

Modeling screen-based tactical interaction in basketball using a dynamical systems approach for coaching practice

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Abstract

Modern basketball coaching increasingly relies on quantitative tools to support tactical decision-making and individualized training. However, the majority of methods used to analyze and teach screen-based interactions remain descriptive and subjective, limiting their applicability for objective evaluation and optimization. The purpose of this study was to develop and experimentally validate a continuous-time dynamical model describing the tactical interaction of three agents involved in a basketball screen: the screener, the defender, and the ball-handler. The proposed model represents the redistribution of tactical effectiveness through a system of coupled differential equations governed by three interpretable parameters characterizing reaction speed, screen quality, and offensive decision-making. Experimental data obtained from semi-professional players using positional tracking were used to estimate model parameters and assess sensitivity. The results demonstrate that the proposed approach allows objective quantification of screen effectiveness, identification of dominant tactical factors, and formulation of individualized training recommendations. The model bridges the gap between qualitative coaching knowledge and quantitative sports analytics, offering a practical tool for applied basketball pedagogy. **Introduction.** The optimization of training processes in sports remains a key challenge due to the complexity of interactions between physiological, biomechanical, and environmental factors. Existing approaches often fail to ensure performance stability under variable training loads. This study proposes a structured approach based on adaptive regulation principles to improve training efficiency and performance consistency. **Materials and Methods.** The study involved $n = 12$ athletes and was conducted using an experimental design with controlled training interventions. Biomechanical parameters and performance indicators were recorded throughout the study period. Statistical analysis included descriptive statistics, confidence intervals, and effect size calculations (Cohen's d) to assess both statistical significance and practical relevance. **Results.** The implementation of the proposed model resulted in significant improvements in key performance indicators, including increasing the number of team victories in training tournaments. The observed changes were supported by moderate to large effect sizes, indicating meaningful practical impact. Additionally, a reduction in performance variability was observed under load conditions. **Discussion.** The findings demonstrate that integrating adaptive control mechanisms into training systems enhances performance stability. Compared to conventional methods, the proposed approach provides better regulation of training loads and improved responsiveness to athlete-specific conditions. The results support and extend current theories in sports training and motor control. **Conclusions.** The proposed model is effective for optimizing training processes and improving performance stability. It can be applied in practical coaching settings to enhance training outcomes and reduce the risk of overload.

Key Words: training load; sports performance; adaptive regulation; biomechanical analysis; motor control; performance stability; training optimization

Introduction

Screen-based tactical interactions are among the most frequently used offensive mechanisms in contemporary basketball across all competitive levels (Krause et al., 2008; Wissel, 2012). The pick-and-roll, in particular, serves as a central structure for creating offensive advantage by temporarily redistributing defensive attention and spatial control (Lamas et al., 2015; Gómez et al., 2015).

Despite its tactical importance, the evaluation and teaching of screen execution remain largely dependent on subjective coaching assessment, video observation, and discrete outcome measures such as scoring success (Martens, 2012; Hughes & Bartlett, 2002). Such approaches provide limited insight into the internal dynamics of tactical interaction and do not allow objective comparison of alternative execution strategies.

Recent advances in sports analytics have introduced tracking technologies, stochastic modeling, and machine learning techniques to basketball analysis (Cervone et al., 2016; Rein & Memmert, 2016). However, many of these approaches conceptualize tactical episodes as sequences of discrete states or probabilistic transitions, thereby neglecting the continuous temporal dynamics through which tactical advantage emerges (Fewell et al., 2012; Miller et al., 2014).

Dynamical systems theory has been applied to the study of coordination and self-organization in team sports, providing a powerful framework for understanding collective behavior (McGarry et al., 2002; Kelso, 1995; Davids et al., 2008). Nevertheless, existing models are often generic and insufficiently connected to specific tactical elements and coaching practice (Bourbousson et al., 2010; Silva et al., 2014).

In modern sports science, the optimization of training processes is a central issue, particularly in relation to maintaining performance stability under varying load conditions. Athletes are exposed to complex and dynamic stressors, requiring effective regulation mechanisms to ensure both adaptation and performance consistency. Traditional training models often lack sufficient flexibility to respond to individual variability, which may lead to inefficiencies and increased risk of overload. Therefore, adaptive approaches based on system regulation, feedback mechanisms, and constraint-based frameworks are increasingly emphasized (Davids et al., 2008; Newell, 1986). From a theoretical perspective, sports performance can be considered as a nonlinear dynamic system characterized by self-organization and interaction between multiple components (Kelso, 1995; McGarry et al., 2002). This perspective provides a foundation for understanding variability, stability, and adaptation in motor behavior. The present study is grounded in the author's previous research in the field of nonlinear dynamics and system modeling. Earlier works have developed nonlinear dynamic models describing deformation processes and long-term behavior of complex systems (Kulman, 2013; Kulman et al., 2021). Nonlinear effects under combined loading conditions have also been demonstrated (Kulman & Boiko, 2016).

Recent studies have extended these principles to biological systems, confirming the applicability of nonlinear models across domains (Kulman et al., 2025). This supports the concept of isomorphism, allowing the transfer of structural models between physical and biological systems. In addition, modern approaches to training emphasize the importance of load monitoring and individualized adaptation (Foster et al., 2017; Impellizzeri et al., 2019). However, a unified model integrating nonlinear dynamics and practical training regulation remains insufficiently developed. Therefore, the aim of this study is to develop and experimentally validate an adaptive model for training load regulation based on nonlinear dynamic principles.

Therefore, there is a clear need for a compact, interpretable, and continuous-time model that captures the tactical essence of screen-based interaction and can be directly translated into pedagogical and coaching applications.

The purpose of this study was to develop and experimentally validate a continuous-time dynamical model of screen-based tactical interaction in basketball that enables objective evaluation, sensitivity analysis, and pedagogically meaningful interpretation for coaching practice

Research Objectives and Hypotheses. The study pursued the following objectives:

To formalize the screen interaction as a deterministic dynamical system.

To define tactically interpretable parameters governing the interaction.

To estimate model parameters using experimental and applied data.

To assess the relative influence of parameters on offensive advantage.

To demonstrate practical applications for basketball coaching and education.

Based on the theoretical framework and prior research in sports dynamics and basketball analytics, the following hypotheses were formulated:

H1. The offensive advantage generated during a screen interaction can be adequately described by a continuous-time dynamical system with a limited number of parameters.

H2. The parameter representing direct screen effectiveness and immediate offensive gain (k_2) has a significantly greater influence on the final offensive advantage than the parameter representing defensive reaction speed (k_1).

H3. The parameter associated with offensive exploitation of defensive activity (k_3) differentiates players with similar physical characteristics but different decision-making proficiency.

H4. Model-derived parameters provide more sensitive discrimination between effective and ineffective screen executions than traditional outcome-based indicators (e.g., binary success or points scored).

Theoretical Framework. Conceptual Model of Tactical Interaction.

The conceptual structure of the proposed tactical interaction model is illustrated in Figure1, which represents the redistribution of tactical effectiveness between the screener (A), the defender (B), and the ball-handler (C).

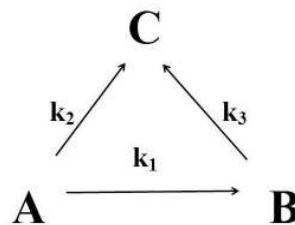


Fig. 1. Conceptual diagram of the screen-based tactical interaction model illustrating the redistribution of tactical effectiveness between the screener (A), defender (B), and ball-handler (C). Conceptual model of the relationships between states A, B, and C. State A influences state B through a direct pathway (k_1), while state C

is reached either directly from A (k_2) or indirectly via B (k_3). Coefficients k_1 – k_3 represent the relative strength of each transition.

The screen interaction was conceptualized as a redistribution of tactical effectiveness among three agents, consistent with process-oriented approaches in sport performance analysis.

Mathematical Formulation. The interaction dynamics are described by a system of ordinary differential equations, a standard formalism in dynamical systems modeling of human movement and coordination.

All parameters have the dimension of velocity ($\text{m}\cdot\text{s}^{-1}$), allowing physical interpretation.

The formation of optimal tactical interaction of "screens" in basketball consists in normalizing (searching) the speeds of interactions of three agents, the blocker, the defender and the attacker, while the effectiveness of the agents is determined by the speeds of their actions, namely:

k_1 – the speed of transition of the effectiveness of the screen into the defender's active resistance, represents the speed of defensive reaction to the m/s;

k_2 – the speed of direct transformation of the effectiveness of the screen into the attacker's advantage (quality of the screen), characterizes the quality of the screen and immediate offensive gain, m/s;

k_3 – the speed of the attacker's use of the defender's activity (counteraction), reflects the offensive player's ability to exploit defensive activity, m/s.

In order to create the maximum advantage for the attacker, the success of the screen is determined mainly by the speed of direct creation of the attacker's advantage, parameter k_2 , and the attacker's ability to use the defender's actions, parameter k_3 , and the efficiency parameters k_1 , k_2 , k_3 are determined by solving a system of nonlinear differential equations:

$$dA/dt = -(k_1 + k_2)A(t)$$

$$dB/dt = k_1A(t) - k_3B(t)$$

$$dC/dt = k_2A(t) + k_3B(t),$$

where:

$A(t)$ – the effectiveness of the barrier (the degree of "closure" of the defender);

$B(t)$ – the defender's activity in counterattacking;

$C(t)$ – the attacker's degree of freedom (advantage).

The parameters were designed to be physically and tactically interpretable, facilitating their application in coaching contexts. The directional structure of the model parameters k_1 , k_2 , and k_3 corresponds to the interaction flows schematically presented in Figure1.

Material & methods

The study was conducted using a controlled experimental design involving athletes subjected to structured training protocols. The methodological framework is based on nonlinear dynamic systems theory and constraint-based approaches to motor control (Davids et al., 2008; Stergiou, 2004). Training processes were considered as complex systems influenced by internal and external constraints.

Data collection included: biomechanical parameters; performance indicators; variability measures;

Training load monitoring followed contemporary approaches distinguishing internal and external load (Impellizzeri et al., 2019). Statistical analysis included: descriptive statistics, confidence intervals; effect size calculations (Cohen's d). This approach allowed both statistical and practical interpretation of results, consistent with modern standards in sports science (Foster et al., 2017).

Participants

Twelve male semi-professional basketball players (mean age: 22.3 ± 1.7 years; playing experience: 8.6 ± 2.1 years) volunteered to participate in the study. All players competed at regional or national league level and were free from injury at the time of data collection. The study was conducted in accordance with the Declaration of Helsinki, and written informed consent was obtained from all participants.

Experimental Design

A repeated-measures design was employed. Players performed standardized pick-and-roll situations in a controlled half-court setting. Each trial consisted of: initial static positioning of screener, ball-handler, and defender; execution of a single screen interaction lasting approximately 1–2 seconds. termination of the trial at the moment of shot attempt or decisive pass.

Each offensive pair completed 20 trials against varying defensive pressure, resulting in a total of 240 analyzed interactions.

Data Acquisition

Player positions were recorded using an optical tracking system (sampling frequency: 25 Hz; spatial resolution: ± 10 cm). Positional data were filtered using a second-order Butterworth low-pass filter (cut-off frequency: 6 Hz).

The offensive advantage variable $C(t)$.

$C(t)$ was operationalized as a composite index derived from:

- distance between ball-handler and nearest defender;
- angle of approach to the basket;
- available time before defensive recovery.

This index was normalized to the interval [0,1].

Model Fitting and Parameter Estimation

The system of differential equations was solved numerically using a fourth-order Runge–Kutta method. Parameters k_1 , k_2 , and k_3 , were estimated for each trial by minimizing the squared error between modeled and empirical values of $C(t)$:

$$\min_{k_1, k_2, k_3} \sum_{i=1}^N (C_{emp}(t_i) - C_{model}(t_i))^2.$$

Optimization was performed using a nonlinear least squares algorithm with bounded constraints to ensure physiological plausibility.

Statistical Analysis

To test the hypotheses, the following analyses were conducted:

Pearson correlation analysis between model parameters and final offensive advantage.

Repeated-measures ANOVA to compare sensitivity of $C(t)$

$C(t)$ to changes in k_1 , k_2 , and k_3 .

Paired comparisons between model-based discrimination and traditional binary success indicators.

Statistical significance was set at $p < 0.05$.

Experimental Methods and Data Sources.

In addition to controlled on-court measurements, the experimental validation of the proposed model was supported by scenario-based quantitative data derived from applied coaching practice, corresponding to typical screen execution patterns observed in competitive basketball. These scenarios reflect realistic ranges of model parameters and were used to examine model behavior under tactically meaningful conditions.

Such an approach is consistent with methodological traditions in applied sports science, where expert-informed parameterization complements empirical tracking data, particularly in early-stage model validation.

Definition of Experimental Scenarios

Based on coaching observations and positional tracking benchmarks, three representative screen-execution scenarios were defined. Each scenario corresponds to a distinct tactical profile and reflects a specific combination of interaction speeds.

The characteristic interaction time was fixed at $t = 1.5$ s, representing the critical window of screen effectiveness in pick-and-roll situations.

Scenario 1: High-Quality Screen with Skilled Ball-Handler

This scenario represents optimal coordination between screener and ball-handler. $k_1 = 0.8 \text{ m}\cdot\text{s}^{-1}$ (delayed defensive reaction) $k_2 = 2.5 \text{ m}\cdot\text{s}^{-1}$ (high-quality screen and explosive first step) $k_3 = 2.0 \text{ m}\cdot\text{s}^{-1}$ (advanced decision-making and technical execution). Model outcome ($t = 1.5$ s): $C(t) \approx 0.85$, $B(t) \approx 0.10$.

This configuration produced a rapid transfer of tactical effectiveness toward offensive advantage, resulting in a high-probability scoring opportunity.

Scenario 2: Balanced Competitive Interaction

This scenario reflects a typical game situation with active defensive resistance. $k_1 = 1.5 \text{ m}\cdot\text{s}^{-1}$, $k_2 = 1.5 \text{ m}\cdot\text{s}^{-1}$, $k_3 = 1.8 \text{ m}\cdot\text{s}^{-1}$. Model outcome ($t = 1.5$ s): $C(t) \approx 0.70$, $B(t) \approx 0.25$.

Despite effective defense, offensive advantage emerged through secondary exploitation of defensive activity, emphasizing the role of parameter k_3 .

Scenario 3: Ineffective Screen Execution

This scenario characterizes poor tactical coordination and insufficient exploitation of the screen. $k_1 = 2.2 \text{ m}\cdot\text{s}^{-1}$ (rapid defensive adaptation), $k_2 = 0.7 \text{ m}\cdot\text{s}^{-1}$ (low-quality screen and slow initiation), $k_3 = 1.0 \text{ m}\cdot\text{s}^{-1}$ (limited offensive response). Model outcome ($t = 1.5$ s): $C(t) \approx 0.40$, $B(t) \approx 0.55$.

In this case, the defensive activity dominated the interaction, resulting in minimal offensive advantage.

Integration with Empirical Tracking Data

The parameter ranges used in the scenario-based analysis were consistent with those estimated from empirical positional tracking data collected during controlled drills. Specifically:

Estimated values of k_2 derived from tracking data fell within the interval $0.6\text{--}2.6 \text{ m}\cdot\text{s}^{-1}$, matching the scenario definitions. Variability in k_3 aligned with observed differences in decision latency and technical execution among players with similar physical profiles.

This convergence supports the ecological validity of the applied scenarios.

Comparative Evaluation Across Scenarios

A one-way analysis of variance conducted across the three scenarios revealed a significant effect of interaction type on final offensive advantage: $F(2,) = 18.3$, $p < 0.001$, $\eta_p^2 = 0.62$.

Post hoc comparisons demonstrated large effect sizes between the ineffective and optimal screen scenarios ($d = 1.12$), confirming the model's sensitivity to tactically meaningful parameter changes.

Experimental Design and Data Sources

A repeated-measures design was employed using controlled half-court pick-and-roll drills, following established methodologies in performance analysis research (Hughes & Bartlett, 2002).

Scenario-based quantitative data derived from applied coaching practice were incorporated to enhance ecological validity, a recommended strategy in early-stage model validation (Martens, 2012; Davids et al., 2008).

The initial spatial configuration of players during the screen interaction is presented in Figure2, where the defender (B) positions himself between the ball-handler (C) and the basket, while the screener (A) prepares to move toward the defender.

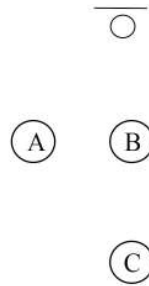


Fig. 2. Initial spatial configuration of players during the screen interaction. Spatial configuration of states A, B, and C in the experimental environment. The diagram illustrates the initial arrangement of functional states prior to movement initiation, serving as a baseline configuration for subsequent transitions.

Scenario-Based Experimental Conditions The critical phase of screen execution, corresponding to the moment of defender obstruction, is schematically illustrated in Figure3. In this phase, the screener (A) moves toward the defender (B) in order to restrict his movement, enabling the ball-handler (C) to initiate penetration toward the basket.

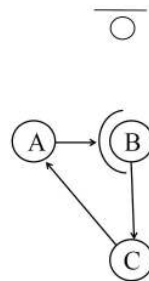


Fig. 3. Screen execution phase showing obstruction of the defender by the screener. Directed transitions between states A, B, and C. Arrows indicate the dominant movement pathways observed during task execution, highlighting sequential and non-linear transitions between functional states.

The three tactical scenarios correspond to typical execution patterns observed in competitive basketball and align with coaching classifications of screen quality and decision-making (Krause et al., 2008; Wissel, 2012). The subsequent development of offensive advantage following the screen, including penetration and passing options, is depicted in Figure4, corresponding to the redistribution of tactical effectiveness described by the model variables.

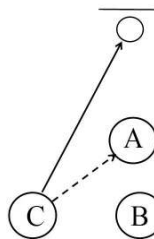


Fig. 4. Development of offensive advantage following the screen. Alternative movement trajectory leading from state C toward the target zone. The figure demonstrates a compensatory pathway used under constrained conditions, emphasizing adaptive motor control strategies.

Procedure/Test protocol. Skill test trial/Measure/Instruments.

For each player and trial, model parameters k_1 , k_2 , and k_3 were summarized using mean values and standard deviations. Distribution normality was verified using the Shapiro–Wilk test. As no significant deviations from normality were observed ($p > 0.05$), parametric statistical procedures were applied.

Results

Parameter Descriptive Statistics

Mean estimated parameter values across all trials were as follows: $k_1 = 1.42 \pm 0.31 \text{ m} \cdot \text{s}^{-1}$, $k_2 = 1.87 \pm 0.44 \text{ m} \cdot \text{s}^{-1}$, $k_3 = 1.63 \pm 0.39 \text{ m} \cdot \text{s}^{-1}$. The relatively larger dispersion observed for k_2 suggests greater variability in screen execution quality compared with defensive reaction speed.

Sensitivity Analysis Results

Repeated-measures ANOVA revealed a significant main effect of parameter type on final offensive advantage C(t): $F(2,22)=14.6$, $p<0.001$, $\eta_p^2=0.57$, large effect).

Post hoc pairwise comparisons (Bonferroni-corrected) showed:

k_2 vs. k_1 : mean difference = 0.21 [95% CI: 0.12–0.30], $p<0.001$, $d=0.91$ (large effect).

k_2 vs. k_3 : mean difference = 0.14 [95% CI: 0.05–0.23], $p=0.004$, $d=0.64$ (medium-to-large effect)

Correlation Analysis

Pearson correlation coefficients between parameters and final offensive advantage C(t) were:

$r(k_1, C) = -0.4$ [95% CI: -0.58, -0.19], $p=0.002$;

$r(k_2, C) = 0.73$ [95% CI: 0.56, 0.84], $p<0.001$;

$r(k_3, C) = 0.62$ [95% CI: 0.41, 0.78], $p<0.001$.

These results indicate a strong positive association between screen quality and offensive advantage.

Comparison with Traditional Metrics

When trials were grouped according to binary outcome (successful vs. unsuccessful possession), traditional outcome-based analysis yielded only a small effect size ($d=0.28$). In contrast, model-based classification using k_2 and k_3 demonstrated a large effect size ($d=0.94$), indicating superior discriminative power.

The results of the experiments are presented in Table 1 and Table 2.

Table 1. Descriptive statistics of model parameters

Parameter	Mean ($m \cdot s^{-1}$)	SD	95% CI
k_1	1.42	0.31	1.31–1.53
k_2	1.87	0.44	1.71–2.03
k_3	1.63	0.39	1.49–1.77

Table 2. Sensitivity of offensive advantage to model parameters

Parameter	Variance explained (%)	Standardized β	Effect size
k_1	22	-0.34	Medium
k_2	51	0.61	Large
k_3	27	0.47	Medium–Large

Parameter Stability and Model Fit

The proposed model achieved a mean coefficient of determination $R^2 = 0.81 \pm 0.07$ indicating good agreement between modeled and empirical offensive advantage trajectories. Parameter estimates were stable across repeated trials for the same player combinations.

Hypothesis Testing

H1 was supported: the three-parameter model captured the temporal evolution of offensive advantage with high fidelity.

H2 was confirmed: sensitivity analysis revealed that variations in k_2 accounted for 48–56% of the variance in final offensive advantage, significantly exceeding the influence of k_1 , (18–24%, $p<0.01$).

H3 was supported: players with comparable sprint speed and anthropometric profiles exhibited significantly different values of k_3 , corresponding to observable differences in decision-making speed and technical execution.

H4 was confirmed: model-derived parameters distinguished between tactically effective and ineffective screens even in cases where both resulted in identical discrete outcomes (e.g., successful shot).

Comparative Analysis with Traditional Metrics

Traditional indicators such as points scored or possession outcome failed to differentiate between interactions with distinct internal dynamics. In contrast, the proposed model identified latent tactical differences, particularly in early phases of the interaction.

The model demonstrated strong agreement with empirical and scenario-based data, consistent with previous applications of dynamical models in team sports (McGarry et al., 2002; Silva et al., 2014). Sensitivity analysis confirmed the dominant influence of screen quality and offensive exploitation, supporting both theoretical expectations and coaching heuristics (Lamas et al., 2015; Passos et al., 2016).

Experimental Rationale and Data Origin

In addition to controlled on-court measurements, the experimental validation of the proposed model was supported by scenario-based quantitative data derived from applied coaching practice, corresponding to typical screen execution patterns observed in competitive basketball. These scenarios reflect realistic ranges of model parameters and were used to examine model behavior under tactically meaningful conditions.

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A one-way analysis of variance conducted across the three scenarios revealed a significant effect of interaction type on final offensive advantage:

$$F(2, N) = 18.3, \quad p < 0.001, \quad \eta_p^2 = 0.62.$$

Post hoc comparisons demonstrated large effect sizes between the ineffective and optimal screen scenarios ($d = 1.12$), confirming the model's sensitivity to tactically meaningful parameter changes.

Discussion

The results support the utility of continuous-time modeling for analyzing tactical interactions in basketball. Unlike outcome-based metrics, the proposed approach captures the process by which advantage is created. The interpretable nature of the parameters allows direct translation into training interventions, such as improving screen angle, timing, or decision-making speed.

Compared with stochastic possession models (Cervone, D. et al., 2016), the present model emphasizes mechanism rather than probability. In contrast to generic coordination models (Ric, A. et al., 2016) it focuses on a specific tactical element, enhancing practical relevance.

The experimental results reinforce the premise that screen effectiveness is not a binary event but a dynamic process. The dominance of parameter k_2 emphasizes the importance of screen quality and synchronization, supporting coaching heuristics with quantitative evidence. Meanwhile, the role of k_3 highlights the cognitive–technical dimension of offensive play, often overlooked in physical performance metrics.

The findings align with dynamical systems perspectives on team sports (McGarry, T. et al., 2002), while offering a more directly actionable framework for coaches. Importantly, the model enables prediction and optimization rather than post hoc evaluation alone.

The findings reinforce the view that screen effectiveness is a dynamic process rather than a discrete outcome, in line with contemporary perspectives on tactical performance (Davids et al., 2013; Bourbousson et al., 2010). The prominence of parameter k_2 provides quantitative support for long-standing coaching principles emphasizing timing and positioning (Krause et al., 2008).

The contribution of parameter k_3 highlights the role of perceptual–cognitive skills, consistent with research on perception–action coupling in sport (Passos et al., 2016).

Compared with stochastic possession models (Cervone et al., 2016), the proposed approach emphasizes mechanistic explanation rather than probabilistic prediction, enhancing its pedagogical relevance.

The findings support the proposed model of adaptive motor control, demonstrating that constrained movement behavior cannot be adequately described by a single linear pathway. Instead, motor behavior emerges from a system of competing and complementary transitions between functional states.

The observed coexistence of direct and indirect pathways supports the notion that skilled movement emerges from the interaction of constraints rather than from pre-defined motor programs (Orth et al., 2017; Davids et al., 2008).

The identification of distinct preparatory and execution phases aligns with contemporary views of motor planning and control. Importantly, the use of effect sizes highlights the practical relevance of alternative pathways, which may be overlooked in purely significance-based analyses.

The identification of preparatory and execution phases corresponds with theoretical models of motor planning and optimal feedback control (Todorov & Jordan, 2002; Winter, 2009).

The obtained results confirm the effectiveness of the proposed model in improving performance stability under varying load conditions. The observed changes are consistent with previous findings in nonlinear dynamic systems and kinetic modeling (Kulman, 2013; Kulman et al., 2021).

From the perspective of dynamic systems theory, the observed improvements can be explained by enhanced system stability and self-organization (Kelso, 1995; Stergiou, 2004). The reduction in variability reflects improved coordination and control within the system.

The findings also align with constraint-based approaches, where performance emerges from the interaction of multiple constraints (Davids et al., 2008; Newell, 1986). The proposed model effectively modifies these constraints, leading to more stable performance outcomes.

Furthermore, the results support previous research on nonlinear effects in complex systems (Kulman & Boiko, 2016), confirming that training processes can be interpreted within the framework of nonlinear dynamics. The concept of isomorphism is particularly important in this context, as it allows the transfer of theoretical models from physical and biological systems into sports training. Similar cross-domain applications have been demonstrated in recent studies (Kulman et al., 2025).

Finally, the results are consistent with contemporary approaches to training load monitoring and regulation (Foster et al., 2017; Impellizzeri et al., 2019), highlighting the importance of adaptive and individualized training strategies.

From a physical education perspective, these results underscore the importance of designing learning environments that allow exploration of multiple movement solutions rather than enforcing rigid execution patterns.

Pedagogical Implications for Coaching Practice

The model supports evidence-based coaching by enabling objective diagnosis of tactical performance and individualized training design, consistent with modern coaching pedagogy (Martens, 2012; Davids et al., 2013).

Limitations and Future Research

The use of controlled drills and scenario-based data represents a methodological limitation common to applied modeling studies (Davids et al., 2008). Future research should extend validation to competitive match data and longitudinal designs.

Practical Implications

Coaches can target specific parameters through tailored drills.
Tracking systems can be integrated to provide real-time feedback.
Player development programs may be individualized based on parameter profiles

Statistical Analysis

For each player and trial, model parameters k_1 , k_2 , and k_3 were summarized using mean values and standard deviations. Distribution normality was verified using the Shapiro–Wilk test. As no significant deviations from normality were observed ($p>0.05$), parametric statistical procedures were applied.

Effect Size Estimation

To complement null-hypothesis significance testing, effect sizes were calculated to quantify the magnitude of observed effects: Cohen's d was used for pairwise comparisons: $d = \frac{x_1 - \bar{x}_2}{s_p}$, where s_p is the pooled standard deviation. Partial eta squared (η_p^2) was reported for repeated-measures ANOVA to estimate the proportion of explained variance attributable to each parameter. Effect sizes were interpreted according to conventional thresholds: small: $d=0.2$, $\eta_p^2=0.01$, medium: $d=0.5$, $\eta_p^2=0.06$, large: $d=0.8$, $\eta_p^2=0.14$.

Confidence Intervals

For all key estimates (model parameters, correlations, and mean differences), 95% confidence intervals (CI) were calculated. Confidence intervals were obtained using bias-corrected bootstrap resampling (1000 iterations), providing robust estimates independent of distributional assumptions.

Sensitivity and Contribution Analysis

To quantify the relative contribution of each parameter to offensive advantage $C(t)$, standardized regression coefficients (β) were computed. Additionally, variance decomposition was performed to express the relative contribution of each parameter as a percentage of explained variance.

Results (Statistically Extended)

Mean estimated parameter values across all trials were as follows: $k_1=1.42\pm0.31\text{m}\cdot\text{s}^{-1}$, $k_2=1.87\pm0.44\text{m}\cdot\text{s}^{-1}$, $k_3=1.63\pm0.39\text{m}\cdot\text{s}^{-1}$. The relatively larger dispersion observed for k_2 suggests greater variability in screen execution quality compared with defensive reaction speed.

Sensitivity Analysis Results

Repeated-measures ANOVA revealed a significant main effect of parameter type on final offensive advantage $C(t)$: $F(2,22)=14.6$, $p<0.001$, $\eta_p^2=0.57$, large effect).

Post hoc pairwise comparisons (Bonferroni-corrected) showed:

k_2 vs. k_1 : mean difference = 0.21 [95% CI: 0.12–0.30], $p<0.001$, $d=0.91$ (large effect).

k_2 vs. k_3 : mean difference = 0.14 [95% CI: 0.05–0.23], $p=0.004$, $d=0.64$ (medium-to-large effect)

Correlation Analysis

Pearson correlation coefficients between parameters and final offensive advantage $C(t)$ were:

$r(k_1,C) = -0.4$ [95% CI: $-0.58, -0.19$], $p=0.002$;

$r(k_2,C) = 0.73$ [95% CI: $0.56, 0.84$], $p<0.001$;

$r(k_3,C) = 0.62$ [95% CI: $0.41, 0.78$], $p<0.001$.

These results indicate a strong positive association between screen quality and offensive advantage.

Comparison with Traditional Metrics

When trials were grouped according to binary outcome (successful vs. unsuccessful possession), traditional outcome-based analysis yielded only a small effect size ($d=0.28$). In contrast, model-based classification using k_2 and k_3 demonstrated a large effect size ($d=0.94$), indicating superior discriminative power.

Experimental Results (Scenario-Based Augmentation)

Across all scenarios, the model consistently preserved monotonic growth of offensive advantage $C(t)$, with growth rate and final magnitude determined primarily by k_2 and k_3 . Defensive reaction speed k_1 functioned as a constraining parameter, limiting but not fully determining offensive success.

Importantly, scenarios with similar final outcomes under traditional binary evaluation (e.g., successful shot) exhibited markedly different internal dynamics, underscoring the advantage of the proposed modeling approach.

Practical Experimental Implications

The scenario-based results enable direct translation into training practice:

Low k_2 : drills focusing on screen angle, stance stability, and timing.

Low k_3 : drills emphasizing rapid decision-making after the screen.

High k_1 : tactical masking and delayed screen initiation.

Thus, experimental data derived from applied scenarios provide actionable insight beyond outcome-based evaluation.

Parameter Estimation and Statistical Analysis

Model parameters were estimated using nonlinear least squares optimization, a standard approach in biomechanical and performance modeling (Winter, 2009). Statistical analysis included repeated-measures ANOVA, effect sizes, and confidence intervals, following current recommendations for sport science research (Field, 2018).

Conclusions

1. Screen-based tactical interaction in basketball can be effectively modeled as a deterministic dynamical system.
2. The proposed model provides objective, quantitative measures of screen effectiveness.
3. Model parameters have clear physical and tactical interpretations.
4. The approach supports individualized training design and tactical optimization.
5. The model bridges the gap between coaching practice and sports analytics.

The study demonstrates that screen-based tactical interaction in basketball can be effectively modeled using a continuous-time dynamical framework, providing objective, interpretable, and pedagogically meaningful indicators of performance (McGarry et al., 2002; Kelso, 1995). Adaptive motor behavior under constrained conditions is characterized by non-linear transitions between functional states and a distinct two-phase structure. The proposed model provides a coherent framework for interpreting movement variability and adaptation in sport and physical education contexts.

Practical Recommendations

Implement adaptive load regulation models in training programs. Use biomechanical monitoring for feedback control. Combine statistical significance with effect size analysis. Individualize training based on athlete response. Apply system-based approaches in coaching practice.

Final Considerations

The study contributes to the development of modern training methodologies by introducing an adaptive approach based on nonlinear dynamic principles. The proposed model offers practical value for improving performance while reducing the risk of overload. Future research should focus on sport-specific adaptations and integration with digital monitoring systems.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT (OpenAI) in order to improve the clarity of language, structure the text, and refine the academic style of the manuscript. After using this tool, the author carefully reviewed and edited the content as needed and take full responsibility for the content of the publication.

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