A MULTI-AGENT DIGITAL TWIN BLUEPRINT FOR ATHLETE INJURY RISK ASSESSMENT AND REHABILITATION PLANNING

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ABSTRACT

Injury risk assessment and rehabilitation planning in high-performance sports require longitudinal, individualized reasoning over heterogeneous athlete data while remaining interpretable and human-aligned. Existing approaches often rely on monolithic predictive models that provide limited transparency and struggle to accommodate evolving athlete baselines and distinct decision processes across coaching and medical workflows. In this paper, we present a blueprint for a multi-agent digital twin system designed to support athlete injury risk assessment and rehabilitation planning. The proposed architecture centralizes multimodal data abstraction within a versioned athlete digital twin and distributes reasoning across specialized agents for risk assessment, rehabilitation planning, and human-facing coordination. By separating state management, domain-specific reasoning, and interaction with coaches and medical staff, the system enables interpretable, event-driven analysis and flexible human-AI collaboration. This paper presents an architectural foundation for future research on personalization, causal reasoning, and human-aligned decision support in athlete health management and related safety-critical domains.

1 INTRODUCTION

Injury prevention and rehabilitation are critical for athlete health and team performance, yet current approaches struggle with a fundamental tension: coaches need rapid, actionable guidance for daily training decisions, while medical staff require detailed, evidence-backed assessments for high-stakes interventions. Consider a professional team managing a star player eleven weeks post-ACL reconstruction. The coach asks, “Can he return to cutting drills?” The answer requires synthesizing biomechanical asymmetry trends, strength test results, pain trajectories, and protocol-defined progression criteria. This process traditionally requires hours of manual expert review and often yields conflicting opinions across coaching and medical staff.

Despite advances in sensing technologies Bahr (2016); Gabbett (2016), translating heterogeneous athlete data into reliable decision support remains difficult. Injury risk is inherently longitudinal and individualized, emerging from cumulative load and tissu morphology, delayed recovery, and subtle deviations rather than isolated events Windt & Gabbett (2017). Rehabilitation planning similarly requires stage-aware reasoning that balances recovery progression with performance demands Petersen et al. (2014). Existing computational approaches frequently rely on monolithic predictive models that map raw data directly to risk scores Rommers et al. (2020); Leckey et al. (2025). While effective in controlled settings, such models provide limited transparency and struggle to accommodate evolving athlete baselines, distinct reasoning processes across risk assessment and rehabilitation, and the multi-stakeholder coordination required in real-world practice Rudin (2019).

Recent advances in multi-agent systems and digital twin concepts suggest that decomposing complex decision-making into specialized, interpretable agents can improve modularity and human alignment in safety-critical domains Zheng et al. (2025); Chen et al. (2025); Long et al. (2026); Choi et al. (2026); Wu et al. (2024); Corral-Acero et al. (2020). However, systematically integrating these ideas into a coherent architecture for athlete health management remains challenging. Such a

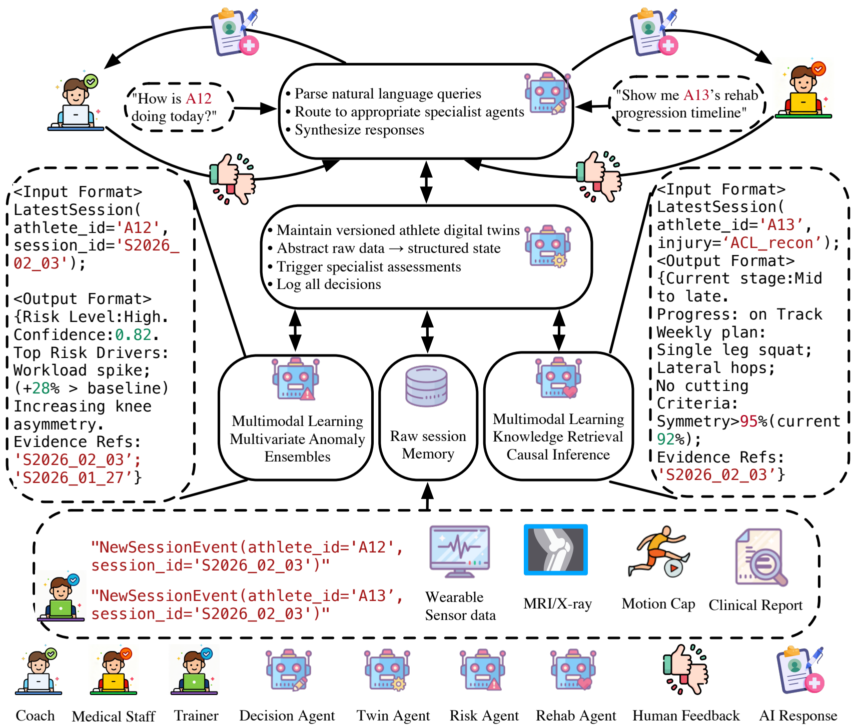

Figure 1: System architecture with four specialized agents coordinated via a versioned digital twin. Risk and Rehabilitation Agents perform domain reasoning over structured athlete states, while the Decision Agent handles natural language interaction. Input-output examples illustrate data flow.

system must balance longitudinal monitoring, personalized baselines, multi-stakeholder workflows, and interpretability.

We propose a multi-agent digital twin blueprint that addresses these challenges through architectural decomposition. A Twin Agent maintains versioned, longitudinal athlete states by abstracting heterogeneous data into structured baselines, trends, and deviations. Specialist agents for risk assessment and rehabilitation planning perform domain-specific reasoning over this shared state, while a Decision Agent coordinates human interaction by translating structured outputs into context-aware responses aligned with coaching and medical workflows. By separating state management, domain expertise, and human coordination, this blueprint enables interpretable, event-driven decision support for athlete health management.

2 System Architecture

2.1 Architectural Overview

As shown in Figure 1, the system consists of five interacting components: a Twin Agent, a Risk Agent, a Rehabilitation Agent, a Decision Agent, and a persistent Raw Session Memory. Multimodal data ingestion and abstraction are centralized within the Twin Agent, which serves as the single source of truth for athlete state. All downstream agents operate exclusively on structured state representations, ensuring modularity, consistency, and traceability across analyses. The system supports both event-driven updates triggered by new athlete sessions and query-driven reasoning initiated by human users.

2.2 Twin Agent and Session Memory

The Twin Agent maintains a continuously updated, versioned digital representation of each athlete by integrating heterogeneous data sources, including wearable sensor data, biomechanical measurements, motion capture, and clinical reports. Raw session data are preserved in a persistent memory layer for auditability and retrospective analysis.

Each `NewSessionEvent` triggers the Twin Agent to incrementally refine the athlete's digital twin. Rather than performing direct prediction, the Twin Agent focuses on state abstraction, encoding individualized baselines, temporal trends, deviations from personal norms, and latent factors relevant to injury risk and recovery. This structured state representation is designed to support downstream ensemble-style risk analysis by providing a consistent and comparable input space for multiple complementary risk estimators. As a result, the abstraction decouples data storage from downstream reasoning and provides a stable interface for all specialist agents.

2.3 Risk Agent: Injury Risk Reasoning

The Risk Agent performs early injury risk and fatigue assessment based on the structured athlete state provided by the Twin Agent. It focuses on identifying deviations from personalized baselines using multimodal and anomaly-aware reasoning, rather than population-level thresholds. To improve robustness, the agent aggregates signals from multiple complementary risk estimators operating on the shared athlete state, forming an ensemble-style risk assessment that captures different perspectives on injury and fatigue risk. The agent produces interpretable risk summaries that highlight key contributing factors with supporting historical evidence.

The Risk Agent supports future integration of reinforcement learning from human feedback to refine risk assessment policies. Responses delivered by the Decision Agent may be reviewed or corrected by coaches or medical staff, and such feedback is used to gradually refine risk assessment policies while preserving stability, interpretability, and safety constraints.

2.4 Rehabilitation Agent: Recovery Planning and Progression

The Rehabilitation Agent supports post-injury monitoring and recovery-oriented decision making. Operating on the shared athlete state, it synthesizes recovery trajectories, evaluates readiness for progression, and generates personalized rehabilitation recommendations that remain coherent with injury risk assessments. To contextualize recovery planning, the agent may retrieve relevant rehabilitation knowledge, such as established protocols, training guidelines, or recovery constraints, and incorporate this information into state-aware reasoning. In addition, the agent supports causal and counterfactual reasoning to assess how potential interventions or adjustments (e.g., workload modification or body composition changes) may influence future recovery trajectories.

Rehabilitation planning also benefits from the same conservative human-in-the-loop feedback mechanism used across the system, allowing recommendations to be reviewed and adjusted by medical staff while preserving medical constraints, interpretability, and safety.

2.5 Decision Agent and Human Interaction

The Decision Agent serves as the primary interface between the system and human users, including coaches and medical staff. It interprets natural language queries, coordinates access to relevant specialist agents, and synthesizes their outputs into concise, context-aware responses. The Decision Agent does not perform primary inference, but instead focuses on coordination, explanation, and alignment with human decision-making workflows.

2.6 System Workflow and Design Rationale

The system follows a hybrid interaction pattern. State-driven updates allow newly completed athlete sessions to trigger asynchronous updates to the digital twin and associated assessments, while query-driven reasoning enables on-demand synthesis of the most recent agent outputs. By centralizing state abstraction and distributing domain-specific reasoning across specialized agents, the architecture balances scalability, interpretability, and extensibility. This design is particularly suitable for safety-critical athlete health and rehabilitation management.

3 Challenges and Future Directions

While the proposed multi-agent architecture provides a structured blueprint for athlete injury risk assessment and rehabilitation planning, several open challenges remain and motivate directions for future research.

A key challenge concerns memory management in longitudinal multi-agent systems. Although the digital twin maintains a versioned athlete state, determining what information to retain, summarize, or discard over extended time horizons remains non-trivial. Accumulating historical data may introduce computational overhead or outdated context, whereas excessive compression risks losing clinically relevant information. Developing principled memory mechanisms that balance temporal fidelity, abstraction, and efficiency is therefore an important open problem.

Data availability and privacy further complicate real-world deployment. Athlete data are inherently sensitive and often distributed across teams or institutions. While cross-population learning could alleviate data sparsity and improve generalization, it must be achieved without centralizing raw data. This motivates the exploration of federated and privacy-preserving learning paradigms that support collaboration while respecting data ownership and regulatory constraints.

Beyond reactive assessment, future systems may adopt a more proactive role by reasoning over longer temporal horizons. Anticipatory analysis could surface emerging injury risks, delayed recovery patterns, or rehabilitation bottlenecks before they become critical, enabling more preventive and strategic decision support.

Finally, integrating causal and counterfactual reasoning remains an open research frontier. Current assessments primarily capture associations within historical data, limiting the system's ability to reason about hypothetical interventions. Incorporating causal models could support more meaningful what-if analyses, such as evaluating how alternative training or rehabilitation strategies might influence future injury trajectories.

These challenges indicate that the proposed architecture should be viewed as a foundation rather than a completed system. Addressing memory management, privacy-aware collaboration, proactive planning, and causal reasoning will be essential for advancing multi-agent digital twin systems toward reliable real-world deployment.

4 Conclusion

We presented a blueprint for a multi-agent digital twin system designed to support athlete injury risk assessment and rehabilitation planning. By centralizing multimodal state abstraction within a versioned athlete digital twin and distributing reasoning across specialized agents, the proposed architecture enables interpretable, event-driven analysis and flexible human-AI interaction in coaching and medical workflows. The system emphasizes a modular separation between state management, domain-specific reasoning, and human-facing coordination, while supporting a coherent end-to-end information flow from natural language queries to structured, evidence-backed recommendations. By prioritizing modularity, transparency, and human-in-the-loop design, this blueprint provides a principled foundation for future research on personalization, causal reasoning, and human-aligned decision support in athlete health management. Beyond sports health, these principles outlined in this work may generalize to other safety-critical domains that require collaborative expert reasoning and accountable human-AI systems.

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