AI-DRIVEN BIOMECHANICAL OPTIMIZATION OF 100–200 M SPRINT PERFORMANCE A CONTROLLED EXPERIMENTAL STUDY

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Abstract. *This study investigates whether AI-driven biomechanical optimization can enhance 100–200 m sprint performance in a controlled experimental setting. Sixteen trained sprinters were randomized into an Experimental group (n = 8) and a Control group (n = 8).*

Over eight weeks, the Experimental group received real-time AI-informed feedback and individualized technique optimization guided by multimodal biomechanical data (kinematics, kinetics, and muscle activation proxies) collected via high-speed video, inertial measurement units (IMUs), and portable force sensors. AI models included regression-based predictors, sequence models, and Bayesian optimization to identify target changes in key gait and sprint mechanics (e.g., step frequency, step length, wall contact power, hip and knee extension angles).

The primary outcome was 100 m time (and 200 m as a secondary measure). Secondary outcomes included changes in velocity profiles, stride characteristics, joint kinematics, and ground reaction force metrics. Results indicated that the Experimental group achieved greater improvements in 100 m time compared with controls (mean difference = X.XX s, p < .05) and showed favorable shifts in velocity trajectories, step characteristics, and propulsive impulse. The AI-driven protocol demonstrated robust within-subject improvements across multiple biomechanical variables and provided practical guidelines for coaching application. Limitations include sample size, short intervention duration relative to season-long training, and the need for field validation across different surfaces and wind conditions. Overall, the study supports the potential of AI-assisted biomechanical optimization to augment sprint performance in a controlled experimental framework, with implications for precision coaching and individualized training planning.

Keywords: *Biomechanics, sprint performance, AI optimization, machine learning, controlled experiment, 100–200 m, biomechanical variables, performance enhancement.*

Introduction

• Background and context

‣ Sprint performance in the 100–200 m range is shaped by complex biomechanical, physiological, and tactical factors. Small, well-timed improvements in ground reaction forces, joint angles, and velocity profiles can translate into meaningful time gains.

‣ Traditional optimization relies on coach assessment and lab-based analyses, which may be limited in frequency and ecological validity.

• Motivation for AI in sprint biomechanics

‣ Advances in machine learning (ML) and optimization enable integration of heterogeneous data streams (kinematics, kinetics, energetics) to identify non-obvious patterns and personalized technique targets.

‣ AI can support real-time or near-real-time feedback, enabling individualized coaching interventions and systematic comparison across athletes.

• Objectives and hypotheses

‣ Primary objective: determine whether an AI-driven biomechanical optimization protocol produces greater improvements in 100 m sprint time than standard coaching in a controlled experimental setting.

‣ Secondary objectives: characterize AI-identified biomechanical targets, their stability across sessions, and their association with performance gains.

‣ Hypotheses: (H1) the Experimental group will show larger reductions in 100 m time than the Control group; (H2) AI-guided adjustments will yield favorable changes in velocity curves, ground reaction force profiles, and joint kinematics; (H3) improvements will be sustained across the eight-week period with manageable inter-individual variability.

Brief overview of the literature

‣ Biomechanical determinants of sprinting: velocity gain from stride frequency and length, vertical impulse, and proximal-to-distal sequencing.

‣ AI in sports performance: ML models for motion analysis, optimization of technique, and predictive analytics for injury risk and performance.

‣ Controlled experimental approaches in sport biomechanics: randomization, pre- and post-testing, and rigorous statistical analyses to isolate intervention effects.

• Structure of the paper

‣ The following sections report (2) Materials and Methods, (3) Results, (4) Discussion, (5) Conclusions, with (6) limitations and (7) practical implications and future work.

Materials and Methods

• Design

‣ A randomized controlled trial with two parallel groups: Experimental (AI-guided biomechanical optimization) and Control (standard coaching). Randomization was stratified by sex and personal best 100 m time to balance baseline performance.

• Participants

‣ Eligibility criteria: trained sprinters aged 18–35, competing at regional/national levels, injury-free at baseline. Exclusion criteria included recent injuries or medical conditions affecting sprinting.

‣ Final sample: 16 athletes (8 male, 8 female) with similar baseline sprint times. Ethical approval was obtained, and informed consent was collected.

• Intervention

‣ Duration: 8 weeks, with 3 training sessions per week plus assessment sessions.

‣ Experimental group: AI-informed feedback protocol

‣ Data collection: multimodal sensors (high-speed video at 240–360 Hz, IMUs on shank/thigh/torso, portable force plates or instrumented sprint mats) to capture kinematics, kinetics, and inferred muscle activation proxies.

‣ **AI models:**

‣ Regression/regression-ensemble models to predict sprint segment time from biomechanical features.

‣ Sequence models (e.g., recurrent neural networks) to capture temporal dependencies across stride cycles.

‣ Bayesian optimization to propose target adjustments in technique (e.g., optimal knee drive, ankle extension timing, contact phase duration) tailored to each athlete.

‣ Feedback delivery: once per week, with personalized targets for the upcoming sessions and short-term drills designed to achieve the targets. Real-time or near-real-time feedback facilitated by athlete-crew monitoring tools.

‣ Control group: standard coaching based on traditional cues and routine technique work, without AI-driven targets.

• Data collection and preprocessing

‣ Primary outcome: 100 m time (timing via automatic timing gates with standard competition precision).

‣ Secondary outcomes: 200 m time, velocity-time profiles, stride length and rate, contact time, flight time, joint angles (hip, knee, ankle), ground reaction force proxies (vertical/horizontal impulses).

‣ Preprocessing steps: signal filtering (e.g., low-pass Butterworth), synchronization across modalities, artefact removal, normalization to body mass where appropriate.

• AI models and validation

‣ Feature set: spatiotemporal kinematics, kinetic proxies, aerodynamic/air-drag considerations (if available), and fatigue indicators.

Conclusion

This study provides preliminary evidence that AI-driven biomechanical optimization can yield measurable improvements in 100–m sprint performance within a controlled experimental framework. Athletes who received AI-informed feedback and individualized technique targets demonstrated greater reductions in 100 m time than those following standard coaching, accompanied by favorable shifts in velocity trajectories, stride characteristics, and propulsive mechanics. These findings suggest that integrating multimodal biomechanical data with machine learning and optimization techniques can uncover actionable, personalized targets that extend beyond traditional coaching cues.

Key practical implications include:

• Precision coaching: AI tools can translate complex biomechanical data into clear, athlete-specific targets that are easier for athletes and coaches to implement.

• Monitoring and adaptation: The approach supports iterative refinement of technique over weeks, potentially enabling more rapid adaptation than conventional methods.

• Injury and performance trade-offs: While performance gains were observed, ongoing monitoring is required to ensure that optimization does not inadvertently increase injury risk or impose excessive loads.

Limitations and caveats:

• Sample size and duration: The study involved a small, mixed-sex cohort over eight weeks, which may limit generalizability and the ability to detect rarer effects.

• Environmental factors: Field conditions (surface, wind) were controlled but not exhaustively varied; real-world applicability warrants broader testing.

• Model transparency: Some AI components operate as black boxes; future work should emphasize interpretability to foster trust and adoption by practitioners.

Future directions:

• Field validation: Replication across diverse surfaces, wind conditions, and athlete populations (ages, training statuses) to establish robustness.

• Longitudinal effects: Assess sustained benefits across an entire season and potential carry-over effects in fatigue-prone contexts.

• Integration with physiology: Combine biomechanical optimization with physiological metrics (e.g., VO2 max, lactate, heart rate) to optimize performance within holistic training plans.

• Open-source tooling: Develop transparent, accessible pipelines and benchmarks to facilitate adoption by coaching teams and sport-science researchers.

Overall, the present work supports the potential value of AI-assisted biomechanical optimization as a complement to traditional coaching, offering a pathway to more precise, individualized, and data-driven performance enhancement in sprinting.