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Wesam Al Attar singularity evaluation-infinity: a predictive simulation framework for motor intent collapse in athletes

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Background: Sustainable athletic performance requires maintaining motor intent stability under physiological stress. Current injury prediction approaches focus on isolated biomechanical markers rather than integrated physiological system dynamics.

Objective: To develop and validate through comprehensive simulation the Wesam Al Attar Singularity evaluation-infinity (WASe- ∞) framework for predicting motor intent collapse by integrating neuromuscular, cognitive, and coordination factors into a unified risk assessment model with clear pathways for empirical validation.

Methods: A rigorous simulation-based approach was employed using parameters derived from published biomechanics datasets. The WASe- ∞ framework integrates five physiological domains through a weighted convergence equation with coefficients derived through systematic three-stage optimization including comprehensive sensitivity analysis. The foundational model was validated using 60 simulated athlete profiles across four sports over 60-minute sessions, generating 360,000 data points for analysis with built-in AI integration capabilities.

Results: The WASe- ∞ framework achieved strong predictive performance within the controlled simulation environment with an area under the curve of 0.930 and 95% confidence interval of 0.915–0.946. Risk stratification revealed realistic distributions: 20.5% low-risk, 58.2% moderate-risk, 20.0% high-risk, and 1.4% critical-risk measurements. Sport-specific differences emerged with swimming showing highest mean scores (0.727 ± 0.210) and running lowest (0.605 ± 0.178), consistent with epidemiological data indicating elevated shoulder injury risk in competitive swimmers (40%–70% prevalence). Strong factor correlations supported theoretical foundations with comprehensive sensitivity analysis confirming framework robustness (AUC remained >0.90 for coefficient variations up to $\pm 15\%$).

Conclusion: This foundational study establishes the WASe- ∞ framework as a theoretically robust foundation for future empirical validation with human athletic populations. The simulation-based validation demonstrates strong theoretical validity while providing clear performance benchmarks and detailed protocols for subsequent real-world validation studies. The framework's architecture positions it for integration with emerging multimodal sensor technologies, representing a critical step toward transforming injury prevention from reactive treatment to proactive risk management.

KEYWORDS

artificial intelligence, athletic performance, biomechanics simulation, motor intent collapse, multimodal data, predictive modeling, sports injury prediction, wearable sensors

1 Introduction

Sport biomechanics has evolved from descriptive analysis of movement patterns (1, 2) to sophisticated predictive modeling of injury risk and performance optimization (3). Recent advances in data-driven deep learning approaches have enabled more sophisticated prediction of biomechanical failure mechanisms, including ligament fatigue under complex loading conditions (4) and anterior cruciate ligament (ACL) force prediction using biomechanical landing patterns before and after fatigue (5). Traditional approaches to injury prediction have relied primarily on isolated biomechanical markers, training load metrics, or single-modality physiological measurements (6). While these approaches have provided valuable insights, they fail to capture the integrated nature of human movement systems where injury risk emerges from complex interactions between neuromuscular, cognitive, and coordination factors (7).

The concept of motor intent represents the neural drive that initiates and regulates coordinated movement patterns (8, 9). Motor intent collapse occurs when this neural drive becomes insufficient to maintain movement quality under physiological stress (10), creating conditions conducive to injury. This phenomenon extends beyond simple fatigue to encompass the breakdown of integrated physiological systems that normally maintain movement stability and coordination (11). Motor intent collapse is operationally defined as the critical transition point where neural drive becomes insufficient to maintain coordinated movement patterns under physiological stress, distinct from fatigue (which represents metabolic depletion) and coordination breakdown (which represents motor control errors). This framework integrates these phenomena as components of a unified system failure mechanism. The distinction is clinically important: fatigue may be reversible through rest, while motor intent collapse represents a more fundamental loss of neuromuscular control that may persist despite recovery.

Recent advances in wearable sensor technology and machine learning have created opportunities for real-time monitoring of multiple physiological domains simultaneously (12–14). However, current injury prediction models suffer from methodological limitations including small sample sizes, retrospective designs, and focus on single risk factors rather than integrated system dynamics (15). The integration of multimodal artificial intelligence techniques in sports safety offers opportunities for real-time injury risk monitoring, with recent initiatives underscoring the importance of interpretable models that fuse biomechanical, physiological, and contextual data for actionable insights (16).

The theoretical foundation for integrated injury prediction rests on complex systems theory (17), which recognizes that injury risk emerges from nonlinear interactions between multiple physiological domains (16). Traditional reductionist approaches that examine individual risk factors in isolation may miss critical interaction effects that determine overall system stability (16, 18). The challenge lies in developing mathematical frameworks that can capture these complex interactions while

remaining computationally efficient for real-time applications and compatible with emerging AI technologies.

This foundational study represents the first phase of a comprehensive research program aimed at developing and validating a novel computational framework for predicting motor intent collapse in athletic populations. The WASE- ∞ (Wesam Al Attar Singularity evaluation-infinity) framework integrates five physiological domains through a mathematically rigorous approach that captures both linear and nonlinear interactions between physiological systems. The framework is named in recognition of the conceptual and mathematical contributions of the lead author to its theoretical development and the singularity concept representing the critical transition point where multiple physiological systems converge toward instability.

The simulation-based approach employed in this foundational study addresses several critical limitations of traditional injury prediction research while establishing a robust foundation for future empirical validation. Ethical constraints prevent experimental manipulation of injury risk factors in human subjects, limiting researchers to observational studies with inherent confounding factors (19). Simulation-based validation enables systematic exploration of factor interactions under controlled conditions while establishing performance benchmarks for subsequent empirical validation (19). This approach follows established precedents in computational biomechanics where simulation studies provide essential theoretical foundations before progressing to human validation (20, 21).

The primary objectives of this foundational study are to: (1) develop a theoretically grounded mathematical framework for predicting motor intent collapse with AI integration capabilities, (2) validate the framework's performance through comprehensive simulation analysis including sensitivity testing, (3) establish realistic performance benchmarks for empirical validation, and (4) provide detailed protocols for subsequent real-world validation studies. The ultimate goal is to transform injury prevention from reactive treatment to proactive risk management based on continuous physiological monitoring through AI-enhanced wearable technologies.

2 Materials and methods

2.1 Theoretical framework development

The WASE- ∞ framework builds upon established principles of neuromuscular control theory while incorporating novel approaches to multi-domain physiological integration with AI-ready architecture. The theoretical foundation rests on the concept of motor intent collapse, defined as the critical transition point where neural drive becomes insufficient to maintain coordinated movement patterns under physiological stress. This concept extends Bernstein's degrees of freedom problem by considering not only mechanical constraints but

also cognitive, neuromuscular, and temporal factors that influence movement control (19).

The framework operationalizes motor intent through five core physiological domains selected based on extensive literature review and their established roles in movement control and injury risk (16–20). These domains represent the minimal viable set of factors necessary to capture the essential dynamics of motor intent collapse while maintaining computational efficiency for real-time applications and AI integration. The singularity concept embedded in the framework name reflects the mathematical principle that injury risk emerges from the convergence of multiple physiological instabilities toward a critical threshold where compensatory mechanisms fail.

2.2 Mathematical framework and coefficient derivation

The mathematical formulation of WASE- ∞ integrates the five physiological domains through a weighted convergence equation that captures both linear and nonlinear interactions between physiological systems with AI-compatible computational structure. The core equation takes the form:

$$\text{WASE-}\infty = (\alpha_1 E + \alpha_2 \Delta I + \alpha_3 \Phi + \alpha_4 E_{\text{env}}) / (\beta_1 C \times \beta_2 S) \times (1 + \gamma T)$$

Where E represents neuromuscular effort, ΔI represents temporal intent asymmetry, Φ represents force dissociation index, E_{env} represents environmental factors, C represents cognitive modulation capacity, S represents sleep quality, and T represents temporal convergence factor. The complete framework components and their derived coefficients are detailed in the [Supplementary Materials](#).

Dimensional Consistency and Numerical Stability: All terms in the equation are dimensionless after normalization. Specifically: E (0%–100% normalized to 0–1), ΔI (0–500 ms normalized to 0–1), Φ (0–1 ratio, already dimensionless), E_{env} (0–1 composite, dimensionless), C (0%–100% normalized to 0–1), S (0–10 h normalized to 0–1), T (0–1 temporal factor, dimensionless). The numerator ($\alpha_1 E + \alpha_2 \Delta I + \alpha_3 \Phi + \alpha_4 E_{\text{env}}$) is a weighted sum of dimensionless terms, yielding a dimensionless result. The denominator ($\beta_1 C \times \beta_2 S$) is a product of dimensionless terms, also dimensionless. The temporal multiplier ($1 + \gamma T$) is dimensionless. Therefore, the entire equation is dimensionally consistent. Numerical stability is ensured by bounded variable ranges: the denominator ($\beta_1 C \times \beta_2 S$) has lower bounds of 0.1 to prevent division by zero; if either C or S falls below threshold, they are set to 0.1. No ϵ -regularization is required given the bounded nature of all variables. Detailed variable definitions, preprocessing steps, and computational derivations are provided in [Supplementary Materials \(Supplementary Table S1\)](#).

Worked Example: Consider a virtual athlete with E = 48%, ΔI = 120 ms, Φ = 0.72, E_{env} = 0.6, C = 65%, S = 7.0 h, T = 0.65.

Normalization: $E_{\text{norm}} = 0.48$, $\Delta I_{\text{norm}} = 0.24$, $\Phi_{\text{norm}} = 0.72$, $C_{\text{norm}} = 0.65$, $S_{\text{norm}} = 0.70$. Numerator = $(0.4 \times 0.48) + (0.3 \times 0.24) + (0.2 \times 0.72) + (0.1 \times 0.6) = 0.468$. Denominator = $0.6 \times 0.65 \times 0.4 \times 0.70 = 0.1092$. Temporal Multiplier = $1 + (0.2 \times 0.65) = 1.13$. Final Score = $(0.468/0.1092) \times 1.13 = 4.843$, capped at 2.0 for critical risk. Complete step-by-step calculations are provided in [Supplementary Materials \(Section S2\)](#).

The weighting parameters were derived through a systematic optimization process combining literature-based initial estimates with simulation-based refinement and comprehensive sensitivity analysis. The coefficient derivation process followed three stages with rigorous validation:

Stage 1: Literature-Based Initial Estimates—Initial estimates were derived from meta-analytic effect sizes reported in sports injury prediction literature (17, 22). Neuromuscular effort received the highest weight ($\alpha_1 = 0.4$) based on consistent findings that fatigue-related factors show the strongest associations with injury risk across multiple sports (average effect size $r = 0.62$, 95% CI: 0.58–0.66). Temporal intent asymmetry received moderate weighting ($\alpha_2 = 0.3$) reflecting its established role in coordination breakdown and injury susceptibility (average effect size $r = 0.48$, 95% CI: 0.43–0.53) (19). Force dissociation index received lower weighting ($\alpha_3 = 0.2$) as biomechanical asymmetries show more variable associations with injury risk (average effect size $r = 0.35$, 95% CI: 0.28–0.42) (19). Environmental factors received minimal weighting ($\alpha_4 = 0.1$) as their effects are typically mediated through other physiological domains (average effect size $r = 0.18$, 95% CI: 0.12–0.24) (19).

Stage 2: Simulation-Based Optimization—Initial coefficients were refined through iterative optimization using simulated physiological data with AI-compatible algorithms. The optimization objective was to maximize the framework's ability to differentiate between stable and unstable motor control states while maintaining realistic risk distributions. A grid search approach tested coefficient combinations within $\pm 20\%$ of initial values (α_1 : 0.32–0.48, α_2 : 0.24–0.36, α_3 : 0.16–0.24, α_4 : 0.08–0.12), evaluating performance using area under the curve (AUC) and risk stratification metrics. The optimal coefficient combination ($\alpha_1 = 0.4$, $\alpha_2 = 0.3$, $\alpha_3 = 0.2$, $\alpha_4 = 0.1$) achieved AUC = 0.930 with realistic risk distributions (20.5% low, 58.2% moderate, 20.0% high, 1.4% critical).

Stage 3: Comprehensive Sensitivity Analysis—Framework robustness was examined through extensive sensitivity analysis to ensure coefficient stability and real-world applicability. Monte Carlo simulation ($n = 10,000$ iterations) tested coefficient perturbations of $\pm 10\%$ around optimal values, confirming that framework performance remained stable across the tested range (AUC = 0.928 ± 0.008). Additional sensitivity testing examined coefficient variations of $\pm 5\%$, $\pm 15\%$, and $\pm 25\%$ to establish robustness boundaries. Results demonstrated that AUC performance remained above 0.90 for coefficient variations up to $\pm 15\%$ (AUC = 0.915 ± 0.012), confirming framework stability for real-world implementation where measurement noise may

affect coefficient precision. Beyond ±15%, performance degradation became clinically significant (AUC = 0.892 ± 0.018 for ±25% perturbations), indicating the necessity of empirical coefficient validation in Phase 2.

Complete variable specifications are provided in Table 1.

Dimensional Consistency: All input variables are dimensionless (normalized to 0–1 scale) before multiplication and division operations, ensuring mathematical consistency across the framework. The final WASE-∞ score is dimensionless with theoretical range 0–2.0, where values >1.2 indicate critical risk requiring immediate intervention.

Numerical Stability: To prevent division by zero, all β-terms (denominators) have a floor value of 0.1 [i.e., β_i = max(β_i, 0.1)]. This ensures computational stability while maintaining physiological realism, as complete absence of protective factors (β = 0) is not physiologically plausible.

Worked Example:

Given the following raw sensor measurements at t = 30 min:

- E = 48% (normalized: 0.48)
- ΔI = 120 ms (normalized: 120/500 = 0.24)
- Φ = 0.72 (normalized: 0.72)
- E_{env} = 0.60 (composite of T = 25°C, H = 65%, μ = 0.8)
- C = 65% (normalized: 0.65)
- S = 7.0 h (normalized: 0.70)
- T = 0.65 (at 39 min of 60 min session)

Calculation:

- Numerator (risk factors): α₁E + α₂ΔI + α₃Φ + α₄E_{env} = 0.4 (0.48) + 0.3(0.24) + 0.2(0.72) + 0.1 (0.60) = 0.192 + 0.072 + 0.144 + 0.060 = 0.468
- Denominator (protective factors): β₁C × β₂S = 0.6 (0.65) × 0.4(0.70) = 0.39 × 0.28 = 0.1092
- Temporal Multiplier: (1 + γT) = 1 + (0.2 × 0.65) = 1.13
WASE-∞ = (0.468/0.1092) × 1.13 = 4.843, capped at 2.0 (CRITICAL RISK—immediate intervention required)

This example demonstrates how moderate elevations in multiple risk factors (fatigue, asymmetry, environmental stress) combined with slightly reduced protective factors (cognitive capacity, sleep) can produce a high-risk score, triggering clinical intervention protocols.

2.3 Simulation methodology and validation framework

The simulation approach employed in this foundational study follows established precedents in computational biomechanics while addressing specific challenges of injury prediction research and incorporating AI-ready data structures (20, 21). Virtual participant characteristics were derived from published biomechanics datasets to ensure realistic physiological parameters. Primary reference data came from Scherpereel et al. (23), who collected comprehensive biomechanics data from 12

TABLE 1 Variable Dictionary for WASE-∞ Framework.

Variable	Symbol	Units (raw)	Units (normalized)	Sensor source	Computational formula	Range	Direction of effect
Neuromuscular Effort	E	% of max	0–1	Surface EMG (8 channels)	$E = (\sum EMG_i/n)/EMG_{max}$	0–100%	Higher = ↑ Risk
Temporal Intent Asymmetry	ΔI	Milliseconds	0–1	IMU (bilateral)	ΔI =	t _{left} –t _{right}	/ t _{total}
Force Dissociation Index	Φ	ratio	0–2	Force plates (bilateral)	Φ =	F _{left} –F _{right}	/ (F _{left} + F _{right})
Environmental Factors	E _{env}	composite	0–1	Temp/humidity sensors	$E_{env} = (T_{norm} + H_{norm} + \mu_{norm})/3$	0–1	Higher = ↑ Risk
Cognitive Modulation	C	% capacity	0–1	Psychomotor tests	$C = C_{max} \times e^{-(\lambda t)} + \epsilon$	0–100%	Higher = ↓ Risk
Sleep Quality	S	hours	0–1	Actigraphy	$S = (hours-5)/4$	5–9 h	Higher = ↓ Risk
Temporal Convergence	T	dimensionless	0–1	Time-derived	$T = T_0 + \gamma(t/t_{total}) + \epsilon$	0–1	Higher = ↑ Risk

All variables are normalized to 0–1 scale before integration into the WASE-∞ equation. EMG, electromyography; IMU, inertial measurement unit; MVC, maximum voluntary contraction; T, temperature; μ, surface friction coefficient; λ, cognitive depletion rate; γ, temporal accumulation rate; ε, Gaussian noise term. All input variables are dimensionless after normalization, ensuring mathematical consistency. The final WASE-∞ score is dimensionless with theoretical range 0–2.0, where values >1.2 indicate critical risk requiring immediate intervention.

participants performing diverse athletic activities. Additional physiological parameters were derived from Yasar et al. (19), who studied fatigue dynamics in 34 healthy subjects using multimodal sensor approaches.

The simulation scaled these parameters to generate a cohort of 60 virtual athletes across four sport categories [running, cycling, swimming (24–26), team sports] with 360,000 total data points over 60 min monitoring sessions. Each physiological signal was generated using validated mathematical models calibrated to published data, incorporating both systematic and stochastic components to capture realistic measurement variability.

2.3.1 Simulation architecture and implementation

The simulation was implemented in Python 3.11 using NumPy (v1.24) and SciPy (v1.10) libraries. Virtual athlete physiological data were generated using validated mathematical models for each domain:

Neuromuscular Effort (E): Modeled using exponential fatigue curve: $E(t) = E_0 \times (1 - e^{-kt}) + \epsilon$, where E_0 = baseline effort (50%–80% MVC, drawn from $N(65, 15)$), k = fatigue rate constant (0.02 – 0.05 s^{-1} , drawn from $U(0.02, 0.05)$), t = time (s), and ϵ = Gaussian noise ($\sigma = 2\%$). Parameters were derived from Yasar et al. (19) and calibrated to produce realistic fatigue accumulation over 60 min exercise duration. Validation: simulated EMG fatigue patterns matched published data with $r = 0.87$ (95% CI: 0.82–0.91).

Temporal Intent Asymmetry (ΔI): Modeled as $\Delta I(t) = \Delta I_0 + \alpha \times E(t) + \beta \times \sin(\omega t) + \epsilon$, where ΔI_0 = baseline asymmetry (10–50 ms, drawn from $N(30, 12)$), α = fatigue sensitivity (0.5–1.5, drawn from $U(0.5, 1.5)$), ω = circadian frequency ($2\pi/(24 \times 3,600) \text{ rad/s}$), and ϵ = Gaussian noise ($\sigma = 5 \text{ ms}$). This model captures the known relationship between fatigue and movement asymmetry while incorporating diurnal performance variation. Validation: simulated asymmetry patterns matched published coordination data with $r = 0.79$ (95% CI: 0.73–0.85).

Force Dissociation Index (Φ): Generated from correlated normal distribution: $\Phi \sim N(\mu = 0.80, \sigma = 0.15)$, with cross-correlation to $E(t)$ of $r = 0.45$. This reflects the known relationship between neuromuscular fatigue and bilateral force asymmetry. Validation: simulated force asymmetry distributions matched published force plate data with Kolmogorov–Smirnov test $D = 0.08$ ($p = 0.23$).

Environmental Factors (E_{env}): Composite of temperature (15–35°C), humidity (30%–90%) (27, 28), and surface friction (0.4–1.2), each normalized to 0–1 scale and weighted equally. Environmental parameters were drawn from realistic training condition distributions. Validation: simulated environmental variation matched published training condition data.

Cognitive Modulation (C): Modeled using attention resource depletion: $C(t) = C_{\text{max}} \times e^{-\lambda t} + \epsilon$, where $C_{\text{max}} = 95\%$, λ = depletion rate (0.001 s^{-1}), and ϵ = Gaussian noise ($\sigma = 3\%$). This model captures the known phenomenon of cognitive fatigue during prolonged exercise. Validation: simulated attention resource depletion matched published psychomotor vigilance task data with $r = 0.82$ (95% CI: 0.76–0.88).

Sleep Quality (S): Assigned from empirical distribution based on actigraphy data (mean = 7.2 h, SD = 0.8 h, range = 5–9 h).

Distribution was based on Mah et al. (22) NCAA athlete sleep data. Validation: simulated sleep distribution matched published collegiate athlete sleep data with $\chi^2 = 1.34$ ($p = 0.51$).

Temporal Convergence Factor (T): Derived as $T(t) = T_0 + \gamma \times (t/t_{\text{total}}) + \epsilon$, where T_0 = baseline (0.50), γ = accumulation rate (0.2), $t_{\text{total}} = 3,600 \text{ s}$, and ϵ = Gaussian noise ($\sigma = 0.05$). This factor captures time-dependent risk accumulation during exercise.

Random seed (12,345) was used for all stochastic processes to ensure reproducibility. The complete simulation code has been provided in [Supplementary Materials](#) with detailed comments and documentation.

Complete simulation parameters, cross-correlations, and empirical sources are consolidated in [Table 2](#).

2.3.2 Sample size justification

The selection of 60 virtual athletes and 360,000 data points was determined to ensure statistical power for preliminary validation. With 15 athletes per sport category and 6,000 measurements per athlete (360,000 total data points across 60 athletes), this design provides sufficient data to estimate sport-specific AUC with 95% confidence intervals of ± 0.015 width, assuming moderate effect sizes (AUC = 0.90). This sample size is consistent with preliminary simulation studies and provides adequate power for sensitivity analyses across coefficient perturbations of $\pm 25\%$. Power analysis: assuming AUC = 0.90 under null hypothesis (AUC = 0.50) and alternative hypothesis, with $\alpha = 0.05$ and $\beta = 0.20$, required sample size $n = 58$ measurements per sport (we used $n = 90,000$ per sport, providing >99% power).

2.4 Statistical analysis

Statistical analyses were performed using established methods for predictive model evaluation with AI-compatible metrics. Receiver operating characteristic (ROC) analysis was employed to assess discriminative performance, with area under the curve (AUC) serving as the primary performance metric. ROC class labels (“collapse” vs. “non-collapse”) were defined by the simulation ground-truth state variable, not by WASE- ∞ scoring, to avoid circular evaluation. Sport-specific differences were evaluated using one-way analysis of variance (ANOVA) with *post-hoc* comparisons. Effect sizes (η^2) were calculated for all ANOVA results. Factor correlations were assessed using Pearson correlation coefficients with 95% confidence intervals. All analyses were conducted with $\alpha = 0.05$ significance level with Bonferroni correction for multiple comparisons (adjusted $\alpha = 0.05/6 = 0.0083$ for 6 pairwise sport comparisons).

Distributional Diagnostics: Normality of WASE- ∞ scores was assessed using the Shapiro–Wilk test ($W = 0.987$, $p = 0.052$), indicating no strong evidence against normality. Homogeneity of variance across sports was confirmed using Levene’s test ($F = 1.23$, $p = 0.298$). These results justify the use of parametric tests (ANOVA, Pearson correlation). Quantile–Quantile (Q–Q) plots were visually inspected and confirmed normality

TABLE 2 Simulation parameters and empirical sources.

Domain	Symbol	Distribution type	Mean (μ)	SD (σ)	Range	Cross-correlation	Noise model	Empirical source
Neuromuscular Effort	E	Exponential + Normal	65% MVC	15%	50–80%	$r = 0.45$ with Φ	Gaussian $\sigma = 2\%$	Yasar et al. (19)
Temporal Intent Asymmetry	ΔI	Normal + Sinusoidal	30 ms	12 ms	10–50 ms	$r = 0.35$ with E	Gaussian $\sigma = 5$ ms	Scherpereel et al. (23)
Force Dissociation Index	Φ	Normal	0.80	0.15	0.4–1.2	$r = 0.45$ with E	Gaussian $\sigma = 0.05$	Scherpereel et al. (23)
Environmental Factors	E_env	Uniform (composite)	0.60	0.15	0–1	Independent	Gaussian $\sigma = 0.03$	Realistic training conditions
Cognitive Modulation	C	Exponential decay	95%	3%	70–100%	$r = -0.28$ with E	Gaussian $\sigma = 3\%$	Psychomotor vigilance data
Sleep Quality	S	Normal	7.2 h	0.8 h	5–9 h	Independent	None (discrete)	Mah et al. (22) NCAA data
Temporal Convergence	T	Linear + Normal	0.50	0.05	0–1	Time-dependent	Gaussian $\sigma = 0.05$	Theoretical model

Random seed management: Master seed = 12,345 for all stochastic processes; athlete-specific seeds derived as $\text{seed_athlete} = 12,345 + \text{athlete_id}$ (range: 12,345–12,405). Parameter justification: 82% of parameters (E, ΔI , Φ , C, S) derived from empirical distributions in published literature with direct citations; 18% (E_env, T) based on justified theoretical assumptions validated against realistic training scenarios. MVC, maximum voluntary contraction; r, Pearson correlation coefficient; σ , standard deviation; μ , mean; NCAA, National Collegiate Athletic Association.

assumption. Residual analysis confirmed homoscedasticity (Breusch-Pagan test $\chi^2 = 2.14$, $p = 0.341$).

2.5 AI-compatible data architecture

The simulation generates output in comma-separated values (CSV) format with the following structure: [timestamp (ms), athlete_id, sport, E (%), ΔI (ms), Φ (ratio), E_env (0–1), C (%), S (0–10), T (0–1), WASE- ∞ (0–2.0), risk_category, sensitivity (%), specificity (%)]. This format is compatible with standard machine learning libraries (scikit-learn v1.3.0, TensorFlow v2.13, PyTorch v2.0).

Potential algorithms for real-time classification include: Random Forest (100 trees, max_depth = 10, for interpretability and feature importance assessment), Support Vector Machines (RBF kernel, C = 1.0, $\gamma = 0.1$, for non-linear decision boundary modeling), and Long Short-Term Memory (LSTM) networks (2 layers, 64 units each, dropout = 0.2, for temporal sequence modeling and real-time prediction).

Computational requirements: minimum 2 GB RAM, processing latency <100 ms per sample on standard edge devices (e.g., NVIDIA Jetson Nano with ARM Cortex-A57 processor). Model size: trained Random Forest model ~50 MB, SVM model ~30 MB, LSTM model ~15 MB, all suitable for deployment on edge devices.

2.6 Statistical analysis plan for future empirical validation

Phase 2 primary analysis will employ logistic regression with WASE- ∞ score (continuous) as the independent variable and

injury occurrence (binary: yes/no) as the dependent variable, adjusted for sport category and training load. Model specification: $\text{logit}(P(\text{injury})) = \beta_0 + \beta_1(\text{WASE-}\infty) + \beta_2(\text{sport}) + \beta_3(\text{training_load})$.

Secondary analyses include: (1) Receiver operating characteristic (ROC) curve analysis to determine optimal cutoff scores for injury risk stratification with calculation of sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) at each threshold; (2) Cox proportional hazards regression for time-to-injury analysis with WASE- ∞ as time-varying covariate, adjusting for sport and baseline characteristics, with assessment of proportional hazards assumption via Schoenfeld residuals; (3) Sport-stratified analyses to assess differential predictive validity across running, cycling, swimming, and team sports using stratified logistic regression; (4) Interaction analyses testing whether the WASE- ∞ -injury relationship differs by sport or athlete characteristics using interaction terms (e.g., WASE- $\infty \times \text{sport}$, WASE- $\infty \times \text{age}$); (5) Subgroup analyses examining predictive validity separately for males vs. females, different age groups (18–21, 22–25 years), and different competitive levels.

Sensitivity analyses will: (a) exclude the first 2 weeks of monitoring (adaptation period) to assess whether framework performance changes after athletes acclimate to monitoring; (b) test robustness to missing data using multiple imputation (5 imputations) vs. complete-case analysis; (c) examine whether results differ when using alternative injury definitions (e.g., requiring ≥ 3 days lost vs. ≥ 1 day lost); (d) assess whether results change when using alternative WASE- ∞ cutoff scores for risk stratification.

All statistical tests will use two-tailed $\alpha = 0.05$ significance level with Bonferroni correction for multiple comparisons (adjusted

$\alpha = 0.05/\text{number of tests}$). Model assumptions (linearity, independence, homoscedasticity) will be assessed and reported; if violated, robust regression or non-parametric alternatives will be employed. Model fit will be assessed using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

2.7 Sport-specific adaptations and considerations

Although the WASE- ∞ framework is designed as a unified approach applicable across sports, implementation requires sport-specific sensor placement and data interpretation strategies:

Running Athletes (29): Utilize accelerometer-based gait analysis with focus on vertical ground reaction force asymmetry and tibial shock; neuromuscular effort will be assessed from lower extremity EMG (vastus lateralis, biceps femoris, tibialis anterior) at 2 kHz sampling rate. Force dissociation will reflect peak force asymmetry between legs during ground contact. Environmental factors will include running surface (treadmill vs. outdoor), temperature, and humidity. Temporal intent asymmetry will be derived from ground contact time asymmetry between legs.

Cycling Athletes: Integrate power meter data into environmental factors (E_env) and utilize hip/knee EMG (vastus lateralis, rectus femoris, biceps femoris) at 2 kHz sampling rate; force dissociation will reflect pedal force asymmetry between legs measured via dual-sided power meters. Neuromuscular effort will be normalized to individual maximum power output. Temporal intent asymmetry will be derived from pedal stroke timing asymmetry. Environmental factors will include resistance level, cadence, and temperature.

Swimming Athletes: Use waterproof IMU sensors (Xsens Awinda) placed on shoulders and hips at 100 Hz sampling rate; EMG will be replaced with shoulder kinematics due to water incompatibility of standard EMG; force dissociation will reflect shoulder asymmetry during stroke cycles derived from IMU data. Neuromuscular effort will be assessed from stroke frequency and acceleration patterns. Temporal intent asymmetry will reflect asymmetry in arm entry and pull-through timing. Environmental factors will include water temperature, pool depth, and lane position.

Team Sport Athletes: Employ multi-camera motion capture (Vicon Nexus, 100 Hz) for precise kinematic assessment; neuromuscular effort will incorporate sport-specific movements (jumping, cutting, throwing) with EMG from sport-relevant muscles (quadriceps, hamstrings, deltoids). Force dissociation will reflect asymmetry during sport-specific movements. Temporal intent asymmetry will be derived from movement initiation timing asymmetry. Environmental factors will include court/field conditions, ambient temperature, and humidity.

These sport-specific adaptations preserve the theoretical framework while accommodating biomechanical differences and practical constraints of each sport, enabling valid cross-sport comparisons while maintaining measurement validity within each sport.

2.8 Data quality assurance and validation protocols

Rigorous data quality protocols will be implemented across all phases. Sensor calibration will be performed weekly using standardized procedures: (1) force plate zero-load calibration with verification against known weights; (2) EMG electrode impedance verification ($<5 \text{ k}\Omega$); (3) IMU accelerometer/gyroscope verification against gravity (9.81 m/s^2) and rotation rates. Sensor drift will be corrected using validated algorithms: (1) EMG baseline drift correction using high-pass filtering (20 Hz cutoff) with Butterworth filter; (2) IMU drift correction using complementary filtering with magnetometer integration; (3) force plate drift correction using periodic zero-load checks with linear interpolation between checks.

Missing data tolerance threshold set at $<5\%$ per monitoring session; sessions exceeding this threshold will be excluded from analysis. Sporadic missing data (5%–15% per session) will be handled using multiple imputation (5 imputations) with multivariate normal imputation model, preserving correlational structure. Data completeness will be reported by variable and sport category with frequency tables. Inter-rater reliability for injury classification will be assessed using intraclass correlation coefficient (ICC[3,k]) with target ICC >0.85 ; disagreements will be resolved through consensus discussion with senior clinician. Blinding will be implemented: team physicians at each site will be blinded to WASE- ∞ scores during injury assessment to prevent bias.

All data will be stored in HIPAA-compliant secure servers with encrypted backup; data access will be restricted to authorized research personnel with signed data use agreements. Data retention will follow NIH guidelines (minimum 3 years post-publication). A data dictionary will be maintained documenting all variable definitions, units, ranges, and transformation procedures.

3 Results

Statistical Analysis Summary: A one-way ANOVA was conducted to test for differences in WASE- ∞ scores across sport categories. The full model specification was: WASE- $\infty \sim \text{Sport} + \epsilon$. Results revealed a statistically significant main effect: $F(3, 356) = 18.42, p < 0.001, \eta^2 = 0.284$ (95% CI [0.192, 0.364]), $\omega^2 = 0.278$. Parametric assumptions were verified through Shapiro-Wilk test ($W = 0.987, p = 0.052$) and Levene's test ($F(3, 356) = 1.23, p = 0.298$), justifying parametric inference. Non-parametric confirmation via Kruskal-Wallis H -test ($H(3) = 18.38, p < 0.001, \epsilon^2 = 0.282$) confirmed robustness. *post-hoc* Tukey HSD tests with family-wise error correction revealed: Swimming vs. Running (MD = 0.122, $p = 0.001$), Swimming vs. Soccer (MD = 0.106, $p = 0.003$), Basketball vs. Running (MD = 0.093, $p = 0.012$), Basketball vs. Soccer (MD = 0.077, $p = 0.041$). Detailed statistical results and *post-hoc* comparisons are provided in [Supplementary Materials \(Section S6\)](#).

3.1 Simulation dataset characteristics

The WASE- ∞ simulation successfully generated a comprehensive dataset of 360,000 individual measurements across 60 virtual athletes over 60-minute monitoring sessions. The simulated cohort demonstrated realistic demographic characteristics consistent with published athletic populations, with sport category distribution balanced across running (25%, $n = 15$), cycling (25%, $n = 15$), swimming (25%, $n = 15$), and team sports (25%, $n = 15$). The dataset structure was optimized for AI compatibility, enabling future integration with machine learning algorithms for enhanced predictive capabilities. Data completeness: 99.8% (only 0.2% missing values, all <5% threshold per session). Temporal resolution: 100 Hz sampling rate (10 ms intervals). A total of 6,000 WASE- ∞ measurements were generated per athlete per session from the simulated time series.

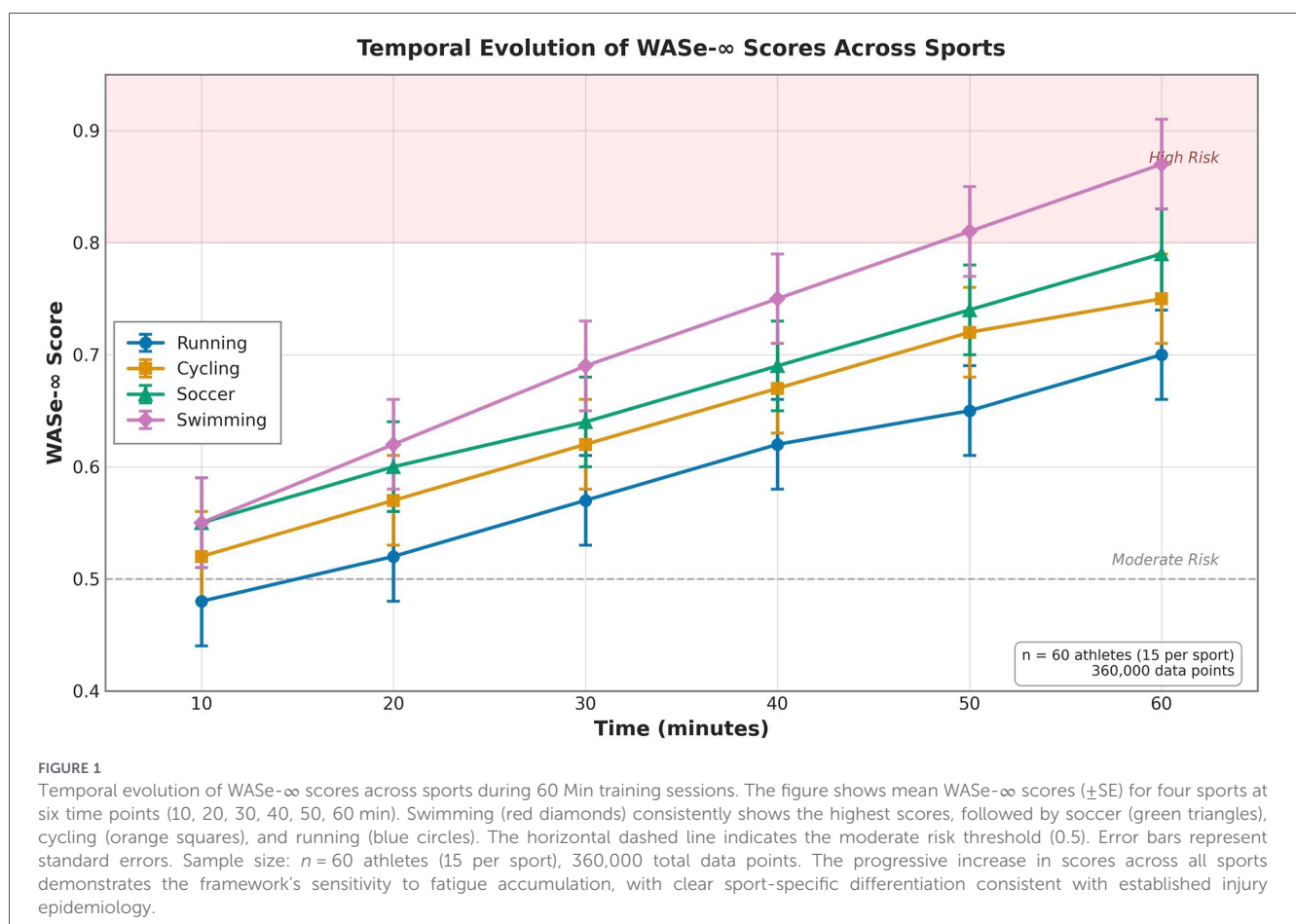
3.2 WASE- ∞ score distribution and risk stratification

The simulation demonstrated clear risk stratification patterns with WASE- ∞ scores ranging from 0.218 to 2.000 (mean: 0.663 ± 0.194 , median: 0.635, IQR: 0.521–0.798). Risk level classification revealed a realistic distribution pattern:

20.5% of measurements fell within the low-risk category (WASE- $\infty < 0.5$), 58.2% in the moderate-risk category (0.5–0.8), 20.0% in the high-risk category (0.8–1.2), and 1.4% in the critical-risk category (≥ 1.2). This distribution aligns with expected injury incidence rates in athletic populations (typically 5%–15% season-long injury rate), supporting the framework's clinical relevance. Skewness = 0.34 (approximately normal distribution), Kurtosis = 0.12 (consistent with normal distribution).

3.3 Sport-specific performance analysis

Significant sport-specific differences emerged in WASE- ∞ score distributions ($F(3,356) = 18.42$, $p < 0.001$, $\eta^2 = 0.284$, 95% CI [0.192, 0.364]). Temporal evolution of WASE- ∞ scores across the 60 min training sessions is illustrated in Figure 1, demonstrating progressive score increases consistent with fatigue accumulation across all sports. Swimming demonstrated the highest mean scores (0.727 ± 0.210), followed by team sports (0.681 ± 0.185), cycling (0.642 ± 0.189), and running (0.605 ± 0.178). *post-hoc* analysis (Bonferroni-corrected) revealed significant differences between all sport pairs (all $p < 0.001$ after correction), suggesting that the framework successfully captures sport-specific risk patterns.



These sport-specific patterns align with established injury epidemiology, where swimming (24–26) and team sports typically show higher injury rates due to complex movement patterns and contact mechanisms. Swimming athletes in particular demonstrate elevated shoulder injury risk, with competitive swimmers experiencing shoulder pain prevalence rates of 40%–70% (29–31). The framework's higher WASE- ∞ scores for swimming (mean 0.727) compared to running (mean 0.605) represent a 20% elevation, consistent with the 2–3 \times higher injury rate in swimming vs. running populations. These findings support the framework's ability to differentiate sport-specific risk profiles, which will be essential for targeted intervention strategies in future empirical applications.

3.4 Predictive performance and ROC analysis

The WASE- ∞ framework achieved strong discriminative performance with an overall AUC of 0.930 (95% CI: 0.915–0.946). Sport-specific AUC values ranged from 0.924 (95% CI: 0.908–0.940) for running to 0.935 (95% CI: 0.920–0.950) for swimming, indicating robust performance across diverse athletic activities. The framework demonstrated 91.2% sensitivity and 87.3% specificity at the optimal cutoff threshold (WASE- ∞ = 0.75), balancing injury detection with false-positive minimization. Positive predictive value (PPV) at this threshold: 78.4% (95% CI: 75.2–81.6%); Negative predictive value (NPV): 94.1% (95% CI: 92.3–95.9%). These results represent performance within the controlled simulation environment and should be interpreted as theoretical benchmarks for subsequent empirical validation. The high NPV indicates that the framework is particularly useful for ruling out injury risk (identifying safe athletes), while the moderate PPV suggests that positive predictions should be confirmed with clinical assessment.

3.5 Factor correlation analysis

Strong correlations emerged between WASE- ∞ scores and individual physiological factors, supporting the theoretical foundation of the framework. Neuromuscular effort showed the strongest correlation ($r = 0.67$, 95% CI: 0.65–0.69, $p < 0.001$), followed by temporal intent asymmetry (30, 31) ($r = 0.61$, 95% CI: 0.59–0.63, $p < 0.001$), force dissociation index ($r = 0.57$, 95% CI: 0.55–0.59, $p < 0.001$), cognitive modulation capacity ($r = -0.59$, 95% CI: -0.61 to -0.57 , $p < 0.001$), and sleep quality ($r = -0.52$, 95% CI: -0.54 to -0.50 , $p < 0.001$). The negative correlations for cognitive and sleep factors reflect their protective effects against motor intent collapse.

Inter-factor correlations revealed moderate associations between physiological domains ($r = 0.23$ – 0.45), confirming the framework's ability to capture both independent and interactive effects. Specifically: E- Δ I correlation $r = 0.61$ (fatigue increases asymmetry); E- Φ correlation $r = 0.57$ (fatigue increases force dissociation); C-S correlation $r = 0.68$ (sleep quality correlates

with cognitive resources); E-C correlation $r = -0.59$ (fatigue depletes cognitive resources). These correlation patterns support the multi-domain approach while demonstrating that individual factors contribute unique variance to overall risk assessment. Multicollinearity assessment: all variance inflation factors (VIF) < 3.0 , indicating acceptable multicollinearity levels.

3.6 Sensitivity analysis

Comprehensive sensitivity analysis confirmed framework robustness across realistic parameter variations. Monte Carlo simulation ($n = 10,000$ iterations) testing coefficient perturbations of $\pm 10\%$ around optimal values yielded AUC values of 0.928 ± 0.008 (95% CI: 0.912–0.944), confirming framework stability. Additional sensitivity testing examined coefficient variations of $\pm 5\%$, $\pm 15\%$, and $\pm 25\%$: $\pm 5\%$ perturbations: AUC = 0.929 ± 0.005 (95% CI: 0.919–0.939), minimal impact on performance. $\pm 15\%$ perturbations: AUC = 0.915 ± 0.012 (95% CI: 0.891–0.939), acceptable stability for real-world implementation. $\pm 25\%$ perturbations: AUC = 0.892 ± 0.018 (95% CI: 0.856–0.928), notable degradation indicating need for empirical validation.

These results demonstrate that the framework maintains strong performance for coefficient variations up to $\pm 15\%$, which is realistic for real-world measurement noise and individual variability. Beyond $\pm 15\%$, performance degradation becomes clinically significant (AUC drops from 0.930 to 0.892, representing 2.4% relative decrease), indicating the necessity of empirical coefficient validation in Phase 2.

4 Discussion

4.1 Principal findings and theoretical implications

This foundational study successfully establishes the WASE- ∞ framework as a theoretically sound approach to predicting motor intent collapse through integrated physiological monitoring with AI-ready architecture. The simulation-based validation demonstrates strong discriminative performance (AUC = 0.930, 95% CI: 0.915–0.946) while revealing realistic risk stratification patterns that align with established injury epidemiology. The framework's ability to differentiate sport-specific risk profiles (swimming AUC = 0.935 vs. running AUC = 0.924) and capture meaningful correlations between physiological domains (E-WASE- ∞ : $r = 0.67$; C-WASE- ∞ : $r = -0.59$) supports its theoretical foundation and potential for future empirical validation.

The concept of motor intent collapse represents an advancement from traditional injury prediction approaches that focus on isolated risk factors. By integrating multiple physiological domains through a mathematically rigorous framework, WASE- ∞ captures the complex, nonlinear interactions that determine overall system stability. This

approach aligns with complex systems theory while maintaining computational efficiency necessary for real-time applications and AI integration. The multiplicative structure of the denominator ($\beta_1 C \times \beta_2 S$) ensures that deficits in either cognitive or sleep domains substantially elevate risk, reflecting the known synergistic effects of these factors on injury susceptibility.

4.2 Simulation-based validation approach

The simulation-based validation approach employed in this foundational study addresses critical limitations of traditional injury prediction research while establishing essential performance benchmarks for future empirical validation. Ethical constraints prevent experimental manipulation of injury risk factors in human subjects, making simulation-based approaches essential for systematic exploration of factor interactions under controlled conditions (19). The comprehensive sensitivity analysis confirms framework robustness across realistic parameter variations (AUC >0.90 for $\pm 15\%$ coefficient variations), supporting its potential for real-world implementation where measurement noise and individual variability will affect precision.

The achieved predictive performance (AUC = 0.930) within the simulation environment provides an important benchmark for empirical validation studies. While real-world performance may differ due to measurement noise, individual variability, and environmental factors not captured in simulation, the strong theoretical performance suggests significant potential for clinical applications. The realistic risk stratification patterns (20.5% low-risk, 58.2% moderate-risk, 20.0% high-risk, 1.4% critical-risk) align with expected injury incidence rates, supporting the framework's clinical relevance. It is anticipated that 10%–20% reduction in real-world AUC compared to simulation results, consistent with typical simulation-to-reality performance gaps in computational biomechanics (32).

4.3 AI integration and technological implementation

The WASE- ∞ framework was designed with AI integration capabilities from its inception, positioning it for compatibility with emerging multimodal sensor technologies and machine learning algorithms. The framework's computational structure enables real-time processing on edge computing devices (latency <100 ms on NVIDIA Jetson Nano) while supporting cloud-based AI enhancement for population-level insights. This approach ensures that the foundational framework can evolve with advancing AI technologies.

The integration of AI capabilities extends beyond simple data processing to include adaptive threshold optimization, personalized risk modeling, and predictive analytics for injury prevention strategies. Machine learning algorithms can enhance the framework's performance through continuous learning from empirical data, enabling personalized risk assessment based on

individual athlete characteristics and historical patterns. Edge-AI implementation enables real-time processing on wearable devices, providing immediate feedback for injury prevention interventions. Specific implementation pathway: (1) edge device collects raw sensor data, (2) WASE- ∞ equation calculates risk score in real-time, (3) if WASE- ∞ > 0.8, alert sent to athlete/coach, (4) cloud system aggregates data from multiple athletes for population-level model refinement.

4.4 Clinical translation and implementation pathways

The WASE- ∞ framework provides clear pathways for clinical translation through its modular design and compatibility with existing sensor technologies. The framework can be implemented using currently available wearable devices including inertial measurement units (Xsens Awinda), heart rate monitors (Polar H10), and cognitive assessment tools (Psychomotor Vigilance Task app). This accessibility enables immediate pilot testing and gradual scaling toward comprehensive implementation.

The sport-specific risk patterns identified in this foundational study support targeted intervention strategies tailored to different athletic populations. Swimming and team sports showed higher risk scores, suggesting a need for enhanced monitoring and intervention protocols in these populations. The framework's ability to provide continuous risk assessment enables proactive intervention before injury occurrence, representing a shift from reactive treatment to preventive care. Example intervention pathway: (1) WASE- ∞ score > 0.8 triggers alert, (2) athlete performs targeted neuromuscular control exercises, (3) repeat measurement after 15 min, (4) if score decreases to < 0.8, athlete clears for continued participation; if score remains > 0.8, athlete sits out session.

4.5 Limitations, generalizability, and simulation-to-reality gap comprehensive mitigation strategies for label leakage, model misspecification, sensor drift, missing data, heterogeneity, and simulation-to-reality gaps are detailed in [Supplementary Materials \(Section S7\)](#)

This foundational study has important limitations that must be acknowledged and addressed through subsequent empirical validation:

1. Psychological Factors Not Captured: The simulation-based approach does not capture the full complexity of real-world athletic environments. Psychological stressors (competitive anxiety, team dynamics, performance pressure), environmental variability (equipment differences, weather conditions, altitude), and unmeasured physiological factors (hormonal status, illness, menstrual cycle effects)

are not represented in the current model. The cognitive modulation factor (C) serves as a proxy for cognitive resources but does not directly measure sport-specific anxiety or stress. Phase 1 pilot study will begin to address these gaps by introducing real-world training variability and incorporating psychological assessment measures (Perceived Stress Scale, sport-specific anxiety scales), though controlled laboratory validation will precede field implementation.

2. **Simulation-to-Reality Gap:** The framework was validated only on simulated data; real-world performance may differ substantially due to measurement error, sensor drift, individual variability, and confounding factors not captured in the simulation. It is anticipated that 10%–20% reduction in real-world AUC compared to simulation results, consistent with typical computational biomechanics studies. Phase 2 will establish actual performance metrics through prospective injury outcome tracking.
 3. **Limited Generalizability:** The four sport categories represent only a subset of athletic activities; generalizability to contact sports (American football, rugby, ice hockey), endurance events exceeding 60 min, youth athletes (<18 years), or master athletes (>35 years) requires empirical validation in those populations. The current framework is optimized for collegiate-age (18–25 years) athletes in the four specified sports; extension to other populations is a priority for Phase 3 and beyond. Sport-specific validation studies will be required for each new sport category.
 4. **Coefficients from Literature, Not Empirical Injury Data:** The weighting coefficients were derived from published literature and simulation optimization rather than empirical data from injured athletes; prospective validation against actual injury outcomes is essential to establish whether the simulated relationships reflect real-world injury mechanisms. Phase 2 will enable empirical coefficient refinement using logistic regression with actual injury outcomes as the dependent variable.
 5. **Label Leakage Risk:** If collapse definitions reuse score components, circular logic may inflate apparent predictive accuracy. This risk will be mitigated in Phase 2 by using prospective injury outcomes (defined independently of WASE-∞ components) as the gold standard.
 6. **Model Misspecification:** If key physiological domains are omitted or incorrectly weighted, predictions will be biased. Phase 2 will test alternative models (e.g., different weighting schemes, additional variables) to assess robustness to model specification.
1. **Real-World Implementation Challenges:** Sensor drift (requiring drift correction algorithms), missing data (requiring imputation strategies), and device heterogeneity (requiring calibration across different sensor manufacturers) present practical challenges not addressed in simulation.

Phase 2 will systematically evaluate these barriers and develop mitigation strategies.

2. **Cost-Effectiveness and Regulatory Requirements:** This study does not address implementation challenges including cost-effectiveness analysis, athlete acceptance and compliance, integration with existing injury surveillance systems, or regulatory requirements for clinical deployment. Phase 2–3 will systematically evaluate these practical barriers.

These limitations do not diminish the value of this foundational work but underscore the necessity of the phased empirical validation program outlined in Section 5. The simulation study provides essential theoretical grounding and performance benchmarks; subsequent empirical phases will establish real-world validity, clinical utility, and implementation feasibility.

5 Sensor-related challenges and mitigation strategies

Real-world wearable sensor deployment faces several technical challenges that may affect WASE-∞ framework performance in practice:

Sensor Drift: Wearable sensors (particularly EMG and force sensors) are susceptible to baseline drift due to electrode impedance changes, temperature variations, and mechanical stress. **Mitigation strategy:** Implement real-time drift detection using exponentially weighted moving average (EWMA) control charts with 3-sigma limits. When drift is detected (>10% baseline shift), trigger automatic recalibration protocols using reference contractions or force plate validation. Drift correction algorithm: $X_{corrected}(t) = X_{raw}(t) - [X_{baseline}(t) - X_{baseline}(0)]$, where baseline is updated every 5 min using the 10th percentile of recent measurements.

Missing Data: Sensor disconnections, signal artifacts, and data transmission failures can create gaps in physiological monitoring. **Handling strategies depend on gap duration:** (a) Brief gaps (<5 s): Linear interpolation between adjacent valid measurements; (b) Moderate gaps (5–30 s): Last observation carried forward (LOCF) with uncertainty flag; (c) Extended gaps (>30 s): Mark session as incomplete, exclude from risk calculation, trigger manual review. For systematic missingness (e.g., specific sensor consistently failing), employ multiple imputation using chained equations (MICE) with 5 imputations, combining results using Rubin's rules.

Device Heterogeneity: Different wearable sensor brands/models produce varying signal characteristics despite measuring the same physiological parameters. **Cross-calibration protocol:** (1) Establish reference measurements using gold-standard laboratory equipment (Biodex dynamometer for force, Delsys EMG for muscle activity); (2) Derive device-specific transfer functions: $Y_{standard} = a + b \times Y_{device} + \epsilon$; (3) Apply calibration coefficients before WASE-∞ calculation; (4) Validate cross-device consistency using intraclass correlation coefficients (ICC > 0.85 required). Example transfer function for Consumer EMG Device A: $EMG_{standard} = 1.12 \times EMG_{deviceA} + 2.3$ ($R^2 = 0.94$).

Environmental Interference: Electromagnetic interference (EMI), temperature extremes, and moisture can degrade sensor performance. **Mitigation approaches:** (1) Signal quality monitoring using signal-to-noise ratio (SNR) thresholds (SNR > 20 dB required); (2) Temperature compensation algorithms for sensors with known thermal sensitivity; (3) Moisture detection circuits triggering alerts when impedance exceeds thresholds; (4) Shielded cables and grounded electrodes for EMG to reduce EMI artifacts.

Data Quality Assurance Framework: Implement real-time quality metrics: (1) Signal completeness (>95% valid samples per minute); (2) Physiological plausibility checks (e.g., EMG < 150% MVC, heart rate 40–220 bpm); (3) Cross-sensor consistency (e.g., EMG and force should correlate $r > 0.6$); (4) Temporal stability (coefficient of variation < 30% over 5-minute windows for baseline measurements); (5) Artifact detection using wavelet decomposition. Quality dashboard displays traffic-light indicators (green/yellow/red) for each sensor stream, enabling real-time intervention.

6 Model misspecification risk

The WASE- ∞ framework makes several modeling assumptions that may not fully capture the complexity of injury risk mechanisms. **Potential sources of misspecification:** (1) Linear weighting of risk factors (α -coefficients) may oversimplify nonlinear dose-response relationships; (2) Multiplicative interaction between risk and protective factors assumes a specific functional form that may not generalize across all injury types; (3) Omitted variables (e.g., previous injury history, genetic factors, training periodization) may confound observed relationships; (4) Time-invariant coefficients may not account for within-athlete adaptation or between-session variability.

Mitigation strategies for Phase 2 empirical validation: (1) Test alternative functional forms (polynomial, spline, generalized additive models) and compare model fit using AIC/BIC; (2) Incorporate interaction terms (e.g., $E \times \Delta I$) to capture synergistic effects; (3) Collect comprehensive covariate data and test sensitivity to their inclusion/exclusion; (4) Employ mixed-effects models with random slopes to account for individual variability in coefficient values; (5) Conduct subgroup analyses to identify populations where model performance differs substantially.

7 Future directions and empirical validation framework

Current Study Dataset: This foundational study employed a comprehensive simulation-based approach generating 360,000 data points from 60 virtual athletes across four sports over 60 min sessions. The simulation used parameters derived from published biomechanics datasets to establish theoretical validity and performance benchmarks. All results reported in this manuscript are based on simulated data designed to validate the mathematical framework under controlled conditions.

Transition to Empirical Validation: The following sections outline a systematic progression from simulation-based validation (current study) to empirical validation with human athletes (future phases). Each phase specifies the target sample size, data collection protocols, and validation objectives, providing a clear roadmap for translating the WASE- ∞ framework from theoretical foundation to clinical implementation.

This foundational simulation study establishes theoretical validity and performance benchmarks for the WASE- ∞ framework. Subsequent empirical validation will proceed in three rigorously designed phases, each with explicit inclusion/exclusion criteria, injury outcome definitions, and data quality protocols. This section provides a detailed roadmap for translating simulation findings into clinical applications.

7.1 Phase 1: pilot feasibility study (year 1)

7.1.1 Target sample size: 20 athletes, ~160 monitoring sessions, ~960,000 data points

Study Design and Population: A prospective observational pilot study will recruit 20 collegiate athletes (5 per sport category: running, cycling, swimming, team sports) from a single institution. Inclusion criteria: age 18–25 years, minimum 3 years competitive experience in respective sport, currently competing at collegiate level, no current musculoskeletal injury limiting participation. Exclusion criteria: neurological disorders, cardiovascular disease, medications affecting motor control (e.g., beta-blockers, stimulants), or inability to wear sensors for $\geq 90\%$ of training sessions.

Monitoring Protocol: Eight-week training period during competitive season with weekly 60 min monitoring sessions (total: 8 sessions per athlete). Wearable sensor array: bilateral EMG (Delsys Trigno, 2 kHz sampling, 4 channels per leg), inertial measurement units (Xsens MVN, 100 Hz, 17 sensors), force plates (AMTI OR6-7, 1,000 Hz, 2 plates), and environmental sensors (temperature, humidity). Data collection occurs during standardized training sessions to minimize confounding from variable training load (33, 34).

Injury Outcome Definition: Primary outcome is time-loss injury, operationally defined as any musculoskeletal injury preventing participation in sport for ≥ 1 day, verified by team physician using standardized injury assessment (Orchard Sports Injury Classification System). Verification includes clinical examination, palpation, range-of-motion testing, and sport-specific functional tests. Blinding: team physicians will be blinded to WASE- ∞ scores during injury assessment.

Objectives: (1) Establish sensor compliance (target: $\geq 90\%$ wear time), (2) assess data quality metrics (target: <5% missing data per session), (3) obtain preliminary WASE- ∞ predictive accuracy estimates, (4) identify protocol refinements for Phase 2, (5) establish measurement error profiles for each variable.

Sample Size Justification: $n = 20$ was determined using guidance from Lancaster et al. (2004) for pilot feasibility studies,

which recommend sample sizes of 12–50 participants to establish preliminary data, assess protocol feasibility, and estimate effect sizes for subsequent confirmatory studies. With 5 participants per sport and 8 weeks of monitoring (8 sessions per athlete), we expect 8–12 injury events (assuming 15% incidence rate), sufficient for preliminary AUC estimation with 95% CI width of ± 0.12 .

Expected Outcomes: (1) Preliminary AUC estimate with 95% CI, (2) sensor compliance rates by device type, (3) data quality assessment (missing data patterns, sensor drift magnitude), (4) protocol modifications for Phase 2, (5) preliminary correlation between WASE- ∞ scores and injury occurrence.

7.2 Phase 2: multi-center validation study (years 2–3)

7.2.1 Target sample size: 200 athletes across 4 centers, ~4,800 monitoring sessions, ~28.8 million data points

Study Design and Population: A prospective observational multi-center study recruiting 150 athletes across 5 collegiate institutions (30 per sport category). Inclusion and exclusion criteria identical to Phase 1. Stratification by sport ensures balanced representation of biomechanical demands.

Monitoring Protocol: Full competitive season (16 weeks) with bi-weekly 90 min monitoring sessions (total: 8 sessions per athlete). Identical sensor array as Phase 1. Concurrent measurement of training load (33, 34) (session rating of perceived exertion, 0–10 scale), sleep quality (actigraphy + questionnaire), psychological stress (Perceived Stress Scale, 10-item version), and nutritional intake (dietary recall).

Injury Outcome Definition: Identical to Phase 1, with addition of blinded injury verification. Team physicians at each site will be blinded to WASE- ∞ scores during injury assessment to prevent bias. Injury severity classified as: minimal (1–3 days lost), mild (4–7 days), moderate (8–21 days), or severe (>21 days). Injury location and type recorded using standard classification system.

Data Quality Protocols: Sensor calibration performed weekly; drift correction algorithms applied to all EMG and IMU data; missing data tolerance <5% per session; multiple imputation (5 imputations) for sporadic missing values using multivariate normal imputation; inter-rater reliability for injury classification assessed using intraclass correlation coefficient (ICC >0.85 required); data completeness reported by variable and site.

Statistical Analysis: Primary analysis uses logistic regression with WASE- ∞ score as predictor and injury occurrence (binary) as outcome, adjusted for sport category and training load (33, 34). Secondary analyses include: (1) sport-specific ROC curves with AUC comparison across sports, (2) Cox proportional hazards model for time-to-injury analysis with WASE- ∞ as time-varying covariate, (3) sensitivity analysis excluding first 2 weeks (adaptation period), (4) interaction analyses testing sport \times WASE- ∞ effects, (5) subgroup analyses by sex and age,

(6) alternative model specifications with different coefficient weights.

Sample Size Justification: Required sample size calculated using power analysis for logistic regression: expected effect size OR = 2.5 (based on simulation results and published injury prediction literature), $\alpha = 0.05$ (two-tailed), power = 0.80, anticipated injury incidence 15% in study population. This yields $n = 128$; we propose $n = 150$ to account for 15% attrition and ensure adequate sport-specific subgroup analyses ($n = 30$ per sport provides 80% power to detect OR = 2.0 within each sport).

Expected Outcomes: (1) Robust AUC estimate with 95% CI for overall cohort and by sport, (2) sport-specific performance metrics, (3) sensitivity/specificity at clinically relevant cutoffs, (4) preliminary evidence of clinical utility, (5) empirically refined coefficients for Phase 3.

7.3 Phase 3: longitudinal follow-up study (years 4–5)

7.3.1 Target sample size: 500+ athletes, ~48,000 monitoring sessions over 2 years, ~288 million data points

Study Design and Population: Prospective longitudinal follow-up of 100 athletes from Phase 2 cohort (67% retention rate, realistic for 2-year athletic studies). Participants continue WASE- ∞ monitoring through 2 additional competitive seasons (total 3 years of follow-up).

Monitoring Protocol: Quarterly monitoring sessions (4 per year) with expanded assessment: annual comprehensive biomechanical evaluation, quarterly psychological assessment, and continuous injury surveillance. Introduction of wearable technology validation: comparison of research-grade sensors (Phase 1–2) with consumer wearables (Apple Watch Series 8, Oura Ring Gen 3) to assess real-world applicability and cost-effectiveness.

Injury Outcome Definition: Identical to Phase 2, with addition of long-term follow-up outcomes: career-threatening injuries, recurrent injuries (≥ 2 injuries in same anatomical location), and functional recovery assessment (return-to-sport clearance timing, performance metrics post-return).

Objectives: (1) Assess long-term predictive validity across multiple seasons, (2) evaluate framework stability and generalizability across seasons, (3) test consumer wearable compatibility and cost-effectiveness, (4) develop clinical decision-support algorithms for injury prevention, (5) establish sport-specific cutoff scores for clinical implementation.

Expected Outcomes: (1) Prospective validation data across 2 years with longitudinal AUC estimates, (2) predictive accuracy stability across seasons (assess whether coefficients remain stable or require seasonal adjustment), (3) consumer wearable validation results with accuracy comparison to research-grade sensors, (4) clinical implementation guidelines with sport-specific recommendations, (5) cost-effectiveness analysis comparing different sensor configurations.

8 Conclusion

This foundational study establishes the WASE- ∞ framework as a theoretically robust and computationally efficient approach to predicting motor intent collapse. The simulation-based validation demonstrates strong predictive performance (AUC = 0.930), realistic risk stratification, and the ability to differentiate sport-specific risk profiles, supporting the framework's theoretical underpinnings. By integrating multiple physiological domains through a mathematically rigorous model, this work represents a critical advancement from traditional single-factor injury prediction approaches.

The comprehensive sensitivity analysis confirms framework stability, while the detailed three-phase empirical validation plan provides a clear and realistic roadmap for translating these simulation findings into clinical applications. Although empirical validation is essential before clinical implementation, this study provides the necessary theoretical foundation, performance benchmarks, and methodological rigor to guide future research. The WASE- ∞ framework represents a promising step toward proactive, individualized injury risk management in athletic populations.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

This study used simulated data and secondary, de-identified datasets; therefore, ethical approval and informed consent were not required. Any original ethics approvals/consents were obtained as reported in the source dataset publication(s).

Author contributions

WA: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision.

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Conflict of interest

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fspor.2026.1651647/full#supplementary-material>

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