learn patterns from data and improve through feedback	Supervised learning, unsupervised learning, deep learning, neural networks, clustering, anomaly detection	Player evaluation, injury prediction, fan segmentation, forecasting, performance modeling, scouting analytics	Predicting player success from early-career data; injury-risk models using workload metrics; clustering players into archetypes; deep-learning tactical analystis using tracking data
Natural Language Processing	Computational techniques for understanding and generating human language	Large language models, sentiment analysis, entity extraction, summarization, topic modeling, conversational AI	Automated content creation, contract analysis, brand monitoring, customer service, multilingual communication	AI-generated game recaps; sentiment tracking during controversial calls; extracting clauses; chatbots answering ticket and merchandise questions

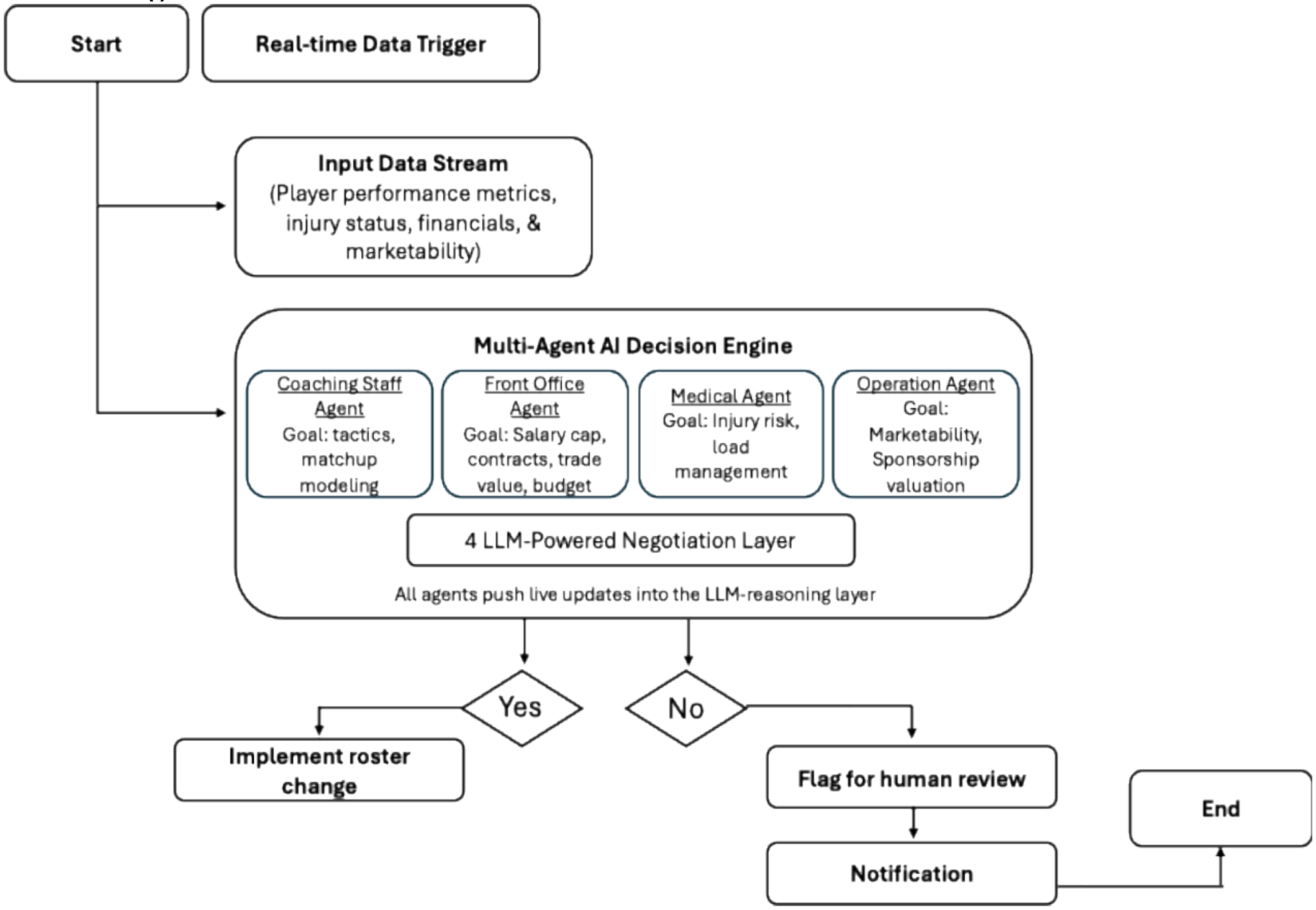
Computer Vision	Systems that interpret visual data from images and video	Convolutional neural networks, pose estimation, action recognition, object tracking, AR/VR overlays	Automated performance analysis, officiating support, broadcast enhancement, biomechanics assessment	Video Assistant Referee and goal-line technology; automatic tagging of passes/shots; AR overlays in broadcasts; pose-based injury-risk evaluation; automated highlight; possession percentage
Reinforcement Learning (RL)	Agents that learn optimal actions through trial & error with reward feedback	Policy optimization, Q-learning, self-play simulation, multi-agent RL	Tactical planning, game simulations, ticket pricing, roster optimization, training design	DeepMind's TacticAI for corner-kick optimization; RL-based dynamic ticket pricing; self-play models identifying optimal substitution patterns
AI Agency	Autonomous systems that integrate perception, reasoning, and action with minimal human oversight	Workflow automation, decision-support systems, multi-agent models, LLM-driven agents	Contract negotiation support, roster planning, automated operations, fan relationship mgmt.	Agents that automate scheduling and reporting; multi-agent systems balancing coaching, medical, and financial priorities in roster decisions; AI assistants drafting contract options

Domain 5: AI Agency and Autonomous Systems

AI agency refers to the idea that modern AI systems can perceive information, reason through it, and take action with very little human supervision (Russell & Norvig, 2021). In sport management, these agents can take many forms, ranging from simple automated workflows to more advanced systems that can review contracts, manage fan relationships, or help coordinate decisions across departments. Much of the daily work in sport organizations involves repetitive tasks such as scheduling meetings, processing transactions, updating databases, or generating reports. AI agents can now handle many of these responsibilities automatically by connecting different systems and triggering actions based on rules or learned patterns (Wang et al., 2024). Tools like n8n and Zapier make this possible even for staff who do not have technical backgrounds, allowing them to build automations through visual interfaces. LLMs extend these capabilities further by making automation conversational. Instead of writing scripts, staff can simply describe what they want the system to do, and the agent converts those instructions into an operational workflow. This lowers the barrier to automation and gives smaller organizations access to capabilities that once required specialized technical teams.

Sport organizations are also complex environments where ownership, coaches, medical staff, and front offices often have different priorities. Multi-agent AI systems help bring these perspectives together. They simulate each stakeholder as an independent agent with its own goals and constraints, and then search for solutions that balance these competing needs. A good example is roster management. A multi-agent system can consider what the coaching staff values in player roles, what the front office needs for salary planning, what the medical team recommends based on injury risk, and what the business operation team sees as important for marketing and fan engagement (see Figure 1). By evaluating all of these perspectives at the same time and identifying options that satisfy as many criteria as possible, the system supports more informed and collaborative decision-making across the organization.

Figure 1. ***Multi-Agent AI Decision Flow***



References

Business Wire. (2025, April 23). NFL and Adobe launch AI-powered fan experience partnership. https://www.businesswire.com/news/home/20250423735818/en/NFL-and-Adobe-Launch-AI-Powered-Fan-Experience-Partnership

Chmait, N., & Westerbeek, H. (2021). Artificial intelligence and machine learning in sport research: An introduction for non-data scientists. Frontiers in Sports and Active Living, 3, 682287. https://doi.org/10.3389/fspor.2021.682287

Claudino, J. G., de Capanema, D. O., de Souza, T. V., Serrão, J. C., Machado Pereira, A. C., & Nassis, G. P. (2019). Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: A systematic review. Sports Medicine - Open, 5(1), Article 28. https://doi.org/10.1186/s40798-019-0202-3

Fei, N., Lu, Z., Gao, Y., Yang, G., Huo, Y., Wen, J., Lu, H., Song, R., Gao, X., Xiang, T., Sun, H., & Wen, J.-R. (2022). Towards artificial general intelligence via a multimodal foundation model. Nature Communications, 13(1), Article 3094. https://doi.org/10.1038/s41467-022-30761-2

Huang, Y. (2024). Levels of AI agents: From rules to large language models (arXiv:2405.06643). arXiv. https://doi.org/10.48550/arXiv.2405.06643

Kim, J. W., Magnusen, M., & Jeong, S. (2023). March Madness prediction: Different machine learning approaches with non□box score statistics. Managerial and Decision Economics, 44(4), 2223-2236. https://doi.org/10.1002/mde.3814

Li, W., Liu, M., Liu, J., Zhang, B., Yu, T., Guo, Y., & Dai, Q. (2025). A review of artificial intelligence for sports: Technologies and applications. Intelligent Sports and Health, 1(3), 113–126. https://doi.org/10.1016/j.ish.2025.05.001

Mateus, N., Abade, E., Coutinho, D., Gómez, M.-Á., & Lago Peñas, C. (2024). Empowering the sports scientist with artificial intelligence in training, performance, and health management. Sensors, 25(1), 139. https://doi.org/10.3390/s25010139

MLB.com. (2025, September 23). MLB announces ABS Challenge System coming to the Major Leagues beginning in the 2026 season [Press release]. MLB. https://www.mlb.com/press-release/press-release-mlb-announces-abs-challenge-system-coming-to-the-major-leagues-beginning-in-the-2026-season

Naveed, H., Khan, A. U., Qiu, S., Saqib, M., Anwar, S., Usman, M., Akhtar, N., Barnes, N., & Mian, A. (2025). A comprehensive overview of large language models. ACM Transactions on Intelligent Systems and Technology, 16(5), 1–72. https://doi.org/10.1145/3744746

NBA.com. (2023, January 24). NBA and Meta announce multiyear partnership extension. https://www.nba.com/news/nba-and-meta-announce-multiyear-partnership-extension

Ortu, M., & Mola, F. (2025). The game beyond the field: On football players' performance through social media, sentiment and topic analysis. Computational Statistics, 40, 2085-2108. https://doi.org/10.1007/s00180-024-01584-0

Rudowsky, I. (2004). Intelligent Agents. Communications of the Association for Information Systems, 14, 275-290. https://doi.org/10.17705/1CAIS.01414

Russell, S., & Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.

Tuyls, K., Omidshafiei, S., Muller, P., Wang, Z., Connor, J., Hennes, D., Graham, I., Spearman, W., Waskett, T., Steel, D., Luc, P., Perolat, J., Ewalds, T., Strub, F., Heess, N., Schmid, M., Gruslys, A., Timbers, F., Omidshafiei, M., . . . Bowling, M. (2021). Game plan: What AI can do for football, and what football can do for AI. Journal of Artificial Intelligence Research, 71, 41–88. https://doi.org/10.1613/jair.1.12505

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998–6008.

Wang, Z., Veličković, P., Hennes, D., Tomašev, N., Prince, L., Kaisers, M., Bachrach, Y., Elie, R., Wenliang, L. K., Piccinini, F., Spearman, W., Graham, I., Connor, J., Yang, Y., Recasens, A., Khan, M., Beauguerlange, N., Sprechmann, P., Moreno, P., . . . Tuyls, K. (2024). TacticAI: An AI assistant for football tactics. Nature Communications, 15(1), 1906. https://doi.org/10.1038/s41467-024-45965-x

Weirich, C., Kim, J. W., Yoon, Y., & Jeong, S. (2025). Advancing NFL win prediction: from Pythagorean formulas to machine learning algorithms. Frontiers in Sports and Active Living, 7, 1638446. https://doi.org/10.3389/fspor.2025.1638446