(Pregledni rad / Paper review)
DOI: 10.46793/ManagSport17-2.238B
UDK: 004.8:796.071.4

TRANSFORMATION OF THE SPORTS COACH ROLE IN THE GENERATIVE AI ERA: FROM ANALYTICS TO STRATEGY CO-CREATION

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ABSTRACT

While traditional sports analytics have focused on descriptive and predictive models to interpret historical data, the emergence of Generative Artificial Intelligence (GenAI) introduces novel capabilities for tactical simulation, content creation, and natural language interaction. This technological shift necessitates a fundamental re-evaluation of the human coach's operational role within high-performance environments. This article critically examines the transformation of sports coaching in the GenAI era. It aims to synthesize current applications of generative models and propose a theoretical evolution from the "Human-in-the-Loop" paradigm to a "Coach-as-Editor" framework, where human expertise is applied to curate rather than originate strategic content. An integrative review of literature published between January 2016 and January 2026 was conducted using Web of Science, Scopus, PubMed, and IEEE Xplore. Following PRISMA guidelines, 39 studies were selected for synthesis across three core operational domains: tactical preparation, physiological load management, and talent identification. The analysis identifies that GenAI considerably enhances coaching efficacy through automated scenario generation, hyper-personalized training prescriptions, and globalized scouting capabilities. However, a SWOT analysis shows that while GenAI democratizes access to elite-level analytics, it introduces critical risks regarding algorithmic hallucinations, data privacy, and potential professional deskilling. The study posits that the future coaching role will transition from "strategic architect" to "sophisticated curator" of AI-generated alternatives. To steer this transition, sports organizations must adopt a phased implementation strategy that focuses

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on ethical governance, data literacy, and the preservation of human contextual judgment, ensuring a symbiotic rather than substitutive relationship between coach and machine.

Keywords: Generative AI, Sports Coaching, Performance Analysis, Strategic Decision-Making, Human-Computer Interaction, Coach Education.

TRANSFORMACIJA ULOGE SPORTSKOG TRENERA U DOBU GENERATIVNE VEŠTAČKE INTELIGENCIJE: OD ANALIZE PODATAKA DO STRATEŠKE KO-KREACIJE

APSTRAKT

Dok su se tradicionalne sportske analize fokusirale na deskriptivne i prediktivne modele za interpretaciju prošlih podataka, pojava generativne veštačke inteligencije uvodi nove kapacitete za taktičku simulaciju, generisanje sadržaja i interakciju na prirodnom jeziku. Ovaj tehnološki pomak zahteva suštinsko preispitivanje operativne uloge ljudskog trenera u okruženjima vrhunskih sportskih postignuća. Ovaj članak kritički ispituje transformaciju sportske trenerske prakse u eri generativne veštačke inteligencije. Njegova svrha je da sintetiše trenutne modalitete primene generativnih modela i predloži teorijski prelaz sa paradigme „čoveka u petlji" (engl. *human-in-the-loop*) na okvir „trenera kao urednika", gde se ljudska ekspertiza primenjuje za selekciju i kuriranje, a ne primarno za kreiranje strateškog sadržaja. Sproveden je sveobuhvatni pregled literature objavljene između januara 2016. i januara 2026. godine pretragom baza podataka Web of Science, Scopus, PubMed i IEEE Xplore. Prateći PRISMA smernice, odabrano je 39 studija za tematsku sintezu u tri ključna funkcionalna domena: taktička priprema, optimizacija trenažnog opterećenja i identifikacija talenata. Analiza potvrđuje da generativna veštačka inteligencija značajno unapređuje efikasnost trenera kroz automatizovano generisanje scenarija, visoko personalizovane planove treninga i globalne kapacitete za skauting. Međutim, SWOT analiza otkriva da, iako ova tehnologija demokratizuje pristup naprednoj analitici, ona istovremeno uvodi kritične rizike u vezi sa AI halucinacijama, privatnošću podataka i mogućom atrofijom ekspertskog znanja usled preteranog oslanjanja na tehnologiju. Studija postavlja tezu da će buduća uloga trenera evoluirati iz uloge „strateškog kreatora" u ulogu „sofisticiranog kuratora" opcija koje generiše veštačka inteligencija. Da bi se uspešno upravljalo ovom tranzicijom, sportske organizacije moraju usvojiti strategiju fazne implementacije koja prioritizuje etičko upravljanje, pismenost o podacima i očuvanje kontekstualnog ljudskog rasuđivanja, osiguravajući time sinergijski, a ne supstitucioni odnos između trenera i mašine.

Ključne reči: generativna veštačka inteligencija, sportski treneri, analiza performansi, strateško donošenje odluka, interakcija čovek-računar (HCI), obrazovanje trenera.

Introduction

The evolution of sports management and coaching has been driven by the pursuit of competitive advantage through systematic information processing.

The emergence of Artificial Intelligence (AI) technologies represented a key development in solving this data processing challenge. Initial AI applications in sports were predominantly analytical, employing regression models and classification algorithms to support descriptive analytics (interpreting historical events) and predictive analytics (forecasting probable outcomes) (Houtmeyers et al., 2021; Li et al., 2025). However, the recent introduction of Generative AI (GenAI) - underpinned by Large Language Models (LLMs) and sophisticated neural network architectures-has established a novel technological frontier (Caron et al., 2023; Li et al., 2025). In contrast to traditional discriminative AI systems that function mainly through data categorization, GenAI possesses the capability to generate novel content, emulate complex tactical scenarios, and produce natural language analytical reports, thereby bridging raw data and human insight (Caron et al., 2023; Dupont, 2025; Tudip, 2025).

Notwithstanding the revolutionary potential of these technologies, the integration of AI into coaching workflows remains inconsistent and faces multiple implementation challenges (Bensalem, 2023; European Parliament, 2024; Naughton et al., 2024). This paper presents a contrasting perspective, proposing that GenAI technologies augment rather than diminish the coaching role (Iowa State University, 2022; Naughton et al., 2024; Open University, 2025). Consistent with emerging conceptual models (Houtmeyers et al., 2021; Naughton et al., 2024; The Decision Lab, 2021), the optimal approach lies in a synergistic model in which an effective human-AI partnership unlocks athletic potential unattainable through either component operating in isolation.

This central thesis argues that future coaching practice will be characterized by a fundamental role transition: from sole strategic architect to sophisticated curator and editor of AI-generated strategic alternatives, thereby widening access to elite-level analytical competencies across organizations of varying resource capacities (European Parliament, 2024; Iowa State University, 2022; Li et al., 2025; Naughton et al., 2024).

In doing so, this review advances two contributions that distinguish it from the existing literature. First, whereas prior scholarship has applied general human-centred AI principles, most notably the Human-in-the-Loop and Human-Centred AI paradigms, to sport in broad terms, this article offers a sport-specific synthesis that reorganizes fragmented evidence across the tactical, physiological, and talent-identification domains around a single integrative construct. Second, building on this synthesis, it proposes the original "Coach-as-Editor" framework, which reconceptualizes the coach from a passive validator of machine outputs into an active curator and editor of AI-generated strategic alternatives, a framing not yet explicitly articulated in the sports coaching literature and one that provides the conceptual backbone for the analysis that follows.

Methodology

To investigate the transformation of the sports coaching role through Generative AI (GenAI), this study utilizes an integrative review framework. This approach provides for the synthesis of diverse data sources, including empirical research, theoretical papers, and technical reports, to develop a holistic understanding of how AI technologies are reshaping coaching workflows, from tactical planning to ethical governance.

Search Strategy and Data Sources

A systematic search strategy was implemented to identify relevant literature published between January 2016 and January 2026. The starting date was selected to coincide with the emergence of the Transformer architecture (e.g., BERT, GPT-1), which serves as the foundational technology for modern Generative AI.

Electronic searches were conducted across four primary databases to ensure interdisciplinary coverage of both sports science and computer science domains:

1. Web of Science (Core Collection)
2. Scopus
3. PubMed (for physiological and injury prevention applications)
4. IEEE Xplore (for technical implementation and algorithmic architecture)

The search strategy utilized Boolean operators to combine three primary keyword clusters:

- Cluster 1 (Technology): "Generative AI," "Large Language Models," "Artificial Intelligence," "Machine Learning," "Computer Vision," "Neural Networks."
- Cluster 2 (Context): "Sports," "Coaching," "Athletic Performance," "Team Sports," "Football/Soccer," "Basketball."
- Cluster 3 (Application): "Tactical Analysis," "Strategy," "Talent Identification," "Injury Prevention," "Decision Support Systems."

Inclusion and Exclusion Criteria

Studies were selected based on the following eligibility criteria to ensure relevance and quality:

Inclusion Criteria:
• Peer-Reviewed: Articles published in recognized scientific journals or high-impact conference proceedings.
• Language: Full-text available in English.
• Relevance: Studies explicitly addressing the application of AI in sports coaching, performance analysis, or sports management.
• Technology Focus: Research involving generative models, predictive analytics, or computer vision applied to sports contexts.

Exclusion Criteria:
• Consumer Fitness: Studies focusing solely on general population fitness apps or gamification without high-performance coaching relevance.
• Esports: Literature focusing exclusively on electronic sports, unless specific transferability to physical sports coaching is demonstrated.
• Purely Technical: Computer science papers focusing solely on algorithmic architecture without practical application or discussion of sports domain implementation.
• Grey Literature: Opinion pieces, blog posts, and non-peer-reviewed media, except for official white papers from recognized governing bodies (e.g., FIFA, IOC).

Screening and Selection Process
The systematic search strategy initially yielded a total of 190 records across the four identified databases. After importing references into the citation management software, 40 duplicate records were identified and removed.

The remaining 150 unique records underwent title and abstract screening. At this stage, 85 records were excluded as they did not meet the primary inclusion criteria; common reasons for exclusion included a primary focus on eSports without physical coaching transferability, consumer-level fitness applications, or non-generative AI technologies.

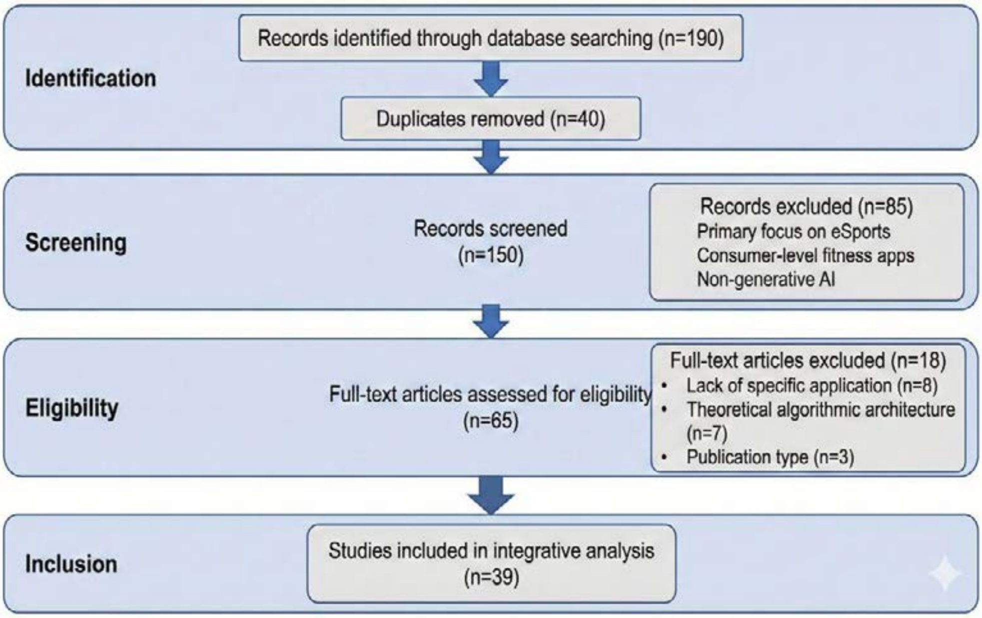
Subsequently, 65 full-text articles were retrieved and assessed for eligibility. A detailed review led to the exclusion of a further 18 articles. Reasons for exclusion at the full-text stage included:

• Lack of specific application to high-performance coaching workflows (n=8);

• Focus on theoretical algorithmic architecture without practical implementation (n=7);

• Publication type (e.g., commentary or non-peer-reviewed white papers) not meeting quality thresholds (n=3).

The final sample consisted of 39 studies (n=39) that formed the core of the integrative analysis.



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Data Analysis and Synthesis

Given the heterogeneity of the included studies, ranging from quantitative performance metrics to qualitative ethical analyses, a thematic synthesis approach was employed. Data was extracted and categorized into four distinct operational domains corresponding to the core functions of the coaching role:

1. Tactical Preparation: Scenario generation, opponent modeling, and strategic simulation.
2. Physiological Management: Load optimization, injury prediction, and personalized training prescription.
3. Talent Identification: Global scouting, predictive performance modeling, and recruitment analytics.
4. Ethical & Organizational Governance: Data privacy, algorithmic bias, and human-AI collaboration frameworks.

These themes form the structural basis of the results and discussion sections (Sections 4 and 5), culminating in the proposal of the "Coach as Editor" theoretical framework (Section 6).

Quality Assessment

To ensure the methodological rigor of the synthesized literature, included studies were appraised using the Mixed Methods Appraisal Tool (MMAT) version 2018. This tool was selected due to the heterogeneity of the sample, which included qualitative case studies, quantitative experimental designs, and technical systems papers. Studies were evaluated on five criteria appropriate to their design (e.g., clarity of research questions, appropriateness of data collection, and integration of results). Studies scoring below 60% on the quality criteria were excluded to minimize bias and ensure that the "Coach as Editor" framework is grounded in validated empirical evidence.

Data Extraction and Synthesis

Data was extracted using a standardized coding form capturing: (1) AI Architecture (e.g., GANs, Transformers, Reinforcement Learning); (2) Sport Context (Team vs. Individual); (3) Coaching Function (Tactical, Physical, Recruitment); and (4) Reported Outcomes (Efficiency gains, decision accuracy, user trust). Due to the divergent nature of the included studies, a narrative synthesis approach was adopted. Findings were clustered logically to map the transition from predictive analytics (traditional AI) to generative co-creation (GenAI), forming the basis for the SWOT analysis presented in Section 5.

Theoretical Framework: Human-Centric AI (HCAI) in Sports Coaching

To elucidate the transformation of the coaching role, this study adopts the Human-Centric AI (HCAI) framework (Shneiderman, 2020a, 2022). While earlier models utilized the "Human-in-the-Loop" (HITL) paradigm-often positioning the human merely as a validator of machine outputs-HCAI posits that high levels of automation need not reduce human control (Shneiderman, 2020a). Instead, the goal is "Augmented Intelligence," in which reliable, safe, and trustworthy AI systems are designed to amplify rather than replace human domain expertise (Shneiderman, 2020a, 2022).

Beyond Prediction: The HCAI Two-Dimensional Framework

Traditional views of automation often assume a zero-sum trade-off: as machine autonomy increases, human control decreases (Shneiderman, 2020a). HCAI challenges this by proposing a two-dimensional framework in which high automation (the AI generating complex tactical scenarios) and high human control (the coach directing strategic intent) coexist (Shneiderman, 2020a).

In the sporting context, this theoretical shift is critical. A purely autonomous system (e.g., an AI automatically substituting players) is unacceptable due to the high stakes of competitive outcomes and athlete welfare (Liu & Zhang, 2021; Naughton et al., 2024). Conversely, a purely manual system fails to leverage the computational scale of modern data. The HCAI model situates the coach not as a passive monitor, but as an active supervisory controller, setting the parameters (prompts), evaluating the probabilistic outputs (generation), and executing the final decision based on contextual wisdom (Liu & Zhang, 2021; Shneiderman, 2020b).

Generative Co-Creation: From Analysis to Synthesis

The emergence of Generative AI (GenAI) represents a functional shift within this framework from discriminative tasks to generative tasks (Bender et al., 2021; Lee, 2025).

- Discriminative AI (Traditional): Asking "What happened?" or "Who is likely to win?" (Classification/Prediction).
- Generative AI (Emergent): Asking "Create three training drills that fix this specific defensive error." (Synthesis/Creation).

This transition moves the theoretical interaction from interpretation to co-creation (Lee, 2025; Shneiderman, 2020a). The AI acts as a "stochastic parrot" or creative engine, producing novel tactical permutations that a human mind might not conceive due to cognitive bias or habit (Bender et al., 2021). The coach's role shifts from originating content to curating these machine-generated artifacts, guaranteeing they align with the team's philosophy and physical constraints (Lee, 2025; Wang & Wang, 2024). This "Generative Co-Creation" loop enables strategic innovation that is data-informed yet human-led (Lee, 2025; Shneiderman, 2022).

The Semantic Bridge: Natural Language as the Control Interface

A core barrier to HCAI adoption has historically been the "epistemic gap" between complex data science outputs and practical coaching intuition (Naughton et al., 2024). GenAI, particularly Large Language Models (LLMs), bridges this gap through semantic interpretability (Fernández et al., 2024; Wang & Wang, 2024).

By enabling coaches to interact with data using natural language (e.g., "Show me clips of Opponent X's corners when they are losing by one goal"), the technology democratizes access to high-level analytics (Fernández et al., 2024; Wang & Wang, 2024). This is consistent with Shneiderman's HCAI principle of "Reliable, Safe, and Trustworthy" systems-the interface is no longer a dashboard of obscure coefficients, but a conversational dialogue (Shneiderman, 2020a). This reduces the cognitive load required to operate the system, allowing the coach to focus entirely on applying insights rather than extracting them (Fernández et al., 2024).

Operationalizing GenAI: A Multi-Domain Synthesis

The practical application of GenAI in sports spans multiple operational domains, including physiological monitoring, tactical planning, talent identification, and organizational management. This section synthesizes contemporary empirical literature to demonstrate how conceptual models are being operationalized within professional sports contexts.

Tactical Preparation and Scenario Generation

The application of Generative AI (GenAI) in sports coaching is most evident in tactical preparation and strategic planning. While foundational research established AI's role in optimizing decision-making processes (Ide, 2025; Teixeira et al., 2025; Wang et al., 2024), recent scholarship indicates a shift from static analysis to dynamic simulation. Unlike conventional predictive models that forecast outcomes based on past events (Teixeira et al., 2025; Souaifi et al., 2025), GenAI systems are increasingly utilized to generate synthetic match scenarios that simulate complex competitive conditions (Wang et al., 2024; Ide, 2025).

From Prediction to Simulation

The current literature demonstrates that GenAI and advanced AI models can ingest extensive historical datasets on prospective opponents to model specific tactical behaviors. Research utilizing hierarchical reinforcement learning approaches has provided empirical support for this capability. For instance, studies have documented that AI-driven real-time tactical decision-making systems can yield quantifiable performance benefits, with reported improvements of 34.7% in tactical accuracy and 28.3% in execution efficiency (Zhang & Li, 2025). These analytical frameworks facilitate the systematic mapping of collective team dynamics, offering coaching staff unprecedented visibility into coordination patterns and potential strategic vulnerabilities (Teixeira et al., 2025; Wang et al., 2024).

Natural Language as a Tactical Interface

A critical advancement identified in the review is the democratization of these complex analytics through Natural Language Processing (NLP). As highlighted by Fernández et al. (2024) and Wang and Wang (2024), the complexity of data science is increasingly bridged by conversational interfaces that allow non-experts to query complex models in natural language. Coaching personnel can now formulate natural language queries-such as “Generate three defensive formations that demonstrate the highest probabilistic efficacy in neutralizing Opponent X’s counter-attacking patterns”-to derive actionable insights (Fernández et al., 2024; Lee, 2025). The system’s ability to generate visual representations of tactical configurations enables coaches to design targeted training drills without advanced coding or statistical expertise (Wang et al., 2024; TacticAI Collaboration, 2024).

Automating the Analytical Workflow

Beyond strategy formulation, GenAI is profoundly transforming the operational workflow of performance analysis through intelligent process automation (Souaifi et al., 2025; Kovoor et al., 2024). The manual burden of video tagging and event correlation has historically been a bottleneck in coaching workflows. However, recent investigations indicate that AI and GenAI-based systems can automate these labor-intensive processes, including tagging, event detection, and pattern recognition in spatiotemporal data (TacticAI Collaboration, 2024; Teixeira et al., 2025). By processing structured and semi-structured data to generate context-specific outputs, such as automated highlight compilations or individualized player performance summaries, these technologies effectively function as autonomous video analysis assistants (Souaifi et al., 2025; Naughton et al., 2024). This automation allows coaching staff to redirect time previously spent on data processing toward the qualitative interpretation of tactical trends (Teixeira et al., 2025; Wang et al., 2024).

Training Load Optimization and Injury Prevention

A critical dimension of contemporary coaching practice centers on ensuring athlete availability through systematic training load management and proactive injury prevention strategies (Kovoor et al., 2024; Souaifi et al., 2025). Comprehensive reviews document how AI technologies empower sports scientists to optimize training loads and mitigate injury risk through advanced data analytics (Souaifi et al., 2025; Naughton et al., 2024). By analyzing data streams generated by wearable sensor technologies, including GPS tracking systems, heart rate monitors, and accelerometers, AI models can predict injury risk by detecting subtle deviations in athlete biomechanics or physiological markers (Kovoor et al., 2024; Guelmemi et al., 2023).

Recent empirical evidence demonstrates that integration of AI and wearable technology in performance enhancement protocols yields substantial gains in efficiency, with studies reporting up to a 16% increase in training efficiency scores and significant reductions in reinjury rates. These findings indicate that AI-driven systems are capable of maximizing performance outcomes through real-time physiological monitoring and adaptive feedback mechanisms (Souaifi et al., 2025; Kovoor et al., 2024).

GenAI extends these capabilities by generating personalized training microcycles tailored to individual athlete profiles (Souaifi et al., 2025; Jain, 2025). Rather than requiring coaches to manually adjust training parameters across large squad populations, GenAI systems can autonomously generate individualized training sessions that account for each athlete's fatigue accumulation, recent match load exposure, injury history, and specific developmental objectives (Souaifi et al., 2025; Mishra et al., 2024). Research examining AI applications in exercise prescription contexts demonstrates that generative and advanced learning models can produce context-specific sports training plans by combining generative architectures with domain-specific knowledge (Souaifi et al., 2025; Kovoor et al., 2024).

The development of AI-based linguistic frameworks for monitoring physical health and sports performance enables sophisticated interpretation of physiological data through natural language processing capabilities (Wang & Wang, 2024; Fernández et al., 2024). Sports health monitoring management systems based on artificial intelligence algorithms can integrate multimodal physiological, environmental, and behavioral data to enhance metabolic health surveillance and optimize training adaptations (Souaifi et al., 2025; Kovoor et al., 2024). This level of personalization is scalable across organizational tiers, enabling resource-constrained amateur clubs to implement individualized training methodologies previously accessible only to elite-level organizations (Kovoor et al., 2024; Naughton et al., 2024).

Talent Identification and Scouting

Athlete recruitment processes are experiencing a fundamental transformation through AI-enabled talent identification systems (Souza et al., 2021; Altmann et al., 2025). Contemporary literature highlights that AI is revolutionizing talent identification by boosting predictive analytics capabilities and expanding the scope of talent search operations (Souza et al., 2021; Teixeira et al., 2025). Traditional scouting methodologies are characterized by subjective observational assessments and limited quantitative data points, constrained by geographical and resource limitations (Souza et al., 2021). In contrast, AI systems can analyze large datasets to identify athletes who conform to specific tactical profiles, including players competing in leagues that lack systematic manual scouting (Altmann et al., 2025; Teixeira et al., 2025).

Systematic literature reviews examining the application of artificial intelligence and machine learning in team sports talent identification show that these technologies are transforming talent identification and development (TID) processes across multiple dimensions (Altmann et al., 2025; Souza et al., 2021). Machine learning approaches enable sophisticated pattern recognition in performance data, facilitating identification of athletes demonstrating developmental trajectories indicative of future elite performance (Altmann et al., 2025; Teixeira et al., 2025).

GenAI can synthesize extensive datasets into accessible scouting reports formatted for coaching personnel and management decision-makers (Altmann et al., 2025; Wang & Wang, 2024). For instance, systems can generate comparative analyses between potential recruits and established elite players, producing detailed assessments that delineate strengths, weaknesses, developmental potential, and stylistic compatibility with existing tactical frameworks (Altmann et al., 2025; Teixeira et al., 2025).

However, the integration of AI in talent scouting raises important considerations regarding algorithmic transparency and decision accountability (Altmann et al., 2025; Souaifi et al., 2025). The development of Explainable AI (XAI) techniques that elucidate how AI systems generate talent recommendations is necessary to maintain transparent selection processes and address ethical concerns (Altmann et al., 2025; Naughton et al., 2024).

SWOT Analysis of GenAI Implementation in Sports

To provide a systematic and balanced evaluation of GenAI integration in sports contexts, this investigation uses SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis, a strategic planning framework that has been extensively utilized in sports science and educational contexts to assess technological innovations and organizational strategies (Sperlich et al., 2023; Yıldız & Çakır, 2016; Yıldız et al., 2024). Recent applications of SWOT analysis have examined distance education in sports sciences (Yıldız & Çakır, 2016), physical education teaching departments (Çetin & Yıldız, 2023), organizational and management processes under digital transformation (Yıldız et al., 2024), and the application of artificial intelligence in sport research, coaching, and performance optimization (Sperlich et al., 2023). This analytical framework enables structured evaluation of GenAI's viability across technical, organizational, and ethical dimensions (Sperlich et al., 2023).

Strengths

The literature confirms that GenAI's main advantage lies in its capacity to process multidimensional data streams-tactical, physiological, and biomechanical-far beyond human cognitive limits (Sperlich et al., 2023; Teixeira et al., 2025). This automation not only quickens decision-making in evolving environments (Sperlich et al., 2023; TacticAI Collaboration, 2024) but also enables the hyper-personalization of interventions, allowing coaches to scale elite-level analytical depth to entire squads without proportional increases in staffing (Sperlich et al., 2023; Naughton et al., 2024).

Weaknesses

Despite these capabilities, the "garbage in, garbage out" principle remains a fundamental constraint, particularly in resource-poor settings lacking robust data infrastructure (Sperlich et al., 2023; Naughton et al., 2024). Furthermore, the "black box" nature of deep learning architectures creates a trust gap; when systems produce "hallucinations"-plausible but factually incorrect tactical outputs-coaches may struggle to validate findings due to a lack of interpretability and the system's inherent inability to account for human psychological nuance (Sperlich et al., 2023; Bender et al., 2021; Shneiderman, 2020).

Opportunities

Beyond immediate performance gains, GenAI offers a path to competitive equity by allowing smaller organizations to substitute financial capital with computational strategic intelligence (Sperlich et al., 2023; A207 Study, 2026). This shift necessitates a revision of educational curricula to emphasize data literacy (Yıldız et al., 2024; A207 Study, 2026). Such educational realignment may, in turn, lead to the discovery of entirely novel tactical paradigms-strategies imperceptible to human observation but revealed through algorithmic pattern recognition (Teixeira et al., 2025; TacticAI Collaboration, 2024; Sperlich et al., 2023).

Threats

The most significant risks are ethical rather than technical. The collection of biometric data elicits serious concerns regarding surveillance and the violation of athlete autonomy (Ethics in Sport AI Group, 2025; Naughton et al., 2024). Moreover, reliance on potentially biased datasets can automate inequality (Ethics in Sport AI Group, 2025; Sperlich et al., 2023). In parallel, over-dependence on these tools threatens to atrophy the intuitive, embodied knowledge that defines expert coaching and may widen the digital divide between elite and amateur levels (Sperlich et al., 2023; A207 Study, 2026). This SWOT analysis shows that while GenAI offers substantial strengths and opportunities for transforming sports practice, successful implementation requires systematic attention to weaknesses and proactive mitigation of threats through robust governance frameworks, educational interventions, and human-centered design principles (Sperlich et al., 2023; Ethics in Sport AI Group, 2025).

Table 1. SWOT Analysis of Generative AI Implementation in Sports.

Internal Factors (Attributes of the Technology)	Strengths (Helpful)	Weaknesses (Harmful)
	1. **Computational Velocity:** Automates time-consuming analysis (video tagging, stat correlation) allowing real-time adjustments.	1. **Data Dependency:** “Garbage in, garbage out”-effectiveness is limited by the quality and volume of input data.
	2. **Multidimensional Synthesis:** Simultaneously processes tactical, physiological, and biomechanical data streams.	2. **Contextual Blindness:** Propensity for “hallucinations” (plausible but false tactical outputs) lacking real-world nuance.
	3. **Hyper-Personalization:** Generates individualized training microcycles for entire squads instantly.	3. **Algorithmic Opacity:** “Black box” reasoning makes it difficult for coaches to trust or explain specific AI recommendations.
	4. **Resource Scalability:** Provides elite-level analytical depth to organizations with limited staff.	4. **Lack of Empathy:** Inability to account for team dynamics, morale, or player psychology.
External Factors (Attributes of the Environment)	**Opportunities (Helpful)**	**Threats (Harmful)**
	1. **Democratization:** Leveling the playing field between wealthy franchises and smaller clubs via accessible AI tools.	1. **Ethical & Privacy Risks:** Surveillance concerns and lack of consent regarding biometric data usage.
	2. **Tactical Innovation:** Discovery of non-linear patterns and “Move 37” style strategies invisible to human observation.	2. **Professional Deskilling:** Risk of coaches losing intuitive “feel” or critical thinking due to over-reliance on automation.
	3. **Educational Reform:** Revitalizing coaching curriculums to focus on data literacy and prompt engineering.	3. **Algorithmic Bias:** Perpetuating historical biases found in training data (e.g., racial or stylistic stereotyping).
	4. **Injury Mitigation:** Proactive identification of injury risks before clinical symptoms appear.	4. **The Digital Divide:** Widening gap between organizations that can afford implementation/infrastructure and those that cannot.

Discussion and Recommendations for Sports Organizations

The transition toward an AI-enhanced coaching paradigm requires a deliberate, strategically coordinated organizational approach. Building upon earlier work by scholars who have long examined the evolving challenges of contemporary sports management (Nestorović et al., 2025), this transformation extends beyond technological adoption to encompass deeper cultural and operational shifts within sports organizations (European Commission, 2024; Sperlich et al., 2023).

The Coach as an “Editor”: Redefining Professional Roles in the AI Era

The integration of Generative AI necessitates a fundamental reconceptualization of the coaching profession. Historically, the sports coach has functioned as a solitary “Author” of strategy, responsible for observing raw data (match performance), synthesizing it through internal cognitive processes, and manually authoring training interventions or tactical plans (Naughton et al., 2024; Teixeira et al., 2025). This model is inherently constrained by bounded rationality-the cognitive limits of the human mind to evaluate vast quantities of variables simultaneously (Simon, 1955; Gigerenzer & Selten, 2001).

In the GenAI era, this role transitions to that of a sophisticated “Editor” and curator of algorithmic possibilities. Figure 1 provides a schematic overview of the proposed framework, positioning the coach as the editorial control point between machine-generated strategic alternatives and their contextualized execution.

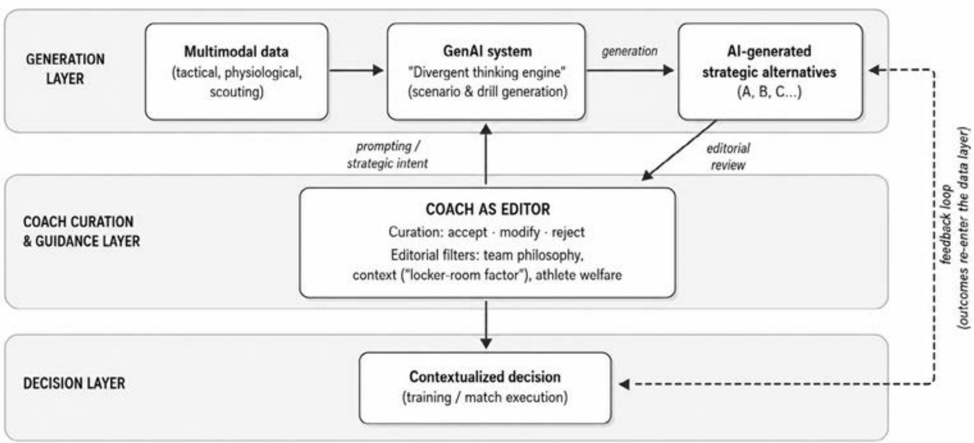

Figure 1. The Coach-as-Editor conceptual framework: the coach directs strategic intent through prompting, while AI-generated alternatives pass through editorial filters (team philosophy, contextual judgement, athlete welfare) before contextualized execution; outcomes feed back into the data layer.

From Cognitive Bottleneck to Divergent Thinking
Where traditional coaches are limited by time and memory, GenAI systems function as "divergent thinking engines." An AI model can ingest data from dozens of previous matches and generate multiple distinct tactical variations to neutralize an upcoming opponent (TacticAI Collaboration, 2024; Zhang & Li, 2025). The coach's role shifts from generating these options (a high-cognitive-load task) to evaluating them (a high-expertise task), consistent with human-AI collaboration models in coaching that position AI as an assistant rather than a replacement (Bender et al., 2021; Shneiderman, 2020; van der Vegt et al., 2025).

In this paradigm, the value of the coach is defined not by the volume of video watched but by the quality of the filter applied to AI outputs, separating statistically optimal from contextually viable strategies, as emphasized in recent discussions on AI-augmented coaching practice (Naughton et al., 2024; Sperlich et al., 2023).

Contextualization and the "Locker Room Factor"
While GenAI excels at identifying structural patterns (e.g., zones from which goals are frequently conceded), it remains blind to contextual nuances-often termed the "locker room factor." Systematic reviews note that AI systems struggle to account for complex psychosocial variables such as morale, interpersonal dynamics, and situational pressure (Ethics in Sport AI Group, 2025; Naughton et al., 2024).

Therefore, the "Editor" applies a critical layer of contextual validation. Conceptual and empirical work on AI in sport consistently shows that human coaches must adapt to or override AI suggestions when they conflict with contextual realities (e.g., fatigue, unreported injuries, match importance), while preserving ecological validity and athlete welfare (Sperlich et al., 2023; Ethics in Sport AI Group, 2025).

Prompt Engineering as a Core Coaching Competency
This role-related transformation introduces a new required competency: Prompt Engineering. Human-computer interaction and human-centered AI research identify the ability to pose precise, context-aware queries to AI systems as a central skill for effective human-AI collaboration (Shneiderman, 2020; Fernández et al., 2024; Wang & Wang, 2024). The capacity to formulate prompts such as "Generate three defensive transition drills for a midfield unit that struggles with communication, prioritizing low physical load" is increasingly recognized as analogous to traditional analytical skills in coaching (Lee, 2025; van der Vegt et al., 2025).
Ultimately, the "Coach as Editor" model does not diminish human agency; rather, it elevates the coach from a technician performing repetitive analytical tasks to a strategic architect, echoing broader findings that AI is most effective when augmenting rather than replacing human coaching relationships (Naughton et al., 2024; van der Vegt et al., 2025).

An Illustrative Scenario: Match Preparation in Professional Football

The practical meaning of the Coach-as-Editor framework can be illustrated by a typical weekly preparation cycle at a professional football club. Facing an opponent that scores predominantly from fast transitions, the head coach instructs the performance-analysis staff to query a GenAI system with a prompt such as: "Using our last ten matches and the opponent's last ten, generate three pressing structures that limit central counter-attacks, each with the associated training drills and estimated physical load." Within minutes, the system returns three tactically coherent alternatives-for example, a high 4-4-2 press, a mid-block 4-3-3 with a screening midfielder, and an asymmetric press directing play toward the touchline-each accompanied by simulated outcome probabilities and ready-made drill designs (cf. TacticAI Collaboration, 2024; Zhang & Li, 2025).

The coach then performs the editorial function that no current system can replicate. The first option is rejected because two key defenders are returning from injury and cannot sustain the required sprint volume; the second is modified because the designated screening midfielder is under visible psychological strain-the "locker room factor" invisible to the model; the third is accepted, with its drills adjusted to the club's training-ground dimensions. The decision, together with the rationale for overriding the statistically optimal option, is documented for subsequent review, consistent with the auditable-oversight practices recommended below. In this scenario, the AI contributes generative breadth-options the staff might not have conceived-while the coach contributes contextual depth: selection grounded in physiological, psychological, and organizational reality. This division of labor is precisely what the Coach-as-Editor framework formalizes.

This reconceptualization should nonetheless be read critically. At present the "Coach-as-Editor" model rests largely on conceptual argument and early pilot or simulation studies rather than on controlled, longitudinal evidence. Moreover, the very automation that frees the coach to curate may, if adopted uncritically, accelerate the deskilling and over-reliance identified as threats in Section 5. Whether the relationship between coach and machine becomes augmentative or substitutive depends less on the capability of the technology than on how organizations govern its use. In practical terms, this implies that clubs and federations should treat editorial oversight as a formal, auditable competency rather than an informal habit: requiring coaches to document the rationale for accepting, modifying, or rejecting AI-generated recommendations; retaining explicit human-override authority over decisions affecting selection and athlete welfare; and periodically reviewing whether reliance on generative tools is strengthening or eroding independent tactical judgement (Sperlich et al., 2023; Naughton et al., 2024; van der Vegt et al., 2025).

Table 2. Comparative Analysis of Traditional Discriminative AI versus Generative AI Capabilities in Sports Coaching.

Operational Domain	Traditional AI (Discriminative/ Predictive)	Generative AI (Creative/Synthetic)	Transformation of Coach's Role
Core Function	**Analysis:** Classifies data (e.g., “Is this a pass?”) and predicts outcomes (e.g., “xG models”).	**Synthesis:** Creates new data (e.g., “Generate a passing drill”) and simulates scenarios.	From **Data Consumer** to **Strategic Co-Creator**.
Tactical Preparation	Identifies historical patterns (e.g., heatmaps, passing networks of past games).	Generates novel “what-if” simulations and synthetic opponent behaviors.	From **Tactical Analyst** to **Scenario Director**.
Interaction Interface	Dashboards, spreadsheets, and rigid visualization tools requiring statistical literacy.	Natural Language Processing (NLP) allowing conversational querying (e.g., “Show me...”).	From **Dashboard Monitor** to **Prompt Engineer**.
Training Prescription	Flags risk factors (e.g., “High injury risk detected due to acute load”).	Authors specific training sessions and drills tailored to mitigate the identified risk.	From **Risk Manager** to **Intervention Designer**.
Talent Identification	Filters players based on statistical metrics and performance KPIs.	Synthesizes scouting reports and compares stylistic fit using unstructured video/text data.	From **Metric Scout** to **Contextual Assessor**.
Output Type	Numerical probabilities, coefficients, and static graphs.	Textual reports, synthetic video clips, and code/diagram generation.	From **Interpreter of Numbers** to **Curator of Concepts**.

Implementation Strategies: A Phased Organizational Approach

For sports clubs and governing federations, the implementation of GenAI should follow a systematically phased approach that addresses the technical, human, and organizational dimensions (European Commission, 2024; Ethics in Sport AI Group, 2025).

Phase 1: Infrastructure Development and Data Governance

Organizations must initially establish robust digital infrastructure capable of collecting, storing, and processing data with appropriate security protocols (European Commission, 2024; Kovoor et al., 2024). This foundational phase encompasses:

- Data collection systems: Integration of wearable sensor technologies, optical tracking systems, and performance monitoring platforms that generate standardized, interoperable datasets (Souaifi et al., 2025; Kovoor et al., 2024).
- Data storage architecture: Implementation of secure, scalable database systems with appropriate access controls and data protection mechanisms (European Commission, 2024; Ethics in Sport AI Group, 2025).
- Computational resources: Acquisition of hardware and cloud computing capabilities sufficient to support AI model training and real-time inference operations (European Commission, 2024; TacticAI Collaboration, 2024).
- Data quality assurance: Establishment of protocols for data validation, cleaning, and standardization to ensure AI systems operate on reliable information (Souaifi et al., 2025; Naughton et al., 2024).

Phase 2: Human Capital Development and Organizational Learning
Investment in human capital development represents a critical success factor that extends beyond traditional sports science education to encompass data literacy and AI competency (Sperlich et al., 2023; European Commission, 2024). Contemporary literature underscores that user-friendliness and comprehensive education programs are essential to overcome adoption barriers and resistance to technological change (Naughton et al., 2024; Ethics in Sport AI Group, 2025).

Specific educational interventions should include:

- Data literacy programs: Training for coaching personnel in fundamental statistical concepts, data interpretation methodologies, and the critical evaluation of algorithmic outputs (Teixeira et al., 2025; Sperlich et al., 2023).
- AI systems orientation: Familiarization with AI capabilities, limitations, and appropriate application contexts to develop realistic expectations and effective utilization patterns (Naughton et al., 2024; Ethics in Sport AI Group, 2025).
- Prompt engineering skills: Development of capabilities in formulating effective natural language queries to AI systems-a competency that will become increasingly central to coaching practice (Shneiderman, 2020; Fernández et al., 2024; Wang & Wang, 2024). Prompt engineering represents the ability to construct queries that elicit useful, contextually appropriate outputs from generative AI systems (Lee, 2025; van der Vegt et al., 2025).

- Interdisciplinary collaboration training: Education in collaborative work practices that bridge traditional disciplinary boundaries between coaching, sports science, and data analytics (Teixeira et al., 2025; Naughton et al., 2024).

Phase 3: Integration and Collaborative Practice Development

The transition from siloed operational structures-wherein data analysts function independently from coaching staff-to integrated, interdisciplinary teams represents a fundamental organizational imperative (Teixeira et al., 2025; Naughton et al., 2024). Research examining interdisciplinary practice in performance sports highlights key features of successful collaboration and provides evidence-based frameworks for sports leaders, coaches, and practitioners to evaluate their collaborative effectiveness (Teixeira et al., 2025; Sperlich et al., 2023).

Ethical Governance and Responsible AI Implementation

Sports organizations must establish comprehensive ethical governance frameworks to guide AI implementation and ensure responsible technological deployment (Ethics in Sport AI Group, 2025; European Commission, 2024).

Critical ethical considerations include:

- Data privacy and protection: Implementation of rigorous protocols safeguarding athletes' personal information, biometric data, and performance metrics in compliance with applicable data protection regulations (Guelmemi et al., 2023).
- Informed consent and transparency: Establishment of clear communication protocols informing athletes how their data is collected, analyzed, and utilized, thereby maintaining trust and respecting autonomy (Naughton et al., 2024).
- Algorithmic accountability: Development of oversight mechanisms ensuring that AI systems support rather than dictate coaching decisions, preserving human agency in critical determinations affecting athlete welfare and competitive outcomes (Sperlich et al., 2023).
- Bias mitigation and fairness: Systematic evaluation of AI systems for likely biases that might disadvantage particular athlete populations, with active measures to guarantee equitable treatment (Glebova et al., 2024).
- Explainability requirements: Adoption of Explainable AI (XAI) approaches that provide transparent rationales for AI-generated recommendations, enabling coaches to understand and critically evaluate system outputs (Sperlich et al., 2023).

Transparency with athletes regarding data-use practices is essential to preserving trust relationships that constitute the foundation of effective coaching (Ethics in Sport AI Group, 2025; van der Vegt et al., 2025). The democratization of coaching services through AI accessibility raises questions about whether AI coaching represents genuine service expansion or merely an ersatz substitute for human coaching relationships, a concern explicitly raised in comparative analyses of AI versus human coaching (van der Vegt et al., 2025; Sperlich et al., 2023).

Conclusion

The integration of Generative AI into the sports industry constitutes a transformative juncture in the historical evolution of athletic coaching and performance management.

The central scientific contribution of this review is twofold. It consolidates a fragmented, multidisciplinary body of evidence into a single sport-specific synthesis spanning tactical preparation, physiological load management, and talent identification. And more originally, it advances the Coach-as-Editor framework, which reconceptualizes the coach from a passive validator of machine outputs into an active curator of AI-generated strategic alternatives-a framing not previously articulated in the sports coaching literature. This framework offers both a theoretical lens for future empirical research and a practical template for organizational implementation.

Key Findings

1. Transformation of Professional Roles: From Author to Editor. The contemporary coaching role is undergoing substantial evolution from sole architect of strategic and tactical decisions to collaborative co-creator and sophisticated editor of AI-generated possibilities (Naughton et al., 2024; Lee, 2025; van der Vegt et al., 2025). However, the literature also identifies important considerations regarding the quality of AI coaching tools, human psychological and emotional responses to AI coaches, and the organizational integration challenges associated with AI coaching implementations (van der Vegt et al., 2025; Ethics in Sport AI Group, 2025; European Commission, 2024).

2. Democratization of Analytics: Leveling the Competitive Landscape. GenAI possesses significant potential to democratize access to sophisticated analytical capabilities, thereby reducing competitive disparities between resource-rich elite organizations and resource-constrained amateur or lower-tier clubs (Wang & Wang, 2024; Teixeira et al., 2025; A207 Study, 2026). However, this democratization raises important ethical and competitive fairness considerations, particularly around unequal access to data infrastructure and expertise (Ethics in Sport AI Group, 2025; Sperlich et al., 2023).

3. Synergy Over Replacement: The Human-AI Partnership Paradigm. The scholarly literature consistently supports conceptualizing AI as a “copilot” rather than a replacement for human coaching expertise (Shneiderman, 2020; Sperlich et al., 2023; Naughton et al., 2024). The synergistic relationship between AI computational capabilities and human contextual intelligence, affective understanding, leadership capacity, and ethical judgment represents the optimal operational model (Ethics in Sport AI Group, 2025; van der Vegt et al., 2025). The human element-encompassing empathy, relational trust, adaptive communication, ethical reasoning, and inspirational leadership-remains irreplaceable and arguably becomes more valuable rather than less so in technology-mediated environments (van der Vegt et al., 2025; Naughton et al., 2024).
4. Ethical Imperative: Governance Frameworks for Responsible AI Implementation. The accelerated adoption of AI technologies in sports contexts introduces substantial ethical risks pertaining to data privacy, athlete autonomy, algorithmic bias, transparency, accountability, and competitive fairness (Ethics in Sport AI Group, 2025; Guelmemi et al., 2023; European Commission, 2024). These multiple ethical challenges necessitate robust governance frameworks, transparent operational protocols, and ongoing ethical deliberation involving diverse stakeholder communities (Ethics in Sport AI Group, 2025; Sperlich et al., 2023).

Limitations

This review synthesizes a rapidly evolving field where data-driven validation lags technological development; many included studies are pilot implementations or simulations, and longitudinal RCTs remain scarce (Sperlich et al., 2023; Teixeira et al., 2025). Additionally, most of the research focuses on elite male team sports, limiting generalizability to other populations and contexts (Ethics in Sport AI Group, 2025). As an integrative review, the synthesis was also constrained by its search scope-four databases and English-language sources only-which may have excluded relevant non-English or grey-literature evidence, and the proposed “Coach-as-Editor” framework is itself a conceptual contribution that awaits direct empirical validation.

Future Directions

- Development of Sport-Specific Large Language Models. The creation of domain-specific Large Language Models trained exclusively on curated, high-quality sports datasets represents a priority research direction (Lee, 2025; Wang & Wang, 2024). Such specialized models would reduce algorithmic hallucinations-instances where AI systems generate plausible-sounding but factually incorrect outputs-by constraining

training data to validated, expert-annotated sports information (Bender et al., 2021; Ethics in Sport AI Group, 2025).

- Longitudinal Data-driven Confirmation Studies. Rigorous longitudinal investigations are needed to empirically validate the impact of GenAI-assisted coaching on competitive outcomes, athlete health metrics, developmental trajectories, and organizational performance across multiple competitive seasons (Teixeira et al., 2025; Naughton et al., 2024). Outcome metrics should encompass not only competitive performance indicators but also athlete well-being, injury incidence, career longevity, psychological development, and satisfaction with coaching relationships (Ethics in Sport AI Group, 2025; van der Vegt et al., 2025).
- Ethical Framework Development and Governance Research. Systematic research addressing the development, validation, and implementation of ethical models specifically tailored to AI applications in sports represents an urgent priority (Ethics in Sport AI Group, 2025; European Commission, 2024). Such frameworks have to address data governance, informed consent protocols, algorithmic transparency requirements, bias mitigation strategies, accountability mechanisms, and protection of athlete autonomy (Ethics in Sport AI Group, 2025; Sperlich et al., 2023). Comparative analyses of regulatory approaches across jurisdictions and competitive levels would inform the development of harmonized international standards while respecting contextual variations (European Commission, 2024). Participatory research methodologies that engage athletes, coaches, administrators, ethicists, and technology developers in the co-creation of governance frameworks would enhance legitimacy and pragmatic applicability (Ethics in Sport AI Group, 2025; A207 Study, 2026).
- Human-AI Interaction and Interface Design. Research examining optimal designs for human-AI interaction in coaching contexts should investigate interface characteristics, communication modalities, and workflow integration patterns that maximize usability, trust, and collaborative effectiveness (Shneiderman, 2020; Fernández et al., 2024). Understanding the psychological, emotional, and relational dimensions of human-AI coaching partnerships requires multidisciplinary approaches integrating sports science, human-computer interaction, organizational psychology, and coaching science (van der Vegt et al., 2025; Naughton et al., 2024).

Concluding Synthesis

In conclusion, the era of Generative AI in sports fundamentally concerns not the displacement of human expertise by machine intelligence but rather the empowerment of coaching professionals through partnership with sophisticated AI assistants (Shneiderman, 2020; Sperlich et al., 2023). This role transformation necessitates reconceptualizing coaching education, professional development, and organizational structures to prepare practitioners for collaborative human-AI practice (European Commission, 2024; Naughton et al., 2024). As technological capabilities continue advancing, scholarly and practical attention must increasingly shift from technological feasibility questions ("What can the technology do?") toward integration and governance questions ("How can it be deployed seamlessly, ethically, and effectively within the human-centric world of sports?") (Ethics in Sport AI Group, 2025; Shneiderman, 2020). The future of sports coaching resides not in artificial intelligence replacing human coaches but in augmented intelligence empowering them, creating synergistic partnerships in which computational power and human wisdom combine to unlock athletic potential unattainable through either component in isolation (Shneiderman, 2020; van der Vegt et al., 2025; Teixeira et al., 2025).

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Recived: 19.02.2026.
Revised: 29.06.2026.
Accepted: 10.08.2026.