The NFL's Digital Prospect

Why AI Reconstruction Leaves Athletes Unprotected

AI reconstruction, searchable football intelligence,
and the emerging law of film-derived athlete models

SantiniResearch.com

SANTINI · LAW · FIRM

ABSTRACT

Just days from the NFL Draft, top prospects are being evaluated not just as athletes, but as AI-generated digital doubles built from film, data, and proprietary modeling. This paper identifies a critical legal gap: the NFL's current rules leave athletes unprotected from employment decisions shaped by this new category of AI physical data. While the CBA protects sensor-collected data, it does not clearly allocate rights over the "digital prospect" – the machine-derived model that can be used to assess movement, injury risk, and market value. That leaves players vulnerable to being labeled, in effect, "high-risk movers" or "non-translatable athletes" through proprietary systems they cannot access, inspect, or contest. The law is currently better at regulating expressive clones than evaluative doubles. The immediate need is not to ban the technology, but to impose governance on AI physical data by establishing rights of provenance, access, and contestability before another draft class enters this legal vacuum.

Scope and Method

This paper relies on public sources only. It distinguishes direct claims supported by public disclosures from reasoned inferences about scouting applications. It does not claim access to any club's non-public draft models, vendor contracts, or proprietary datasets.

WHY THIS MATTERS NOW

- **The Draft Is the Pressure Point:** In the final days of evaluation, clubs are not just reviewing film – they are increasingly translating prospects into machine-readable models that can shape draft position, role projection, and market value.
- **What About the Players' Rights?:** Recent media coverage has begun to acknowledge AI's growing role in draft evaluation, but it still leaves the player-rights and governance implications largely unaddressed. [33]
- **The Legal Gap Is Immediate:** The NFL's Collective Bargaining Agreement protects sensor-collected data, but it does not clearly allocate rights over the film-derived "digital prospect" now emerging from AI reconstruction and model-based scouting.
- **Players Cannot See or Challenge the Labels:** These systems can generate highly consequential judgments – including movement-based risk and translatability assessments – without giving athletes any meaningful right to inspect, contest, or contextualize the result.
- **The Right Response Is Governance:** The problem is not AI scouting itself, but the absence of rules around provenance, access, and contestability before this model becomes normalized across the league.

I.

The End of Observation
Scouting Replaced by Reconstruction

The old scouting question was descriptive: what did the evaluator think he saw on film, and did the forty-yard dash or pro day confirm it? The new question is reconstructive: can the play itself be converted into a machine-readable account of how the athlete moved, what constraints he faced, and whether those movement patterns, especially around and through physical contact, look like ones that have translated to the NFL before? The prospect, in other words, is increasingly treated not only as a person to be watched but as a movement system to be modeled against the physical rigors of NFL contact and competition. [2-13]

This paper advances three claims, grounded in publicly available evidence but necessarily limited by the opacity of team draft evaluation processes. First, football has already crossed an important threshold from watching players to reconstructing them. Second, the most consequential near-term use case is probably not a single prospect score, but a searchable database of football reps that allows clubs to retrieve comparable movement patterns and physical contact scenarios, isolate translatable traits, and decide which plays really 'look NFL' once the rep is encoded as data. Third, the law still under-specifies who controls the resulting player model when it is derived from public film, private context, and club-built comparison logic rather than directly from a wearable on the athlete's body. [4-13, 20-29]

The trench is the clearest place to see the change. Offensive and defensive line play happens in compressed space, under heavy occlusion (blocked from camera view), and through contact. Those are exactly the conditions in which stopwatch metrics and clean drills lose descriptive power. If a system can reconstruct how a prospect maintains speed, posture, leverage, and path once the rep becomes messy and physical, it can answer a more football-native question than the combine was designed to answer. What emerges is the NFL digital prospect: a player reconstructed from film into a form that can be measured through the course of physical contact, compared against NFL rep libraries, queried for translatable movement traits, and, in bounded ways, simulated to estimate how his movement, in various body positions, while dealing with physical contact, around a messy line of scrimmage crowded with big men, would play in NFL conditions. [2-10, 29]

> “Once a club transforms film into searchable intelligence, it is no longer merely watching the athlete – it is building a model of him.

II. The New Scout
How Film is Transformed into AI Physical Data

The public record no longer supports a simplistic view in which teams either use 'film' or 'analytics.' Instead, the evidence suggests a multilayered stack. First, film-to-tracking systems convert All-22 into player coordinates and contextual physical metrics. SkillCorner publicly markets automated XY tracking from All-22 video, including on- and off-camera movement, alongside physical metrics such as speed, acceleration, separation, and get-off time. Teamworks now markets products for both NFL and college football that use frame-level tracking, connect every metric back to film, and express the output as coach-native traits rather than generic numerical dashboards. Second, league model layers already translate tracking into football judgments. AWS and NFL Next Gen Stats describe Pressure Probability as a system that identifies rushers, blockers, and their matchups, then measures the speed, magnitude, and evolution of pressure through a play. Third, broader player-model layers now exist in the form of the NFL's Digital Athlete, which combines video, tracking, and simulation to produce player-specific risk and training insights. Public disclosures describe the components of this stack, but emerging reporting and industry commentary suggest it is already being applied more aggressively in draft evaluation. [1-10, 30-33]

That stack matters because it produces what this paper calls AI physical data. The phrase does not mean that a team has hidden force plates beneath every snap. It means that the system derives football-relevant physical states from video and tracking: burst off the snap, acceleration into traffic, speed retention after first contact, body orientation during recovery, separation created or lost, path efficiency, and the way movement quality degrades or survives when the rep is compromised. The shift is from isolated testing to contextual physical inference. A prospect is no longer judged only by how he moves in shorts; he is judged by how his film-derived movement profile is likely to translate inside tighter, more physical NFL geometry. [2-10]

> This isn't scouting anymore. It's reconstruction – and the athlete has no idea he's been rebuilt.

III. The New Frontier
Searchable Intelligence & Partial Simulation

Once a rep is encoded as movement, body state, and context, the next logical step is not simply grading. It is retrieval. Teamworks openly describes its platform as a “digital scout” that evaluates traits at the frame level, adjusts for situation and opportunity, and links each metric back to curated film. SkillCorner similarly offers scalable All-22 tracking and standardized physical metrics across large multi-season datasets. In parallel, the sports-analytics literature has long treated play retrieval as a core problem. That literature is not NFL draft-room proof by itself, but it makes the inference straightforward: the ingredients for a searchable rep database already exist. [2-6, 13]

For trench evaluation, that could mean granular levels of search previously unheard of, for example, isolating reps defined by matchup context such as a 260-pound defensive end against a 315-pound offensive tackle, and comparing how those reps evolve after contact. The real edge lies in what follows: mapping the movement geometry, timing, and post-contact changes against an internal library of NFL plays that have likewise been encoded with AI physical data to determine whether the prospect moves and continues to move through equivalent contact in the same way as players who consistently win in the NFL. The value is finding a comp at the level of underlying movement and interaction. The cleanest way to describe this technology is through pose estimation, where software locates key body points to follow a tracked skeleton. This adds a body-state layer, estimating how the player was organized while moving. It allows evaluators to see whether a prospect still functions once the rep leaves the clean, pre-contact world. [2-8, 11-13, 29]

Based on public disclosures, the frontier is best described as partial simulation. The NFL says the Digital Athlete captures 3D player movement with synchronized cameras and uses video and other data to run millions of simulations and estimate injury risk. AWS and the NFL’s work on Pressure Probability shows a similar version of this logic: identify the relevant actors, reconstruct the interaction, and then model how the play evolves under those conditions. This is not a full video-game, generative simulation of a draft prospect’s entire career, but a bounded form of scenario modeling built on reconstructed movement and learned football relationships. [7-10]

The paradigm shift is therefore from outcomes to movement signatures. Traditional film asks: what happened on the play? Searchable football intelligence and partial simulation ask what physical and spatial pattern produced the play, and how often has that pattern translated to successful NFL play before? While ordinary football film does not yet provide ground-truth force numbers for every trench rep, clinical and performance systems already use video analysis to measure the observable effects of force, including deceleration, displacement, and speed retention through contact. [4-10, 13, 29]

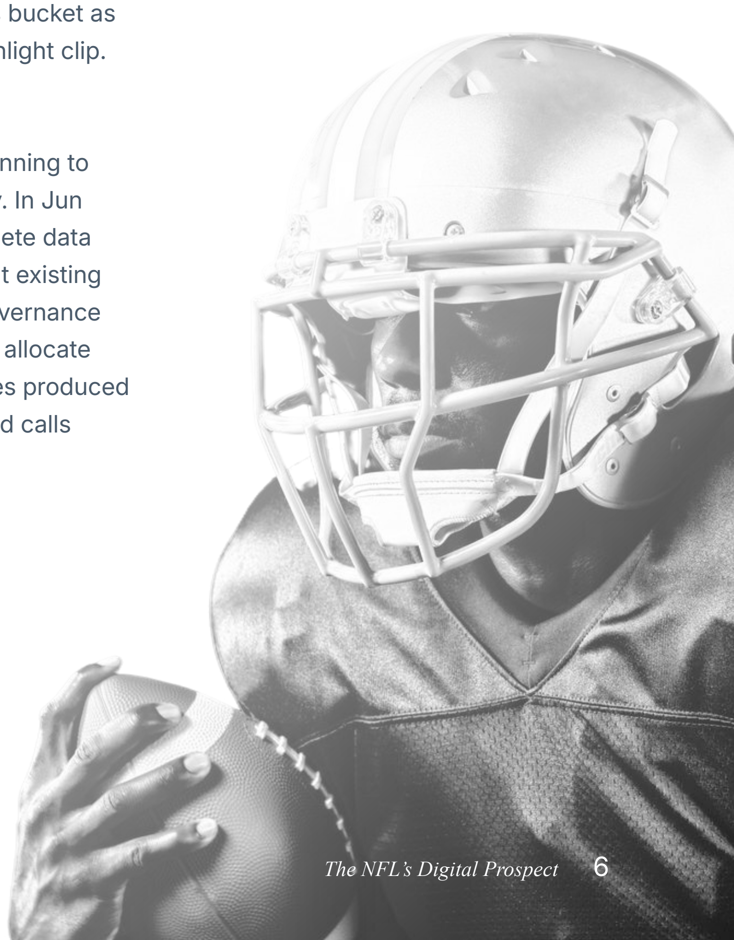
> “A club may know more about how your body moves under pressure than you do – and you have no right to see it.

IV. Legal Vacuum
Why No One Owns the AI-Derived Athlete Double

The AI-derived prospect is a legal orphan: the NFL's existing CBA is a narrow baseline that explicitly addresses player ownership of sensor-collected data but fails to govern the much broader category of film-derived AI physical data, leaving a critical gap in player protection. Article 51, section 14 states that each individual player owns his personal data collected by approved sensors, while also allowing club staff access, forbidding commercial use by players, and prohibiting the use of sensor data in contract negotiations. That baseline matters because it proves football already recognizes that athlete-generated data implicates ownership, governance, and bargaining power. But it is only a baseline, and a narrow one. It speaks directly to sensor-collected data. It does not clearly answer who controls the prospect model derived from film analysis, similarity search, and club-built inference layers. [20]

The digital prospect is legally harder because it splinters into multiple layers that need not share an owner. The source footage may be controlled by a broadcaster, league, conference, school, or scouting service. The extracted coordinates, event labels, and contextual features may be governed by vendor or club contract. The trained model, feature engineering, and comparison embeddings are likely to be claimed as club or vendor intellectual property. The player's identity, however, remains bound up in all of it. A club may therefore possess a prospect profile that is deeply personal in function because it predicts how the athlete moves, degrades, recovers, or compares to others. But this profile would not fit neatly into the same rights bucket as a wearable or a public highlight clip. [20-25]

Recent scholarship is beginning to name this problem directly. In Jun Woo Kwon's article on Athlete data sovereignty, he argues that existing privacy law and sports-governance frameworks do not clearly allocate rights over the digital traces produced through play or training and calls for an athlete-centric sovereignty model. Kevin Nguyen's paper in the Colorado Technology Law Journal similarly argues that players should be able to exercise ownership rights over motion data and that any expansion of collection and use should be limited, transparent, and consent-based. The important point for football is that these arguments do not lose force merely because the data were inferred from film rather than measured by a chest strap. If the output materially represents the athlete's body and materially influences employment decisions, the governance problem remains. [21-22]



Continued →

IV. Legal Vacuum (Continued)

Broader digital-twin and inferred-data scholarship points the same way. Burr and coauthors, writing in AI & Society, explain that digital-twin ownership questions fracture across raw data, processed datasets, algorithms, and the model itself. Reuters' 2024 digital-twin analysis likewise warns that privacy law's concepts of minimization, deletion, consent, and explainability map awkwardly onto continuous, individualized replicas whose value depends on historical data and predictive use. Sorrentino and López-Guzmán's work on avatars in Frontiers in Virtual Reality reaches an especially relevant, albeit unfinished, conclusion: inferred data can be as revealing and consequential as explicitly collected biometric data, yet legal protections often remain unclear precisely because the information was inferred rather than directly captured. That insight is central here. A frame-by-frame model, built from individual moments of video, may never look like the athlete in the way an AI-generated image does, but it may still reveal and operationalize a highly individualized representation of the athlete's body and tendencies. [23-25]

Publicity, NIL, and digital-replica law only partially solve this. California's AB 2602 and the proposed NO FAKES Act are aimed at unauthorized, outwardly identifiable digital replicas of a person's voice or visual likeness. NCAA NIL rules similarly focus on commercial use of name, image, and likeness. Those regimes matter because they show a growing willingness to protect digital identity. But they do not squarely reach the internal scouting model that may never be shown to the public, may not present the athlete's face or voice at all, and may nonetheless affect draft grade, roster value, training decisions, or a market label such as 'high-risk mover' or 'non-translatable athlete.' The resulting gap is not one of visibility but of function: the law is better at regulating expressive clones than evaluative doubles. [26-28]

> The law is better at regulating expressive clones than evaluative doubles.

V.

The Path Forward
A Rights Framework for the Digital Prospect

A workable governance framework must focus less on whether the source was a wearable or a camera, and more on whether the resulting model materially represents and evaluates the athlete. The key principle is derived-data parity: rights should not evaporate merely because a team inferred the information instead of measuring it directly. While public film is a legitimate scouting input, when that film is transformed into a persistent, searchable, high-value player model, procedural safeguards must attach to the outputs that drive employment decisions.

These safeguards should be informational and procedural. At minimum, any governance framework should provide athletes transparency regarding which data categories feed the model; whether film-derived outputs are merged with private training or medical records; and whether materially adverse conclusions can be challenged. In football terms, the primary risk is the creation of an internal prospect double, complete with latent traits and risk labels, that follows an athlete from the draft room to free agency without any practical way for the player to inspect or contest the underlying inferences.

This framework also requires a rigid boundary between internal evaluation and secondary exploitation. A club's internal use of a model to rank prospects is distinct from repurposing that model for commercial products, external training, or avatar-like reuse. Football needs a sport-specific structure that reaches internal evaluative doubles before they are converted into monetized identity products.

> “Derived-data parity: rights should not evaporate merely because a team inferred the information instead of measuring it directly.

VI. Conclusion
The Athlete Needs Governance

The public record suggests that NFL teams now possess the ingredients to reconstruct players from film into data-rich models that are measured, compared, and partially simulated. However, the law remains fragmented, covering sensor data and NIL rights but failing to govern the film-derived digital prospect. This gap is manageable if football adopts a rights framework focused on provenance, access, and contestability. Once a club transforms film into searchable intelligence, it is no longer merely watching the athlete; it is building a model of him. The choice is clear: either the league adopts governance, or it leaves every digital prospect a legal orphan.

> “The choice is clear: either the league adopts governance, or it leaves every digital prospect a legal orphan.

References

1. Los Angeles Rams, "Rams and SprintAI join forces to revolutionize player management with AI-powered insights," October 2, 2024. Accessed April 14, 2026.

2. SkillCorner, "American Football," Accessed April 14, 2026.

3. SkillCorner, "UFL chooses SkillCorner to Provide Player Tracking and Scouting Insights," April 17, 2025. Accessed April 14, 2026.

4. Teamworks, "Intelligent Player Personnel Platform for NFL," Accessed April 14, 2026.

5. Teamworks, "Video-First, Data-Driven Coaching Solution for NFL," Accessed April 14, 2026.

6. Teamworks, "The Future of Football Player Evaluation" and "Teamworks Intelligence for College Sports," Accessed April 14, 2026.

7. Entin, Ari. AWS, "Crunching the Numbers with Next Gen Stats: Unveiling the Impact of Defensive Pressure in the NFL," AWS for M&E Blog, September 20, 2023. Accessed April 14, 2026.

8. Entin, Ari. AWS, "Feel the Pressure with new online game Playbook Pass Rush from AWS and NFL Next Gen Stats," November 9, 2023. Accessed on April 14, 2026.

9. Langton, Jennifer. NFL.com, "Building a Digital Athlete: Using AI to rewrite the playbook on NFL player safety," February 1, 2024. Accessed on April 14, 2026.

10. NFL.com, "Advancing Player Health and Safety with the Digital Athlete," January 11, 2026. Accessed April 14, 2026.

11. Ajmeri, Omar and Shah, Ali, "Using Computer Vision and Machine Learning to Automatically Classify NFL Game Film and Develop a Player Tracking System," MIT Sloan Sports Analytics Conference research paper.

12. Johnson, Neil, "Extracting Player Tracking Data from Video Using Non-Stationary Cameras and a Combination of Computer Vision Techniques," MIT Sloan Sports Analytics Conference research paper.

13. Wang, Zheng et al., "Effective and Efficient Sports Play Retrieval with Deep Representation Learning."

14. Texas A&M, "Kratik Malhotra - Director of Sports Science & Analytics," staff directory, Accessed April 14, 2026.

15. MIT Sloan Sports Analytics Conference, "Kratik Malhotra," speaker profile, Accessed April 14, 2026.

16. Malhotra, Kratik,"College Football Analytics: Analyzing Tracking Data and Film Concurrently to Get an Upper Hand,"MIT Sloan Sports Analytics Conference, 2020 session page.

17. Seifert, Kevin, "How AI is Pushing NFL Draft Prep 'to a different level'" April 11, 2026. Retrieved April 14, 2026.

18. Hale, David, "FSU rides GPS technology to title," ESPN, June 22, 2014.

19. Texas A&M Athletics, "Texas A&M Sports Science Launches AI Platform with Gemini Sports Analytics," October 18, 2023; "Introduction to the Monitoring Process at Texas A&M," January 24, 2024; Accessed April 14, 2026.

20. NFL and NFLPA, *Collective Bargaining Agreement (2020-2030)*, Article 51 section 14 and related player-data provisions; Accessed April 14, 2026.

21. Kwon, Jun Woo, "Athlete data sovereignty: addressing the legal and policy gaps in sports technology," Frontiers in Sports and Active Living, December 2025, 7.

22. Nguyen, Kevin, "Who Owns the Digital Athlete?," Colorado Technology Law Journal, Volume 23, Issue 2, October 24, 2025.

23. Burr, Christopher David et al., "Realising the digital twin: a thematic review and analysis of the ethical, legal, and social issues for digital twins in healthcare," AI & Society, February 7, 2026.

24. Sorrentino, Giacomo, and López-Guzmán, Javier, "Rethinking privacy for avatars: biometric and inferred data in the metaverse," Frontiers in Virtual Reality 6, May 11, 2025.

25. Illman, Erin, "Avoiding growing pains in the development and use of digital twins," Reuters, August 20, 2024.

26. California Labor Code, Section 927.

27. Senators Coons, Blackburn, Klobuchar, and Tillis, "NO FAKES Act" one-pager, Accessed April 14, 2026.

28. NCAA, "NIL (Name, Image, Likeness)"' official resource page, accessed April 14, 2026.

29. Uhlrich, Scott D. et al., "OpenCap: Human movement dynamics from smartphone videos," PLOS Computational Biology, October 19, 2023; OpenCap / Stanford Mobilize Center, "OpenCap," informational pages. Accessed April 15, 2026.

30. Connolly, Oliver, in Read Optional Podcast, "2026 NFL Draft Tiers & Evaluations: Interior Defensive Linemen – Part II," hosted by Jon Ledyard (April 3, 2026), at 45:56–47:23 and 1:50:21–1:50:50.

31. Zierlein, Lance. Comment on X (formerly Twitter), April 6, 2026, 11:03 p.m., in reply to a post by @ BillyM_91 (April 6, 2026, 8:00 p.m.) quoting Oliver Connolly's remarks in Read Optional Podcast, "2026 NFL Draft Tiers & Evaluations: Interior Defensive Linemen – Part II," hosted by Jon Ledyard (April 3, 2026), at 45:56–47:23 and 1:50:21–1:50:50.

32. Connolly, Oliver, in Read Optional Podcast, "2026 NFL Draft Tiers & Evaluations: Wide Receivers – Part I," hosted by Jon Ledyard (March 17, 2026), at 7:55–8:17.

33. Seifert, Kevin. "How AI Is Pushing NFL Draft Prep to 'a Different Level.'" ESPN, April 11, 2026. Accessed April 15, 2026.

Frank Santini is a personal injury attorney and public safety researcher whose work focuses on accident causation, roadway safety, and emerging transportation risks, as well as toxic chemicals, dangerous products, medical errors, and the growing impact of technology on safety and accountability. He is the founder of Santini Personal Injury & Car Accident Law, a firm representing injury victims in matters involving motor vehicle crashes, commercial trucking collisions, medical malpractice, and other catastrophic injuries.

Santini is a graduate of Muhlenberg College in Allentown, Pennsylvania, and Stetson University College of Law in Gulfport, Florida, where he graduated first in his class among full-time students. In addition to litigation, Santini conducts independent research through Santini Research, examining topics such as tractor trailer accidents, e-bike crash risks, AI-driven systems, and emerging public safety issues affecting communities, as well as the evolving rights of individuals in data-driven environments, including professional athletes.

He is the author of a published article in the American Bar Association's Law Practice Management Journal and has participated in dozens of speaking engagements throughout the country. His recent work expands into areas such as artificial intelligence, digital reconstruction, and athlete data rights, exploring how new technologies are reshaping risk, performance evaluation, and legal accountability in industries like professional sports, including the NFL.

Beyond his legal work, Santini is involved in community and charitable initiatives that support local organizations and families in need. His work often bridges legal analysis, public safety research, and forward-looking policy issues to better understand and communicate the factors, both traditional and technological, that contribute to preventable injuries and systemic risk.

SANTINI • LAW • FIRM

SantiniResearch.com