

Building a Physics-Informed, Explainable Artificial Intelligence Biomechanical Model of Basketball Free-Throw Performance: A Prospective Multisite Study Protocol

Sumaia Salem Alsaraireh

Al- Balqa' Applied University

sumaya.dmour@bau.edu.jo

Abstract

Background. The basketball free throw is standardized by rule yet remains a complex, athlete-specific coordination task. Prior work has identified associations involving release height, release speed and angle, backspin, center-of-mass control, joint coordination, and movement variability. However, most studies have used small samples, selected discrete variables, sex-restricted cohorts, or analyses that do not preserve the nested structure of repeated shots. Recent artificial intelligence (AI) studies demonstrate that pose sequences and wearable signals can classify free-throw phases or player skill, but high apparent accuracy does not by itself establish athlete-independent prediction, calibration, biomechanical validity, or actionable feedback.

Objective. This protocol describes the development and external validation of a physics-informed, explainable AI model that integrates three-dimensional whole-body kinematics, ball-release dynamics, contextual state, and optional kinetic and electromyographic data to predict free-throw outcome and quantify individualized performance determinants.

Methods. A prospective multisite repeated-measures study will recruit an operational target of 240 basketball players: 180 for model development and temporal validation and 60 from an independent site for external validation. Each athlete will perform 45 analyzed free throws under rested, fatigue, and evaluative-pressure conditions. Synchronized multi-camera markerless motion capture, high-speed ball tracking, and force platforms will quantify joint kinematics, center-of-mass behavior, ground reaction forces, ball-release position and velocity, spin, and hoop-entry geometry; surface electromyography will be optional. A task-specific criterion-validity substudy will compare markerless estimates with marker-based motion capture. Transparent mixed-effects and regularized models will be benchmarked against a multimodal temporal architecture combining a spatiotemporal graph encoder, temporal attention, engineered release mechanics, and a differentiable physics-consistency term. All preprocessing, feature learning, tuning, and calibration will occur within athlete-disjoint nested resampling. A locked model will then undergo

external-site and temporal validation. Primary evaluation will emphasize log loss, Brier score, calibration slope and intercept, area under the receiver operating characteristic curve, area under the precision–recall curve, and athlete-clustered confidence intervals. Explainability will require resampling stability, measurement reliability, biomechanical feasibility, and replication in held-out athletes.

Discussion. The protocol addresses recurrent weaknesses in sports AI by aligning the unit of validation with the athlete, separating prediction from causal interpretation, validating measurement error in the target task, and embedding physical plausibility into model development. The intended product is not a universal “ideal” shooting form but a calibrated, uncertainty-aware estimate of how whole-body coordination and ball-flight mechanics jointly relate to performance for a defined athlete and context.

Keywords: basketball; free throw; biomechanics; artificial intelligence; machine learning; markerless motion capture; ball trajectory; explainable AI; prediction model; sports analytics

1. Introduction

1.1 The free throw as a constrained but individualized motor task

The basketball free throw offers an unusually controlled setting for studying skilled human movement. The target, regulation distance, and absence of an active defender are standardized, yet the performer must coordinate the lower limbs, trunk, shooting arm, hand, and ball within a narrow temporal window. The task therefore combines a stable external goal with many internally available movement solutions. Reviews of basketball shooting have consequently emphasized that successful performance emerges from multi-segment coordination rather than from a single joint position (Okazaki et al., 2015).

Classical trajectory analyses established that ball-release height, speed, angle, spin, and lateral alignment jointly determine the feasible entry region at the hoop. Importantly, the numerical “optimum” changes with the assumptions of the model and the performer. Hamilton and Reinschmidt (1997) predicted a representative optimum near a 60° release angle under a sagittal-plane formulation that incorporated individual release variability, whereas Tran and Silverberg (2008) reported a lower model-specific launch angle near 52° under a different three-dimensional simulation and release-height assumption. Dynamic contact models further show that backspin, lateral deviation, inflation pressure, and ball–rim or ball–backboard interactions alter the capture region (Gablonsky & Lang, 2005; Okubo & Hubbard, 2006). These findings argue against imposing one universal angle or speed as a coaching prescription.

The performer-side literature leads to the same conclusion. Skilled shooting has been associated with coordinated elbow–wrist behavior, postural control, timing between peak center-of-mass height and release, and control of trial-to-trial variation (Button et al., 2003; Mullineaux & Uhl, 2010; Verhoeven & Newell, 2016). In a markerless motion-capture study, proficient shooters displayed lower knee and center-of-mass velocities, greater normalized release height, and less forward trunk lean than non-proficient shooters, although the differences between made and missed shots within proficient performers were small for

most variables (D. Cabarkapa, D. V. Cabarkapa, Miller, et al., 2023). A sensor-based study likewise found that knee and elbow flexion, elbow height, and forearm orientation differentiated proficiency, with forearm angle contributing to within-group outcome discrimination (Cabarkapa et al., 2021).

The inconsistency of apparently important variables across studies should not be interpreted simply as failed replication. It may reflect differences in skill level, anthropometry, sex, measurement technology, analytical resolution, fatigue, pressure, and the distinction between explaining proficiency across athletes and explaining makes versus misses within the same athlete. For example, release-speed variability was strongly and inversely associated with shooting performance within individuals, whereas release-angle variability was not (Slegers et al., 2021). Individual-specific release strategies can also outperform a single population optimum (Slegers, 2022). Movement variability is therefore not uniformly detrimental; its location, structure, timing, and relation to the task's solution manifold matter (Bartlett et al., 2007). Learning stage, shooting distance, and sex may also alter the available coordination strategy, further limiting universal prescriptions (Ammar et al., 2016; D. Cabarkapa, D. V. Cabarkapa, Philipp, Eserhaut, et al., 2022; Silverberg et al., 2018).

1.2 Why an AI-assisted biomechanical model is needed

Traditional analyses typically reduce a shot to several discrete values sampled at preparation or release. That approach is interpretable, but it can discard the temporal organization through which a shooter arrives at the release state. Schmidt (2012) showed that neural-network representations of joint-angle displacement and velocity trajectories could identify free-throw phases, individual characteristics, and skill-related movement organization. More recent work has used a single wrist-worn inertial sensor and a convolutional neural network to classify professional versus recreational players with reported accuracy up to 88% (Guo et al., 2023). PoseShot combined video features, joint-angle sequences, convolutional layers, bidirectional long short-term memory, and transformer encoders to recognize five free-throw action phases with a reported macro-F1 of 95.76% (Hsu et al., 2026).

These studies establish technical feasibility but do not complete the scientific problem. Phase recognition is not equivalent to predicting whether the ball enters the basket, and player-level classification is not equivalent to identifying modifiable within-athlete determinants. Moreover, randomly separating frames, windows, or trials can place observations from the same performer in both training and test sets. The model may then recognize the athlete or recording environment rather than generalizable mechanics. Data leakage through feature selection, nuisance adjustment, repeated individuals, or preprocessing outside resampling can markedly inflate apparent machine-learning performance, especially in small samples (Rosenblatt et al., 2024).

A credible model must therefore satisfy several conditions simultaneously. It must preserve the time series, represent known release physics, account for repeated attempts nested within players, generalize to unseen athletes and sites, produce calibrated probabilities rather than only labels, quantify uncertainty, and explain predictions in a

manner that is stable and biomechanically feasible. It must also demonstrate that the underlying markerless measurements are sufficiently valid for the target movement. Contemporary validation studies show promising agreement for selected tasks, but errors vary by joint, plane, task, camera configuration, and algorithm (Bae et al., 2024; Liang et al., 2022; Yoma et al., 2025).

1.3 Study aim

The primary aim is to develop and externally validate a physics-informed, explainable AI model that estimates the probability of a successful basketball free throw from whole-body biomechanics, ball-release dynamics, and context. Secondary aims are to estimate continuous ball-flight outcomes, characterize athlete-specific successful-release manifolds, quantify the effects of fatigue and evaluative pressure on prediction and calibration, and determine whether multimodal temporal modeling adds value beyond transparent statistical baselines.

2. Objectives and Hypotheses

The study will address four prespecified objectives. First, it will quantify the reliability and criterion validity of the measurement system during free-throw shooting. Second, it will develop models for binary shot success and continuous release or hoop-entry outcomes. Third, it will test transportability across athletes, time, sex, playing level, and sites. Fourth, it will evaluate whether model explanations are stable, plausible, and sufficiently individualized to support future feedback research.

Objective	Primary hypothesis	Falsification criterion
Measurement validity	Task-specific markerless estimates will show acceptable joint- and plane-specific agreement with a marker-based reference for prespecified primary variables.	Bias or random error is large relative to the smallest biomechanically meaningful difference, or reliability confidence intervals cross the unacceptable range.
Predictive performance	The physics-informed multimodal model will improve athlete-level held-out log loss and Brier score over the best transparent baseline.	The athlete-bootstrap confidence interval for the paired performance difference includes no practically important improvement.
Generalization	Calibration and discrimination will remain acceptable in the external-site cohort	Marked calibration drift, subgroup failure, or performance

Objective	Primary hypothesis after the model is locked.	Falsification criterion substantially below the prespecified minimum.
Interpretability	Stable explanatory features will concentrate around mechanically defensible coordination and release variables.	Attribution rankings are unstable across resamples, depend on unreliable measurements, or fail to reproduce in external data.

The principal mechanistic hypothesis is that success will be better predicted by a combination of release mechanics and temporally organized coordination than by any isolated joint angle. A second hypothesis is that within-athlete variability—particularly variability in release speed, lateral alignment, spin-axis orientation, and the timing of release relative to center-of-mass motion—will contain predictive information beyond athlete-level mean technique. A third hypothesis is that fatigue and pressure will alter both movement organization and model calibration; accordingly, a model trained only in a rested, low-pressure laboratory state will not be assumed to generalize to competitive contexts.

3. Methods

3.1 Design and reporting framework

This is a prospective, multisite, repeated-measures observational study comprising a measurement-validation substudy, a model-development cohort, temporal validation, and independent external-site validation. The protocol will be preregistered before recruitment. The observational component will be reported according to STROBE (von Elm et al., 2007). Prediction-model development and validation will adapt TRIPOD+AI reporting principles, including transparent definition of the target population, outcome, predictors, missingness, resampling, calibration, fairness, open science, and intended use (Collins et al., 2024). Risk of bias and applicability will be assessed with PROBAST+AI (Moons et al., 2025).

3.2 Setting and participants

Participants will be recruited from at least two universities, clubs, or performance centers with regulation basketball facilities. Eligible participants will be aged 18–35 years, have at least one year of organized basketball experience, and be medically able to perform maximal intermittent activity and repeated shooting. Recruitment will seek balanced representation by sex and a broad distribution of playing level, from recreational to professional. Left- and right-handed shooters will be eligible; laterality will be harmonized analytically rather than excluded.

Exclusion criteria are a current injury that alters shooting mechanics, surgery within the previous six months without full clearance, acute illness, inability to complete the

standardized fatigue task, or failure of critical measurement channels across the prespecified proportion of trials. Medication and health information will be limited to variables needed for safety and interpretation. Participation will not depend on prior free-throw percentage.

3.3 Sample-size strategy

The operational target is 240 athletes: 180 in the development cohort and 60 at an external site. Each athlete will contribute 45 analyzed attempts, yielding a nominal 8,100 development trials and 2,700 external trials before exclusions. These trial counts must not be mistaken for independent sample sizes, because shots are clustered within athletes.

The final recruitment target will be confirmed after a blinded pilot using simulation. Simulations will preserve the observed athlete-level distribution of success, intraclass correlation, sex and skill strata, missingness, and the anticipated number of predictor parameters. Development sample size will target an expected global shrinkage factor of at least .90, a small difference between apparent and optimism-adjusted model fit, and precise estimation of the overall event proportion, following the principles of Riley et al. (2019). External-validation size will be chosen to provide useful precision for calibration-in-the-large, calibration slope, discrimination, and Brier score rather than relying solely on fixed event-count heuristics (Riley et al., 2021; Riley et al., 2024). If the pilot indicates inadequate effective sample size for the planned deep model, the architecture will be simplified or recruitment increased before outcome labels are inspected for comparative performance.

3.4 Experimental conditions

After informed consent, anthropometry, playing history, handedness, habitual free-throw routine, and recent training load will be recorded. Participants will complete a standardized dynamic warm-up followed by ten familiarization shots. The 45 analyzed attempts will be divided into three blocks of 15 and administered in a counterbalanced order.

The **rested condition** will use standard free-throw rules with 10–15 seconds between attempts. The **fatigue condition** will follow a validated basketball-specific intermittent exercise protocol and begin when the athlete reaches a prespecified relative heart-rate and rating-of-perceived-exertion criterion. The exact conditioning task will be identical across sites, with heart rate and elapsed recovery time recorded before each shot. Fatigue can change shooting mechanics and accuracy, and effects may differ by sex, exercise mode, shot distance, and protocol; it must therefore be measured rather than inferred from shot order alone (D. Cabarkapa, D. V. Cabarkapa, Ciccone, et al., 2023; Li et al., 2021; Li et al., 2025; Uygur et al., 2010).

The **evaluative-pressure condition** will combine a visible score, performance ranking, standardized verbal instructions, and a meaningful but ethics-approved incentive. State anxiety and perceived pressure will be measured immediately before the block. The manipulation will be reported in full and treated as context, not as a diagnostic assessment.

3.5 Instrumentation and synchronization

The preferred configuration uses at least eight synchronized global-shutter cameras sampling at 120–240 Hz for three-dimensional pose reconstruction, a dedicated high-speed camera sampling at 240 Hz or more for ball release and spin, and force platforms sampling at 1,000 Hz. Optional surface electromyography will be sampled at 1,000–2,000 Hz from a prespecified, limited muscle set. The EMG component is secondary because electrode placement, normalization, cross-talk, and practical burden may limit transportability, even though neuromuscular timing and muscle synergies provide useful mechanistic information (Fan et al., 2024; Pakosz et al., 2021).

Hardware synchronization is preferred. If any device cannot receive the same trigger, a light-emitting diode and acoustic impulse detectable by all systems will define a common synchronization event. Residual offsets will be estimated from cross-correlation of ball, wrist, and force signals and reported. Calibration quality, reprojection error, dropped frames, pose confidence, force-platform contact, and ball-trajectory completeness will be stored for each trial.

3.6 Markerless measurement validation

At least 30 athletes spanning sex, body size, clothing variation, and skill level will perform the protocol simultaneously with the markerless system and a laboratory marker-based reference. Test–retest reliability will be assessed in a second session. Agreement will be evaluated for prespecified primary angles and velocities, center-of-mass measures, release position, and event timing.

The analysis will report bias, mean absolute error, root mean square error, Bland–Altman limits of agreement, intraclass correlation coefficients with 95% confidence intervals, standard error of measurement, and minimum detectable change. Correlation alone will not be accepted as evidence of agreement. Existing validation and repeatability studies show that deep-learning markerless systems can achieve strong performance for some variables, but validity is task-, plane-, joint-, and system-specific (Bae et al., 2024; D. Cabarkapa, D. V. Cabarkapa, Philipp, Downey, & Fry, 2022; Hauenstein et al., 2024). A markerless variable will enter the primary model only if its error is acceptably small relative to the expected biomechanical contrast and its test–retest reliability is adequate. Otherwise, it will be excluded or designated exploratory.

3.7 Coordinate systems and biomechanical reconstruction

The global coordinate system will define the positive y-axis from the free-throw line toward the basket center, the positive z-axis vertically upward, and the positive x-axis laterally. Anatomical coordinate systems will follow current biomechanical conventions where applicable. The body will be modeled as a linked rigid-body system comprising the feet, shanks, thighs, pelvis, trunk, upper arms, forearms, and hands. Segment parameters will be scaled to individual anthropometry.

For segment s , with mass m_s and instantaneous center position $r_s(t)$, whole-body center of mass will be calculated as

$$r_{COM}(t) = \frac{\sum_{s=1}^S m_s r_s(t)}{\sum_{s=1}^S m_s}.$$

Joint rotations will be obtained from anatomically defined local coordinate systems. Angular velocity and acceleration will be derived after gap handling and low-pass filtering. Filter cutoffs will be selected by residual analysis and reported separately for pose trajectories, ball tracking, force signals, and EMG. All transformations, filter parameters, and event algorithms will be frozen before the external test set is opened.

When force data are available, inverse dynamics will estimate net joint moments and powers. Instantaneous joint power is

$$P_j(t) = M_j(t) \cdot \omega_j(t),$$

where $M_j(t)$ is the net moment and $\omega_j(t)$ is joint angular velocity. Positive and negative work will be obtained by integrating the corresponding portions of the power curve over prespecified phases. Because inverse dynamics can amplify kinematic error, kinetic estimates derived from markerless inputs will remain secondary unless task-specific validation demonstrates acceptable accuracy.

3.8 Event detection and movement phases

Each shot will be segmented into five events and four phases. Event E0 is movement onset; E1 is minimum center-of-mass height or the deepest whole-body countermovement; E2 is initiation of final upward propulsion; E3 is ball release; and E4 is the end of follow-through. The preparation phase spans E0–E1, propulsion spans E1–E3, the release window spans 100 ms before E3 through 50 ms after E3, and follow-through spans E3–E4.

Ball release will be detected as the first frame at which hand–ball distance increases monotonically while ball speed remains above a prespecified threshold for successive frames. Automated labels will be verified against high-speed video by assessors blinded to the shot outcome during event correction. Phase durations will be preserved as outcomes. For curve analysis, each phase will be time-normalized to 101 samples; the native sampling rate will be retained for peak magnitudes and event timing.

3.9 Ball-release and flight reconstruction

The observed ball center at release is $r_0 = (x_0, y_0, z_0)$, its initial velocity is $v_0 = (v_x, v_y, v_z)$, and its angular velocity is ω_0 . Release speed and elevation angle are

$$v_0 = \sqrt{v_x^2 + v_y^2 + v_z^2}, \quad \theta_0 = \tan^{-1} \left(\frac{v_z}{\sqrt{v_x^2 + v_y^2}} \right).$$

The no-drag reference trajectory is

$$r(t) = r_0 + v_0 t + \frac{1}{2} g t^2.$$

A higher-fidelity model will add aerodynamic drag and a Magnus term:

$$m\dot{v} = mg - \frac{1}{2}\rho C_D A \|v\| v + \frac{1}{2}\rho C_L A \|v\|^2 \hat{n}(\omega, v),$$

where m is ball mass, ρ is air density, A is reference area, C_D is the drag coefficient, C_L is the lift coefficient, and $\hat{n}$ gives the Magnus-force direction. Release parameters will be estimated by robust nonlinear least squares against the observed post-release trajectory. The model will produce release height, speed, elevation angle, lateral angle, backspin, spin-axis tilt, apex height, hoop-plane entry angle, radial and lateral error, and predicted rim intersection.

Ball physics will constrain rather than predetermine the analysis. Classical models show why small combinations of speed, angle, height, and spin can produce or eliminate a feasible trajectory (Brancazio, 1981; Hamilton & Reinschmidt, 1997; Tran & Silverberg, 2008). Empirical evidence also indicates that backspin alignment and its variability can affect shooting accuracy (Slegers & Love, 2022). Nevertheless, coefficients and collision assumptions from prior simulations will not be treated as ground truth for every ball or gym. Physics residuals will be estimated and subjected to sensitivity analysis.

3.10 Outcomes

The primary outcome is binary free-throw success. It will be assigned independently from synchronized ball tracking and video, with disagreements adjudicated by a third assessor. Secondary categorical outcomes are swish, rim-assisted make, backboard-assisted make, short miss, long miss, left miss, and right miss, collapsed when class counts are insufficient. Continuous secondary outcomes include hoop-plane radial error, lateral error, entry angle, apex, rim-clearance margin, and ball-release variables.

A secondary individualized consistency index will quantify how far a trial's release vector departs from that athlete's distribution of successful releases. For athlete a , trial i , and release vector q_{ai} , the regularized Mahalanobis distance is

$$D_{ai} = \sqrt{(q_{ai} - \mu_a)^\top (\Sigma_a + \lambda I)^{-1} (q_{ai} - \mu_a)}.$$

The mean μ_a , covariance Σ_a , and regularization λ will be estimated using training data only. Lower values denote greater consistency with the athlete's learned successful-release manifold. If an athlete contributes too few successful attempts to estimate a stable covariance matrix, a hierarchical population prior will be used and uncertainty will be reported.

3.11 Candidate predictors and biomechanical feature engineering

The predictor set will be prespecified in a versioned data dictionary. Variables will be retained as full time series when possible and summarized into discrete metrics only when a clear biomechanical interpretation exists. The use of both representations is important because discrete values can miss localized coordination changes close to release; increased elbow-wrist coordination variability in misses, for example, was observed during only the final 16 ms before release in prior work (Mullineaux & Uhl, 2010).

Domain	Prespecified variables	Model representation
Anthropometry	Height, mass, arm span, hand size, segment lengths	Athlete-level standardized covariates
Context	Sex, level, site, condition, session, shot order, heart rate, perceived exertion, pressure score	Continuous and categorical covariates
Stance and posture	Stance width and stagger, foot orientation, trunk lean, pelvis orientation, center-of-mass height and sway	Discrete values and normalized curves
Lower-limb kinematics	Ankle, knee, and hip angles, ranges, velocities, accelerations, event timings	Discrete, temporal, and coordination features
Upper-limb kinematics	Shoulder, elbow, forearm, wrist, and hand angles and velocities; elbow height; lateral deviation	Discrete, temporal, and coordination features
Coordination	Continuous relative phase, vector-coding angle, coupling variability, proximal-to-distal timing, release-to-COM peak offset	Trial- and athlete-level features
Kinetics	Ground reaction force, impulse, joint moments, powers, positive and negative work	Optional secondary modality
Neuromuscular	EMG onset, offset, normalized amplitude, and muscle-synergy weights	Optional secondary modality

Domain	Prespecified variables	Model representation
Ball release and flight	Height, speed, angles, backspin, spin-axis tilt, apex, entry geometry, rim clearance	Mechanistic mediators and predictors
Variability	Within-athlete SD, coefficient of variation, entropy, and distance from successful manifold	Session and rolling-window features

Centering choices will follow the inferential target. Athlete-level means will represent between-athlete differences, while trial values centered on each athlete's mean will represent within-athlete departures. This separation prevents a variable that distinguishes skilled from less-skilled players from being misinterpreted as the variable that explains a particular make or miss. Prior studies show why the distinction matters: group differences can be evident even when within-proficient made-missed contrasts are small (D. Cabarkapa, D. V. Cabarkapa, Miller, et al., 2023).

3.12 Artificial intelligence architecture

Three transparent comparators will precede the proposed deep model. Baseline 1 will be a generalized linear mixed-effects model with an athlete random intercept and a small number of prespecified random slopes. Baseline 2 will be elastic-net logistic regression using engineered features. Baseline 3 will be a calibrated gradient-boosted tree model. These comparators establish whether complexity provides practically meaningful benefit.

The proposed model will have two principal branches. The temporal branch will receive normalized skeletal trajectories and, where available, force and EMG channels. A spatiotemporal graph-convolutional encoder will use the anatomical skeleton as its graph, after which a temporal convolution or transformer block will learn longer-range dependencies. A mask channel will distinguish observed, interpolated, and missing frames. The static and physics branch will receive anthropometry, context, engineered coordination features, and measured ball-release variables. A gated late-fusion layer will combine the branches while allowing performance when an optional modality is absent.

The network will use multi-task heads to estimate shot probability and continuous release or hoop-entry outcomes. The total loss is

$$L = L_{BCE} + \lambda_r L_{release} + \lambda_p L_{physics} + \lambda_c L_{calibration},$$

where L_{BCE} is binary cross-entropy for make-miss outcome, $L_{release}$ is a robust regression loss for measured release variables, $L_{physics}$ penalizes disagreement between predicted release conditions and the observed hoop-plane trajectory, and $L_{calibration}$ discourages poorly calibrated probabilities. Loss weights, model depth, hidden dimensions, dropout, and learning rate will be tuned exclusively inside the inner resampling loop.

This architecture extends prior free-throw AI in three ways. It predicts outcome and continuous mechanics rather than only skill or movement phase; it imposes athlete-independent evaluation; and it uses physics as an auxiliary constraint. The temporal design is informed by evidence that both early neural networks and modern convolutional–recurrent–transformer combinations can represent shooting sequences (Hsu et al., 2026; Schmidt, 2012). Wearable-sensor reviews similarly support machine learning for reconstructing biomechanical time series, while cautioning that validation must match the intended task and population (Gurchiek et al., 2019).

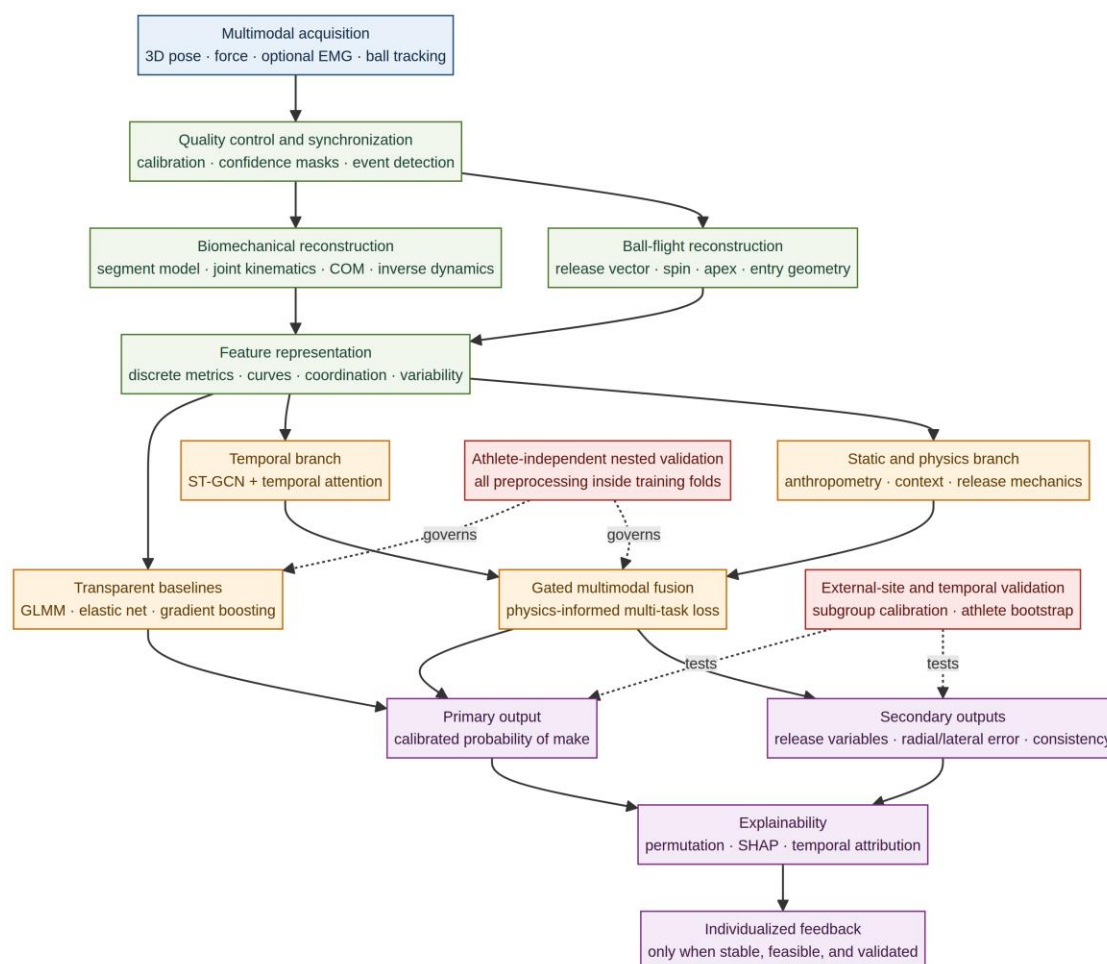


Figure 1. Proposed physics-informed multimodal workflow.

Figure 1. Proposed workflow from synchronized acquisition to individualized feedback. Validation components govern model development rather than serving as optional post hoc checks.

3.13 Missing data and quality control

Every missing value will be accompanied by a reason code: occlusion, synchronization failure, force-platform miss, ball-track loss, EMG artifact, participant withdrawal, or administrative error. Short pose gaps below a prespecified duration may be interpolated

using a method selected during the pilot. Longer gaps will be represented by masks or will lead to modality-specific exclusion. Multiple imputation will be used only for suitable tabular predictors and will be fitted independently inside each training fold. Outcome labels will not be imputed.

Automated quality-control flags will be reviewed without access to predicted outcomes. Preprocessing logs will record calibration error, percentage of low-confidence frames, gap duration, filter settings, event corrections, and reasons for exclusion. Sensitivity analyses will compare the primary pipeline with complete-case analysis and stricter quality thresholds.

3.14 Model development and athlete-independent validation

The development cohort will use repeated nested group cross-validation. In the outer loop, athletes—not trials—will be assigned to folds, so every attempt from one athlete remains in one partition. Within each outer-training set, an inner group-resampling loop will choose preprocessing parameters, feature selection, imbalance handling, hyperparameters, loss weights, and probability calibration. The untouched outer-test fold will estimate generalization to unseen athletes. Performance estimates will be pooled across outer folds with athlete-clustered uncertainty.

After model selection, the full development pipeline will be locked, retrained on all eligible development data, and evaluated once in the independent external-site cohort. The external site will differ in operators and camera environment and, where feasible, include a different competitive population. A separate temporal test will evaluate a later session from development-site athletes. The temporal analysis is distinct from external validation because it tests within-athlete stability over time rather than transport to new athletes and settings.

No session mean, athlete-specific successful manifold, scaling parameter, imputation model, feature-selection decision, synthetic oversampling procedure, or calibration mapping may use information from an outer-test or external-test athlete. If personalized adaptation is evaluated, it will be declared as a separate use case: the model may observe a fixed initial calibration set from a new athlete and will then be tested only on subsequent attempts. This design directly addresses leakage risk from repeated observations (Rosenblatt et al., 2024).

3.15 Performance measures and uncertainty

The primary predictive criteria are log loss and Brier score because they evaluate probabilistic accuracy. Calibration will be described using calibration-in-the-large, calibration intercept, calibration slope, and a smoothed calibration curve. Discrimination will be reported with the area under the receiver operating characteristic curve (AUROC) and the area under the precision–recall curve (AUPRC). Sensitivity, specificity, balanced accuracy, and macro-F1 will be secondary and will be reported only at thresholds defined in the development data.

Continuous outcomes will be evaluated with mean absolute error, root mean square error, explained variance, and Bland–Altman agreement where appropriate. Confidence intervals will be generated by bootstrap resampling athletes, preserving all trials within each sampled cluster. Differences between models will use paired athlete-level bootstrap resamples. Statistical uncertainty, calibration, and the magnitude of improvement over simple baselines will be emphasized rather than a single accuracy value.

Target	Primary measures	Secondary measures
Make–miss probability	Log loss, Brier score, calibration intercept and slope	AUROC, AUPRC, balanced accuracy, macro-F1
Release and flight variables	Mean absolute error with athlete-bootstrap 95% CI	RMSE, explained variance, agreement plots
External usefulness	Calibration curve and threshold-specific net benefit	Decision-curve analysis and operating points
Measurement reliability	ICC with 95% CI, SEM, minimum detectable change	Typical error and within-athlete coefficient of variation

Performance will be reported overall and by sex, playing level, site, handedness, fatigue state, and pressure condition. Subgroup analyses are primarily diagnostic: wide intervals will be displayed and absence of a statistically significant difference will not be interpreted as equivalence. A fairness concern will be flagged when a subgroup shows clinically or practically important deterioration in calibration or error, even if discrimination remains similar.

3.16 Complementary statistical analysis

Prediction and explanation will be separated. The primary explanatory model will be a generalized linear mixed-effects model:

$$\text{logit}\{P(Y_{a ic} = 1)\} = \beta_0 + u_{0a} + \sum_k \beta_k X_{a ic, k} + \sum_m \gamma_m C_{a ic, m} + u_{1a} T_{a ic},$$

where $Y_{a ic}$ is the outcome for athlete a , attempt i , and condition c ; u_{0a} is an athlete random intercept; X denotes biomechanical predictors; C denotes contextual covariates; and u_{1a} is a prespecified random slope for shot order or condition if the data support its estimation. Within-athlete centering will separate whether a player who generally uses a larger value performs differently from others from whether that player performs differently when deviating from his or her usual technique.

Full time-normalized curves will be analyzed using statistical parametric mapping or functional data analysis, with the method and multiplicity control prespecified. Functional principal components will summarize dominant patterns of movement variation. Such

methods avoid restricting inference to arbitrarily chosen instants and are increasingly used for biomechanical curves (Dannenmaier et al., 2020; Pataky et al., 2023; Serrien et al., 2019). These analyses will characterize associations and candidate mechanisms; they will not be presented as causal effects of changing technique.

3.17 Explainability and biomechanical plausibility

Engineered-feature models will be interpreted with conditional permutation importance and SHAP values. The temporal model will be examined using integrated gradients, temporal occlusion, and joint-channel ablation. A single explanation map will not be considered sufficient. Explanation stability will be quantified across bootstrap refits using rank correlation, selection frequency, and the consistency of effect direction.

A variable or temporal region will be eligible for an individualized coaching hypothesis only if it passes four gates: (a) measurement reliability is acceptable; (b) importance is stable across resamples; (c) the direction and magnitude reproduce in held-out athletes or sessions; and (d) the suggested change remains within anatomically feasible and physically compatible limits. Counterfactual perturbations will be constrained so that combinations of joint positions and ball-release variables are realistic. Explanations will be described as predictive associations; neither SHAP values nor saliency maps establish that deliberately changing one feature will cause a shot to be made.

3.18 Sensitivity, ablation, and robustness analyses

The contribution of each design choice will be tested through prespecified ablations: engineered kinematics only, ball-release mechanics only, context only, temporal pose only, no physics-consistency loss, no optional kinetic or EMG modality, and no personalized calibration. The model will also be evaluated under reduced camera views and added pose noise to estimate deployment robustness.

Sensitivity analyses will examine alternative release-event definitions, filtering choices, minimum pose-confidence thresholds, fatigue criteria, outcome definitions, and class weighting. Site-specific recalibration will be permitted only after unadjusted external performance is reported. If substantial heterogeneity is observed, a hierarchical model with site effects will be presented as an update rather than as the original external-validation result.

3.19 Reproducibility and data governance

The protocol, analysis plan, feature dictionary, hyperparameter search space, and exclusion rules will be preregistered. Code, environment files, frozen model weights, and a model card will be released in a versioned repository when licenses and governance permit. Deidentified trajectories and derived features will be shared under participant consent; identifiable video will not be openly released unless consent explicitly covers such use. Data documentation will follow FAIR principles to the extent compatible with privacy and consent (Wilkinson et al., 2016).

The model card will define the intended population, required hardware, expected failure modes, excluded uses, subgroup performance, uncertainty, and update policy. Versioning is essential because changes in pose-estimation software, camera geometry, ball-tracking algorithms, or calibration procedures can alter the predictor distribution even when the basketball task is unchanged.

3.20 Ethics and participant safety

Institutional review board or research ethics committee approval will be obtained at each site before recruitment. All participants will provide written informed consent. The fatigue protocol will include medical screening, standardized stopping criteria, access to first aid, and the right to withdraw without penalty. The pressure manipulation will avoid humiliation, coercion, or disclosure of individual rankings outside the research setting.

Video is potentially identifiable biometric data. Storage will therefore use encryption, access control, retention limits, and a documented separation between identity keys and analytical data. Any secondary use for algorithm training will require consent consistent with that purpose. Automated feedback will not be represented as medical advice, talent-selection authority, or a substitute for a qualified coach.

4. Planned Results and Reporting Template

No empirical results are reported because this article is a prospective protocol. The final study will follow the sequence below so that unsuccessful or negative findings cannot be hidden behind model complexity.

First, a participant-flow diagram will report recruitment, exclusions, usable trials by modality, and reasons for missingness. A baseline table will summarize age, anthropometry, playing experience, habitual free-throw percentage, sex, handedness, and site. The distribution of makes and misses will be presented at athlete and trial levels for each condition.

Second, the measurement-validity substudy will report joint- and plane-specific error and reliability. Primary-model variables that fail the prespecified validity threshold will be visibly marked and excluded before predictive comparison. Third, descriptive biomechanics will show the distribution and time-normalized curves of center-of-mass motion, joint kinematics, coordination, and release variables without selecting only significant contrasts.

Fourth, model performance will be reported for every comparator and the proposed architecture using identical outer folds. A calibration plot, receiver operating characteristic curve, precision-recall curve, and decision curve will accompany the numeric estimates. The locked external-site results will appear separately from internal resampling. Fifth, subgroup and condition-specific calibration will be reported with confidence intervals. Finally, explanation stability, ablations, and failure examples will be displayed. The final paper will not use the language of “human-level” or “expert-level” performance unless a blinded, prespecified human-comparator experiment is completed.

Table shells for the completed study

Model	Log loss	Brier score	Calibration		AUROC	AUPRC
			intercept	slope		
Mixed-effect logistic baseline	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated
Elastic net	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated
Gradient boosting	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated
Physics-informed multimodal model	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated	To be estimated

Validation domain	Population	Main question	Prespecified output
Internal	Unseen development-cohort athletes	Does the pipeline generalize beyond the athletes used for fitting?	Repeated nested group cross-validation
Temporal	Later session from known athletes	Is prediction stable over time?	Calibration, Brier score, and drift diagnostics
External	Athletes from an independent site	Does the locked model transport to a new setting and case mix?	Full probabilistic performance with 95% CIs

Validation domain	Population	Main question	Prespecified output
Subgroup	Sex, level, handedness, condition	Does performance or calibration differ materially?	Stratified estimates with uncertainty

5. Discussion

5.1 Expected scientific contribution

The proposed study is designed to move beyond two common simplifications: the search for a universal ideal shooting posture and the presentation of high classification accuracy as sufficient evidence of usefulness. A free throw is an outcome of a coordinated dynamical system. Joint motion shapes the hand trajectory; hand motion shapes release position, velocity, and spin; those release conditions interact with gravity, aerodynamic forces, and the basket; and the complete chain is constrained by the athlete's morphology, skill, fatigue, and pressure state. A model that omits either temporal coordination or ball physics may predict well in a narrow dataset but provide weak scientific insight.

The framework therefore combines population-level structure with athlete-specific organization. Evidence that successful strategies differ between individuals, and that variability can be functional along a solution manifold, makes personalization a scientific requirement rather than a marketing feature (Slegers, 2022; Verhoeven & Newell, 2016). The individualized consistency metric and explicit within-athlete centering are intended to distinguish a technically unusual but repeatable strategy from a harmful deviation.

5.2 Why release variables alone are insufficient

Release conditions are proximal determinants of ball flight and should carry strong predictive signal; kinetic and kinematic evidence from two- and three-point shooting also indicates that the movement solution changes with distance and proficiency (D. Cabarkapa, Fry, D. V. Cabarkapa, et al., 2022). Nevertheless, a release-only model does not explain how the athlete generated those conditions, and it may provide feedback too late in the movement chain to be actionable. Conversely, a body-only model can ignore the fact that different joint organizations may converge on mechanically equivalent releases. Multi-task learning links the two levels: it asks the temporal body representation to predict the ball state while also estimating the final outcome.

The model also allows the evidence to contradict expectations. In prior research, greater release height has been associated with proficiency across athletes, but within proficient shooters it did not behave as a simple monotonic determinant of makes (D. Cabarkapa, D. V. Cabarkapa, Miller, et al., 2023). The proposed analysis will therefore prefer calibrated nonlinear relationships and within-athlete contrasts over fixed coaching rules. Any recommendation to increase release height, flex a joint further, or change timing must be tested against the athlete's complete release vector and confidence interval.

5.3 Generalization, calibration, and leakage

The most consequential methodological choice is athlete-level separation. A trial-level random split can produce thousands of apparently independent samples while allowing the model to learn stable personal appearance, body proportions, movement signatures, or camera backgrounds. Such a model may perform impressively yet fail on the first new athlete. Nested group validation prevents this form of contamination and also places feature engineering, imputation, normalization, and calibration inside the training process.

Calibration is equally important. A coach deciding whether to intervene needs to know whether a predicted 70% probability behaves like 70% in relevant athletes and conditions. AUROC can remain unchanged even when all probabilities become systematically too high under fatigue. For this reason, probabilistic scores and calibration plots are primary, while threshold metrics are secondary. External validation is not a ceremonial final table: it is the point at which the proposed model can fail, require recalibration, or demonstrate limited applicability.

5.4 Interpretability without causal overclaiming

Explainable AI methods can identify influential variables or time regions, but their outputs are conditional on the model, data distribution, and correlated predictors. A high attribution for wrist velocity does not prove that deliberately increasing wrist velocity will improve performance. The same ball speed could be generated by different proximal-to-distal combinations, and changing one component may destabilize another. The four-gate interpretation rule—reliability, resampling stability, held-out replication, and biomechanical feasibility—is intended to prevent visually compelling but scientifically fragile feedback.

A future intervention trial will be required to establish whether feedback based on this model improves free-throw accuracy. The present protocol develops and validates the measurement and prediction system; it does not test causal effectiveness. This distinction is central to responsible translation.

5.5 Anticipated limitations

The protocol has several foreseeable limitations. First, an operational target of 240 athletes may still be modest for a high-capacity temporal network, particularly for subgroup analysis. Pretraining, architectural restraint, and strong baselines may reduce but cannot eliminate this problem. Second, standardized fatigue and pressure cannot reproduce the full emotional, perceptual, and tactical context of competition. Third, markerless motion capture may be less accurate for rapid wrist, finger, and ball-contact events than for larger lower-limb motions. The high-speed ball camera and marker-based substudy are intended to quantify, not conceal, this limitation.

Fourth, force platforms and EMG improve mechanistic resolution but reduce scalability. The gated multimodal design will allow comparison between a laboratory-rich model and a deployable camera-only model. Fifth, a binary make-miss label contains outcome noise because a mechanically similar release can interact differently with the rim. Continuous

hoop-plane error and swish/rim-contact categories will provide more information. Finally, the study will identify predictive associations; intervention effects, injury implications, and long-term skill acquisition require separate designs.

6. Conclusion

This protocol specifies a rigorous route for building an AI-assisted biomechanical model of basketball free-throw performance without reducing technique to one ideal angle or treating repeated shots as independent observations. The design integrates whole-body temporal coordination, ball-flight physics, contextual state, task-specific measurement validation, athlete-independent nested resampling, external validation, calibration, and stability-based explainability. If executed as specified, the study can produce a reproducible and falsifiable model of how athletes generate successful release conditions and can establish whether individualized feedback is scientifically defensible. Publication claims must remain contingent on collected data: the present document is a publication-oriented protocol, not evidence that the proposed model has already achieved predictive or coaching benefit.

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