

Research article

A Non-Linear Conceptual Framework for Individualized Injury Risk Assessment in Situational Sports: Systems-Based Model and Proof-of-Concept Study

Serhii Kozin ¹, Vladimir Potop ², Zhanneta Kozina ^{3,*}, Oleksii Kozin ⁴, Ratko Pavlovic ⁵, Ilona Mihajlovic ⁶ and Nikola Radulovic ⁷

Citation: Kozin S., Potop V., Kozina Z., Kozin O.4, Pavlovic R., Mihajlovic I., Radulovic N. - A Non-Linear Conceptual Framework for Individualized Injury Risk Assessment in Situational Sports: Systems-Based Model and Proof-of-Concept Study *Balneo and PRM Research Journal* 2026, 17(3): 1070

Academic Editor(s):
Constantin Munteanu

Reviewer Officer:
Viorela Bembea

Production Officer:
Camil Filimon

Received: 28.07.2026
Published: 30.09.2026

Reviewers:
Carmen Delia Nistor-Cseppento
Himena Zippenfening

Publisher's Note:
Balneo and PRM Research Journal stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2026 by the authors. Submitted for open-access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>)

- 1 Department of Physical Rehabilitation and Health, National University of Pharmacy, Ukraine;
- 2 Department of Physical Education and Sport, University Center Pitesti, National University of Science and Technology Politehnica Bucharest, Romania;
- 3 Department of Olympic and Professional Sports, Sports Games and Tourism, H.S. Skovoroda Kharkiv National Pedagogical University, Ukraine;
- 4 Scientific and Pedagogical Laboratory of Biophysics, Biomechanics and Kinesiology, H.S. Skovoroda Kharkiv National Pedagogical University, Ukraine;
- 5 Faculty of Physical Education and Sports, University of East Sarajevo, Bosnia and Herzegovina;
- 6 Faculty of Sport and Physical Education, University of Novi Sad, Serbia;
- 7 Faculty of Sport and Physical Education, University of Novi Sad, Serbia.

* Correspondence: zhannata.kozina@gmail.com

Abstract: Injury prevention in situational sports is challenged by dynamic, unpredictable, and multifactorial environments. Existing linear models often fail to capture complex interactions among multiple risk factors. We developed a non-linear conceptual framework for individualized injury-risk assessment based on the logistic (sigmoid) function, treating the athlete as a complex open system. The model integrates physiological, technical, psychological, anthropometric, injury-history, recovery, and situational factors into an integrated risk index (Z), transforming it into a probability bounded between 0 and 1. A retrospective pilot study of 237 athletes examined the framework's feasibility. The framework structures risk progression through latent, accelerated, and saturation phases using the "Safety Window" concept for load management. In the pilot study, the empirical binary logistic regression served as a bounded probabilistic transformation of composite risk domain scores (AUC=0.740; Hosmer–Lemeshow $p=0.908$), confirming internal proof-of-feasibility rather than dynamic factor interaction modeling.

Keywords: injury prevention, non-linear modeling, situational sports, logistic function, complex adaptive systems, fatigue, training-load management, decision-support systems

Preprint Notice: A preliminary conceptual version of this manuscript was archived as a preprint (DOI: 10.20944/preprints202606.0975.v1). This submission represents a significantly expanded version augmented with a retrospective pilot empirical illustration and quantitative performance analyses

1. Introduction

Injury prevention in sports remains one of the core challenges in modern sports science and coaching practice, particularly in situational sports characterized by dynamic, unpredictable, and rapidly changing competitive environments (such as team games, combat sports, and sports involving the navigation of natural obstacles) [1–3].

Sports injuries can lead to temporary interruptions in the training process and competition participation, long-term functional impairments, or even the premature termination of an athletic career, underscoring the practical and scientific importance of effective injury prevention strategies [4–6].

In situational sports, the occurrence of an injury is rarely determined by a single factor; rather, it emerges from a complex interaction of physiological, technical, psychological, and anthropometric variables [7–9]. A substantial body of scientific literature has identified numerous factors associated with sports injury risk, including fatigue, previous injuries, overload, technical deficiencies, biomechanical asymmetry, insufficient recovery, and psychological stress [3, 10–13]. However, most studies have traditionally focused on isolated predictors, whereas the occurrence of injuries in real-world sporting situations results from the combined interaction of multiple factors rather than the influence of any single variable.

Despite an extensive array of multidisciplinary research, traditional injury risk mitigation strategies demonstrate limited efficacy in situational sports [14–16]. This limitation stems from a methodological contradiction. For a long time, sports science has been dominated by a reductionist approach based on the linear modeling of risk factors [17–19]. Within this paradigm, an injury is viewed as a direct consequence of the isolated impact of individual variables (e.g., anatomical characteristics, localized strength deficits, or fatigue).

However, a living organism functioning under competitive stress represents a complex, open biomechanical system [3, 6, 7, 9]. In sports, the relationship between internal factors (such as proprioception and joint stiffness) and external triggers (such as opponent actions or terrain architecture) is fundamentally non-linear [20–23]. The non-linear nature of how predictors influence injury risk is characteristic of each individual factor and, to an even greater extent, of their cumulative effect. The cumulative impact of these predictors intensifies the non-linear nature of their influence on injury risk. Consequently, traditional analysis overlooks the synergistic interaction of factors and the non-linearity of the link between predictors and injury risks [6, 7, 9, 21].

Injury risk in situational sports develops as a non-linear systemic process rather than a simple linear effect of isolated variables. The interaction of fatigue, technical preparedness, psychological stress, anthropometric predisposition, and previous injury history can gradually accumulate within the athlete's functional system. Once a critical threshold is reached, compensatory mechanisms can become insufficient, leading to a rapid, non-linear acceleration in injury risk [20, 22, 24].

In coaching practice, injury prevention strategies are frequently based on standardized approaches, including warm-up protocols and neuromuscular preventive exercises, which have demonstrated positive effects in reducing injury rates [25–28]. However, such approaches may not fully account for the individualized and situational combinations of physiological, technical, psychological, and contextual risk factors that may interact differently within a specific athlete under competitive conditions [29–32]. This limitation is particularly pronounced in situational sports, where injury risk depends not only on the athlete's internal state but also on dynamic external circumstances. These include match intensity, contact load, decision-making pressure, unpredictable actions of opponents or teammates, environmental variability, and sport-specific situational demands [29–32]. Under these conditions, an injury can occur when situational demands exceed the athlete's adaptive, functional, technical, or psychological capacities.

An athlete may demonstrate high technical proficiency, excellent physical fitness, and an adequate capacity to maintain biomechanical stability under normal conditions, yet remain vulnerable to injury when adverse factors accumulate, such as excessive fatigue, insufficient recovery, psychological stress, elevated situational pressure, or unexpected biomechanical perturbations. Such combinations of factors may remain compensated up to a critical threshold, beyond which the risk of injury escalates non-linearly [7, 9, 21, 22].

Despite the recognition of multifactorial injury mechanisms, relatively little attention has been paid to conceptual frameworks that integrate multidimensional physiological, technical, psychological, situational, and individual risk factors into a unified, individualized, non-linear injury risk architecture tailored for situational sports. Existing predictor-based studies frequently identify statistically significant associations but offer limited utility for real-time training management and decision-making in sports practice. In situational sports, injury occurrence depends not only on athlete-related factors but also on dynamic characteristics such as match intensity, contact load, decision pressure, and specific game-situational demands [22, 33, 34]. Existing models rarely integrate these domains into a single cohesive structure.

Thus, contemporary injury research has demonstrated that sports injuries are inherently multifactorial. However, authors frequently analyze individual risk factors in isolation rather than their complex interaction. Another challenge lies in the fact that sample-level findings do not allow for individualized risk assessment, even though injury risk depends heavily on the unique characteristics of individual athletes. Furthermore, situational sports involve dynamic interactions among athletes, which generates an increased risk of injury. Up to a certain point, as the values of an individual factor or the cumulative values of risk factors increase, adaptive systems successfully protect the athlete's body from injury. However, injury risk escalates non-linearly with an increase in both the isolated and cumulative effects of predictors, ultimately reaching a danger zone where the probability of injury becomes critically high.

In this regard, there is a need for a conceptual non-linear model that views injury risk not as the isolated effect of individual predictors, but as an emergent, threshold-based process resulting from the dynamic interaction of multiple factors [6, 7, 9, 21, 33]. Such a framework could provide a structural basis for future individualized risk-assessment systems, training-load management, and decision-support tools in sports practice [20, 23].

The present study was designed as a conceptual and methodological contribution rather than as the development of a finalized predictive tool. Its primary purpose was to establish a systems-based non-linear architecture that integrates heterogeneous injury-related factors into a composite risk index and transforms this index into an individualized injury probability using a logistic function. The use of a bounded logistic transformation is consistent with non-linear approaches that represent threshold transitions and saturation in complex biological and sports systems [20, 21]. The empirical component was conceived as a proof-of-concept illustration of the feasibility and internal coherence of this approach, rather than as a definitive sport-specific validation of the model.

Therefore, the aim of this study was to develop a non-linear multifactorial framework for individualized injury-risk assessment in situational sports. The proposed framework is intended to serve as a theoretical foundation for future sport-specific model calibration, prospective validation, and practical decision-support applications.

2. Materials and Methods

2.1. Study Design

This study combined conceptual model development with a retrospective pilot empirical illustration. The conceptual component focused on constructing a theoretical framework based on published evidence, principles of complex systems theory, and mathematical approaches to non-linear probabilistic risk representation. No experimental intervention was performed. The empirical component consisted of a retrospective pilot analysis of questionnaire data obtained from 237 athletes participating in situational sports.

The conceptual design was based on the premise that injury occurrence in situational sports is a multifactorial and dynamic process resulting from interactions among physiological, technical, psychological, recovery-related, individual, and situational factors, rather than from the isolated effect of a single predictor. Accordingly, a non-

linear, systems-oriented framework was developed to represent the cumulative and threshold-dependent nature of injury risk.

The proposed model was constructed using published information on sports injury risk factors, principles of complex systems theory, and mathematical approaches to non-linear probabilistic risk representation. The objective of the conceptual component was not to determine universally applicable empirical coefficients, but to develop a structural injury-risk model that could serve as a theoretical foundation for sport-specific calibration, prospective validation, and individualized injury-risk assessment in applied sports practice.

Alongside the theoretical development, a retrospective pilot analysis was conducted using questionnaire data from athletes participating in situational sports. This empirical component was not intended to produce definitive or sport-specific coefficients, nor to provide external validation of the framework. Rather, it served as a proof-of-concept illustration of whether the integrated logistic risk index could demonstrate a systematic and theoretically consistent relationship with retrospectively reported injury occurrence.

2.2. Methodological Basis

2.2.1. Theoretical Background

The theoretical foundation of the proposed model is rooted in a systems approach to sports injury etiology, which views injury occurrence as an emergent outcome of dynamic interactions among multiple risk factors rather than the isolated impact of a single variable [3, 9, 20, 35, 36]. Within this methodological framework, sports injuries are conceptualized as the result of multifactorial processes involving internal and external determinants that interact non-linearly under specific situational conditions.

The proposed model is also anchored in the concept of multifactorial injury risk, which recognizes that physiological, biomechanical, technical, psychological, and contextual factors collectively contribute to injury onset. The relative importance of these domains may vary depending on the individual athlete, the sport, and specific competitive situations [6, 7, 9].

To mathematically represent injury probability, the model employs a non-linear probabilistic transformation based on logistic modeling. This approach allows for the conversion of cumulative, multidimensional risk inputs into a bounded probability scale [37–40]. This approach reflects the assumption that injury probability remains relatively low under compensated conditions but can escalate rapidly when combinations of adverse factors exceed an individual's critical threshold.

Accordingly, the proposed model was defined as a conceptual non-linear framework for individualized injury-risk assessment. It integrates complex-systems logic, multifactorial injury etiology, and non-linear probabilistic transformations into a unified theoretical architecture for future applications in sports injury prevention.

The empirical component was designed as a retrospective proof-of-concept illustration of the feasibility and internal coherence of the proposed framework, rather than as a definitive sport-specific validation study.

2.2.2. Conceptual Factor Domains

The proposed model incorporates several conceptual domains of injury-related factors identified in the sports injury literature as potentially relevant to injury occurrence in situational sports. Each conceptual domain may be operationalized using different measurable variables depending on the specific sport, available equipment, study design, and research objectives.

Physiological Factors

This domain encompasses the athlete's functional states related to fatigue, neuromuscular readiness, recovery status, accumulated workload, and adaptive physiological capacity. These variables can influence the athlete's ability to maintain safe movement patterns under escalating situational demands [37–40].

Technical Factors

Technical determinants reflect sport-specific movement quality, motor control, biomechanical efficiency, landing mechanics, cutting techniques, and overall technical proficiency. These factors can alter the capacity to mitigate injury mechanisms under dynamic competitive conditions [18, 41, 42].

Psychological Factors

Psychological determinants include emotional stress, anxiety, decision-making pressure, attentional control, mental fatigue, confidence, and other psychological states that can alter neuromuscular regulation and behavioral responses in sport-specific situations [18, 41, 42].

Anthropometric (Individual) Factors

Anthropometric and individual factors comprise athlete-specific baseline data, including anthropometric characteristics, age, indicators of structural or functional body asymmetries, and related metrics [3, 10, 22, 29]. This group of factors can either mitigate or exacerbate injury risk depending on the sport, individual athletic tasks, and contextual demands.

Injury History Factors

This indicator accounts for the presence of previous injuries and their respective severity. In the established literature, this group of factors typically increases the baseline risk of subsequent injury recurrence [44–46].

Situational (External) Factors

Situational determinants represent contextual external influences, such as match intensity, contact load, unpredictable opponent actions, environmental conditions, game-specific tactical demands, and other situational characteristics capable of altering injury risk exposure [1, 2, 35, 36].

Recovery Factors

Recovery determinants consist of indicators reflecting the quality of recovery processes. Adequate recovery is assumed to have a protective function and to reduce overall injury risk.

The relative contribution of each factor domain was assumed to vary according to the specific sport, athlete characteristics, and situational context. This variability further supports the need for individualized non-linear injury-risk modeling.

To enhance the practical interpretability of the proposed architecture, representative conceptual factor domains and variable coding examples were synthesized.

The seven domains are summarized in Table 1. Physiological, psychological, history-related, and situational factors are expected to contribute primarily to increased injury risk, whereas technical proficiency and adequate recovery are mainly considered protective. Anthropometric and individual characteristics may exert either positive or negative effects depending on the sport, the athlete, and the specific situational demands. The variables presented in Table 1 illustrate the conceptual structure of the framework rather than a fixed set of predictors. Different measurable indicators may be selected depending on the intended application, available data, and technological resources. It should be clarified that while the overarching conceptual framework adopts a systems-based perspective, the empirical implementation utilizes an additive linear predictor Z . Non-linearity in this statistical baseline is restricted to the logistic sigmoid transformation ($Z \rightarrow P$), rather than explicitly modeled interaction terms or non-linear predictor synergies.

Table 1. Conceptual domains and examples of variables that may characterize each domain

Domain	Representative Factors	Expected Influence on Risk
Physiological	Fatigue, neuromuscular exhaustion [37, 38, 47–49]	Mainly positive (increases risk)
Technical	Skill level, movement quality, landing technique [18, 41, 42]	Mainly protective (reduces risk)
Psychological	Stress, anxiety, decision pressure [3, 10, 22]	Positive (increases risk)
Anthropometric / Individual	Sex, age, body composition [3, 22, 29]	Context-dependent
History-related	Previous injury, recurrence tendency [44–46]	Positive
Situational / External	Match intensity, contact load, competition stage [1, 2, 35, 36]	Positive
Recovery	General well-being, sleep quality, hormonal balance [39, 40]	Mainly protective (reduces risk)

The variables presented in Table 1 illustrate the conceptual structure of the proposed injury-risk model rather than the exact set of predictors used in the pilot empirical illustration. Depending on the available data, different measurable indicators may be selected to represent each conceptual domain. In the present pilot study, only questionnaire-derived variables were included to demonstrate the feasibility of the proposed architecture. Future studies may replace or complement these variables with objective biomechanical, physiological, wearable sensor, or laboratory measurements while preserving the same conceptual architecture. Accordingly, the same conceptual framework can be implemented using different sets of measurable variables depending on the intended application, data availability, and technological resources.

2.2.3. Mathematical Formulation of the Model and Proposed Non-Linear Injury-Risk Equation

The logistic function was selected to represent injury risk because it can describe non-linear processes in biological and adaptive systems that involve phases of relative stability, accelerated change, and subsequent saturation. Logistic regression is frequently used in sports-injury research as a statistical classification method for identifying factors associated with injury occurrence. In the present framework, however, the logistic function is also interpreted conceptually as a representation of the transition from a compensated functional state to a threshold region in which the combined effects of multiple adverse factors may produce a rapid increase in injury probability.

Unlike polynomial regression models, which may generate predicted values below 0 or above 1, the logistic transformation constrains the estimated probability to the biologically meaningful interval from 0 to 1. This property makes the logistic function suitable for representing injury probability. It also corresponds to the assumption that adaptive mechanisms may initially compensate for accumulating adverse influences, whereas injury probability may increase disproportionately once the combined exposure exceeds the athlete's individual adaptive capacity [6, 7, 9, 20, 21].

The mathematical structure of the proposed framework assumes that injury risk can be represented by the cumulative contribution of several weighted injury-related factors. These factors are combined into an integrated injury-risk index, denoted as Z .

The general structure of the index is expressed as follows (formula 1):

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n \quad (1)$$

where:

Z is the integrated injury-risk index;

X_i is the coded or standardized value of the i -th injury-related factor;

β_0 is the intercept;

β_i is the coefficient associated with factor X_i ;

n is the total number of factors included in the model.

The factors may represent fatigue, technical proficiency, psychological stress, recovery status, anthropometric or individual characteristics, previous injury, situational demands, or other variables relevant to the specific sport and application. The sign and magnitude of each coefficient determine the direction and relative contribution of the corresponding factor to the integrated injury-risk index.

For conceptual and practical purposes, the individual factors can be organized into broader domains, including physiological, technical, psychological, anthropometric or individual, injury-history, situational, and recovery-related factors. The contribution of each domain may be represented by the combined contribution of the variables assigned to that domain. The specific variables and coefficients may vary according to the sport, athlete population, study design, available data, and intended application. This domain-based structure allows heterogeneous information to be integrated within a single injury-risk architecture without prescribing a fixed set of predictors.

The integrated injury-risk index is transformed into an estimated probability of injury using the logistic function:

$$P_{injury} = 1/(1 + e^{-Z}) \quad (2)$$

where:

P_{injury} is the estimated probability of injury occurrence,

e is Euler's number,

Z is the integrated injury-risk index.

The logistic transformation constrains the estimated probability to the interval from 0 to 1.

The proposed relationship between Z and P_{injury} is illustrated by the S-shaped logistic curve presented in Figure 1. At relatively low values of Z , the estimated injury probability increases gradually, reflecting the presumed ability of physiological, biomechanical, technical, and psychological compensatory mechanisms to maintain system stability. As the integrated index approaches the threshold region, the curve becomes steeper, indicating a more rapid increase in injury probability. At high positive values of Z , the curve approaches its upper asymptote because probability values cannot exceed 1.

The proposed framework therefore involves two analytical stages. First, relevant predictors are selected from the proposed conceptual domains and combined into the integrated injury-risk index Z . Second, the value of Z is transformed into an individualized injury probability, P_{injury} , using the logistic function. This structure is intended to represent injury risk as an emergent, threshold-dependent process resulting from the combined influence of multiple factors rather than as the isolated effect of a single predictor.

In the conceptual formulation, the coefficients are treated as structural parameters that require sport-specific calibration. Their signs and magnitudes may vary according to the sport, athlete characteristics, measurement procedures, competitive conditions,

and coding of the variables. In the retrospective pilot illustration, preliminary coefficients were estimated using binary logistic regression to demonstrate the feasibility and internal coherence of the proposed framework. These coefficients were not intended to represent definitive sport-specific parameters, universal thresholds, or prospectively validated prediction rules. Further prospective studies will be required to estimate stable coefficients, examine potential interactions among risk factors, and determine the applicability of the model across different sports and athlete populations.

2.2.4. Graphical Representation

The conceptual non-linear model of individual injury risk is presented graphically as an S-shaped logistic curve (Figure 1). The relationship between the integrated injury risk index (Z) and injury probability is distinctly non-linear. At low values of Z , injury probability increases slowly because physiological and biomechanical compensatory mechanisms are sufficient to maintain system stability. As the integrated risk index approaches the threshold region around $Z \approx 0$, the curve becomes markedly steeper, indicating a rapid increase in injury probability. At higher positive values of Z , the curve gradually approaches its upper asymptote, reflecting the natural limitation of probability values to the interval between 0 and 1.

The graph illustrates the transition from a compensated state to a critical zone in which relatively small increases in the integrated risk index are associated with disproportionately large increases in injury probability. This threshold behavior provides the theoretical basis for individualized injury monitoring and preventive decision-making.

Figure 1 also illustrates the practical interpretation of the proposed framework by distinguishing low-, moderate-, and high-risk zones. Athletes located within the moderate-risk region may require closer monitoring because additional adverse factors may shift the system toward the steepest part of the curve, where injury probability increases most rapidly.

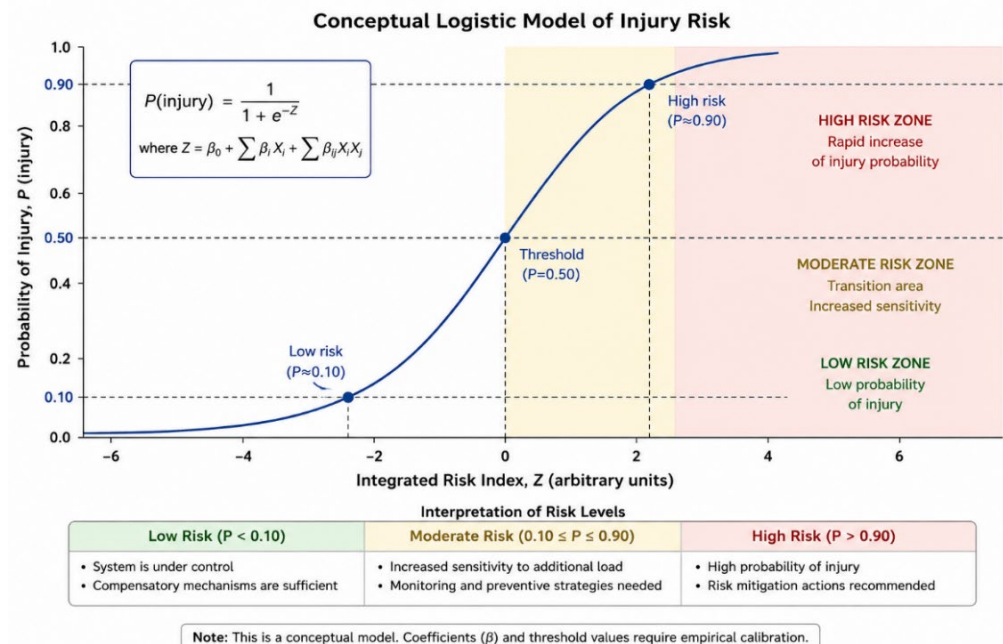


Figure 1. S-shaped logistic curve of injury probability as a function of the integrated risk factor index (Z)

2.5 Pilot empirical illustration

2.5.1 Participants

The pilot empirical illustration was based on data from 237 athletes (155 men and 82 women) representing team sports, combat sports, racket sports, and nature-based sports (e.g., climbing and alpine skiing). Athletes of different qualification levels (city, national, international, and world level) participated in the study. The outcome variable was the occurrence of at least one sports injury during the previous 12 months.

Table 2. Characteristics of the participants

Characteristic	Value
Participants	237
Men	155
Women	82
Age	22.67 ± 6.78 years
BMI	23.29 ± 3.00 kg/m ²
Team sports	144
Combat sports	35
Racket sport	27
Nature sports	31
Athletes with injury	107 (45.1%)

2.5.2. Conceptual Factor Domains

To enhance the practical interpretability of the proposed architecture, representative conceptual factor domains and variable coding examples were synthesized.

The specific factor domains (or clusters) contributing to injury risk are detailed below (Table 1). The first domain (Physiological) encompasses fatigue metrics and related indicators, which primarily increase overall injury risk. The second domain (Technical) comprises indicators such as skill level, motor (athletic) qualification, and balance maintenance capabilities. This group of factors predominantly acts as a protective mechanism, serving to mitigate injury risks. The third domain is Psychological, containing variables such as emotional stress, anxiety, and decision-making pressure, which collectively elevate injury vulnerability.

The fourth domain represents Anthropometric and Individual characteristics of the athlete, including anthropometric profiles, age, and structural or functional body asymmetries. This group can either reduce or increase injury risk depending on the specific sport, athlete tasks, and related contextual demands. The fifth domain, Injury History, accounts for the presence of previous injuries and their respective severity, typically increasing the baseline risk of subsequent injury recurrence.

The sixth domain involves Situational Factors, which include contextual external metrics such as match intensity, contact load, competition stages, and specific tactical or strategic objectives. This cluster generally exacerbates overall injury risk exposure. Finally, the seventh domain, Recovery, consists of indicators that ensure the quality of recovery processes, thereby performing a protective function and minimizing injury probability.

The conceptual domains and representative variables are presented in Table 1. In the pilot illustration, these domains were operationalized using questionnaire-derived indicators.

The variables presented in Table 1 illustrate the conceptual structure of the proposed injury-risk model rather than the exact set of predictors used in the pilot empirical illustration. Depending on the available data, different measurable indicators may be selected to represent each conceptual domain. In the present pilot study, only questionnaire-derived variables were included to demonstrate the feasibility of the proposed architecture. Future studies may replace or complement these variables with objective biomechanical, physiological, wearable sensor, or laboratory measurements

while preserving the same conceptual architecture. Accordingly, the same conceptual framework can be implemented using different sets of measurable variables depending on the intended application, data availability, and technological resources.

2.5.3. Questionnaire

A structured questionnaire was developed based on the literature and included measurable variables representing the proposed conceptual domains. A structured self-administered questionnaire was specifically developed for this pilot study based on previously identified injury-related factors reported in the scientific literature. The questionnaire included items representing demographic characteristics, training experience, physiological status (fatigue, recovery, sleep), psychological factors (stress, anxiety, burnout), technical self-assessment, previous injuries, anthropometric characteristics, and self-perceived injury risk. All variables were coded numerically and subsequently used as candidate predictors in the logistic regression model. The questionnaire was designed to provide a practical illustration of how the proposed conceptual domains can be operationalized in future applications of the current framework.

When processing the survey data using a logistic model, we excluded variables that were inherently correlated with each other and with the dependent variable (injuries in the past 12 months).

The questionnaire was developed for this exploratory proof-of-concept study on the basis of injury-related domains identified in the literature. It was not intended as a fully validated psychometric instrument. Several constructs were represented by single-item 1–5 ordinal ratings to maintain operational feasibility in field-based and high-performance monitoring settings. Consequently, these measures should be regarded as preliminary operational indicators rather than validated multi-item scales.

Table 3. Athlete survey parameters for injury risk factors

Nº	Variable (SPSS)	Label (SPSS)	Type	Measure	Coding	Block
1	Age*	Age (years)	Numeric	Scale	Years	Demographics
2	Sex*	Sex	Numeric	Nominal	1=Male; 2=Female	Demographics
3	SportName	Sport type	String	Nominal	Text	Demographics
4	SportType	Sport category	Numeric	Nominal	1=Team; 2=Combat; 3=Racket; 4=Nature	Demographics
5	Level*	Sport qualification	Numeric	Ordinal	1–4	Demographics
6	ExpYears	Sport experience (years)	Numeric	Scale	Years	Demographics
7	Injury12m**	Sports injury during previous 12 months	Numeric	Nominal	0=No; 1=Yes	Outcome
8	InjCount	Number of injuries during previous 12 months	Numeric	Scale	0,1,2...	Outcome
9	InjSite	Most serious injury location	Numeric	Nominal	1–15	Outcome
10	Severity	Severity of the most serious injury	Numeric	Ordinal	1=Mild; 2=Moderate; 3=Severe	Outcome
11	PrevInjury	History of sports injuries during the preceding three years	Numeric	Nominal	0=No; 1=Yes	History
12	CareerInj	Number of injuries during sports career	Numeric	Ordinal	1–4	History
13	Fatigue*	Physical fatigue	Numeric	Ordinal	1–5	Physiology
14	Sleep*	Sleep deficiency	Numeric	Ordinal	1–5	Physiology
15	Recovery*	Incomplete recovery	Numeric	Ordinal	1–5	Physiology

16	Pain*	Chronic pain or discomfort	Numeric	Ordinal	1–5	Physiology
17	Stress*	Stress level	Numeric	Ordinal	1–5	Psychology
18	Anxiety*	Pre-competition anxiety	Numeric	Ordinal	1–5	Psychology
19	Burnout*	Emotional exhaustion	Numeric	Ordinal	1–5	Psychology
20	Technique*	Technique stability under fatigue	Numeric	Ordinal	1–5	Technique
21	Coordination*	Coordination deterioration	Numeric	Ordinal	1–5	Technique
22	TechFatigue*	Difficulty maintaining technique under fatigue	Numeric	Ordinal	1–5	Technique
23	CompCount	Number of competitions	Numeric	Scale	Number	Situation
24	MajorComp	Participation in major competitions	Numeric	Nominal	0=No;1=Yes	Situation
25	Uncertainty*	Competition uncertainty	Numeric	Ordinal	1–5	Situation
26	SelfRisk*	Self-rated injury risk	Numeric	Ordinal	1–5	Outcome
27	Height	Height (cm)	Numeric	Scale	cm	Anthropometry
28	Weight	Weight (kg)	Numeric	Scale	kg	Anthropometry
29	BMI*	Body Mass Index	Numeric	Scale	kg/m ²	Anthropometry

Notes: * - Survey indicators (independent variables) that were processed in logistic regression.

** - dependent variable (Injury12m – Sports injury during the previous 12 months) in the logistic analysis of survey data

Although the candidate predictors in this pilot study were subjective and questionnaire-derived, existing sports science literature confirms that self-reported fatigue, sleep quality, and stress markers demonstrate a high correlation with objective physiological indices (such as heart rate variability and neuromuscular power) and provide a reliable, low-cost baseline for real-time athlete monitoring.

Injury occurrence was assessed retrospectively by self-report as the presence of at least one sports injury during the previous 12 months. A separate questionnaire item assessed the history of sports injuries during the preceding three years.

2.5.4. Statistical analysis

Statistical analyses were performed using IBM SPSS Statistics version 29.0 (IBM Corp., Armonk, NY, USA). Continuous variables are presented as mean $\pm$ standard deviation, whereas categorical variables are presented as frequencies and percentages.

Binary logistic regression (Enter method) was applied to estimate preliminary coefficients for the proposed integrated injury risk model. The dependent variable was the occurrence of at least one injury during the previous 12 months (0 = no injury, 1 = injury). Independent variables included demographic, physiological, psychological, technical, anthropometric, recovery-related, and self-perceived injury risk factors obtained from the questionnaire.

Model performance was evaluated using the likelihood ratio test, Nagelkerke's coefficient of determination (R^2), the Hosmer–Lemeshow goodness-of-fit test, and the area under the receiver operating characteristic curve (AUC). Odds ratios (Exp(B)) and their 95% confidence intervals were calculated for all predictors.

To evaluate the relationship between the integrated injury risk index and the observed injury rate, athletes were ranked according to their predicted integrated risk index (Z) and divided into ten consecutive groups of approximately equal size. For each group, the mean integrated risk index and the observed injury rate were calculated. A nonlinear logistic function was then fitted to these grouped data using least-

squares regression in Microsoft Excel. The goodness of fit was assessed using the coefficient of determination (R^2) and the root mean square error (RMSE).

Statistical significance was accepted at $p < 0.05$.

To prevent multicollinearity and ensure parameter stability, candidate predictors were screened prior to modeling. Variables exhibiting bivariate correlation coefficients $r > 0.70$ or Variance Inflation Factors (VIF) > 5.0 were excluded. Sixteen representative predictors were subsequently retained in the final additive binary logistic regression model.

3. Results

3.1. Preliminary Empirical Illustration of the Conceptual Framework

Although most individual predictors showed relatively weak independent associations with injury occurrence, their integration into a composite injury risk index produced a pronounced logistic relationship with the observed injury rate. This finding demonstrates that the additive integration of multiple questionnaire-derived variables was associated with retrospectively reported injury occurrence in this pilot sample. It does not, however, demonstrate or estimate dynamic interactions among predictors.

To provide an initial empirical illustration of the proposed methodological framework, the model was applied to questionnaire data obtained from 237 athletes representing different situational sports. Logistic regression was used to estimate preliminary coefficients for the integrated risk index. The resulting model demonstrated apparent discrimination in the development sample (AUC = 0.740). The Hosmer–Lemeshow test ($p = 0.908$) provided no evidence of gross lack of fit; however, this result should not be interpreted as proof of validated calibration.

Table 4. Performance of the pilot logistic model

Parameter	Value
Number of athletes	237
Number of predictors	16
Injury prevalence	107 (45.1%)
AUC ROC	0.740
Hosmer–Lemeshow p	0.908
Nagelkerke R^2 (Logistic fit)	0.236

Notes: Nagelkerke $R^2 = 0.236$ — the model explains some of the variability, but, like most biomedical models, not all of it.

AUC = 0.740 — the model demonstrated apparent discrimination between injured and uninjured athletes in the development sample.

Hosmer–Lemeshow $p = 0.908$ — provided no evidence of gross lack of fit; however, this result should not be interpreted as proof of validated calibration.

The grouped descriptive analysis showed an increasing observed injury rate across increasing values of the integrated risk index. This analysis is presented as an illustrative description of the relationship between the fitted index and observed injury occurrence and does not constitute independent calibration validation.

Table 5. Logistic regression coefficients

Indicators	B	Standard Error	Wald	Significance	Exp (B)	95% Confidence Interval for EXP(B)	
						Lower	Upper
Age	0.005	0.024	0.042	0.838	1.005	0.959	1.053
Sex	-0.483	0.325	2.216	0.137	0.617	0.326	1.165
Level	0.248	0.202	1.503	0.22	1.282	0.862	1.906
Fatigue	-0.208	0.16	1.695	0.193	0.812	0.594	1.111
Sleep	0.119	0.147	0.657	0.418	1.127	0.844	1.503
Recovery	0.167	0.186	0.799	0.371	1.181	0.82	1.703
Pain	0.379	0.146	6.769	0.009	1.461	1.098	1.944
Stress	0.096	0.164	0.342	0.559	1.1	0.798	1.517
Anxiety	0.148	0.139	1.123	0.289	1.159	0.882	1.523
Burnout	-0.097	0.162	0.359	0.549	0.907	0.66	1.247
Technique	0.041	0.218	0.035	0.852	1.041	0.679	1.597
Coordination	0.2	0.187	1.145	0.285	1.221	0.847	1.76
TechFatigue	-0.163	0.184	0.785	0.376	0.849	0.592	1.219
SelfRisk	0.339	0.175	3.763	0.052	1.404	0.996	1.977
BMI	-0.295	0.069	18.161	0	0.745	0.65	0.853
Uncertainty	-0.177	0.147	1.44	0.23	0.838	0.628	1.119
Constant	4.504	1.806	6.217	0.013	90.347		

a Variables entered in step 1: Sex, Level, Fatigue, Sleep, Recovery, Pain, Stress, Anxiety, Burnout, Technique, Coordination, TechFatigue, Uncertainty, SelfRisk, Age, BMI. Note on coefficient directions: Negative regression weights for variables such as BMI ($\beta = -0.295$), Fatigue ($\beta = -0.208$), and Burnout ($\beta = -0.097$) reflect statistical suppressor effects, inter-variable collinearity, or retrospective reporting patterns in this cross-sectional sample, rather than protective biological mechanisms.

Athletes were ranked according to the integrated injury risk index and divided into consecutive groups. The observed injury rate increased progressively with increasing values of the integrated index and closely followed the expected logistic curve, providing preliminary empirical support for the proposed present approach.

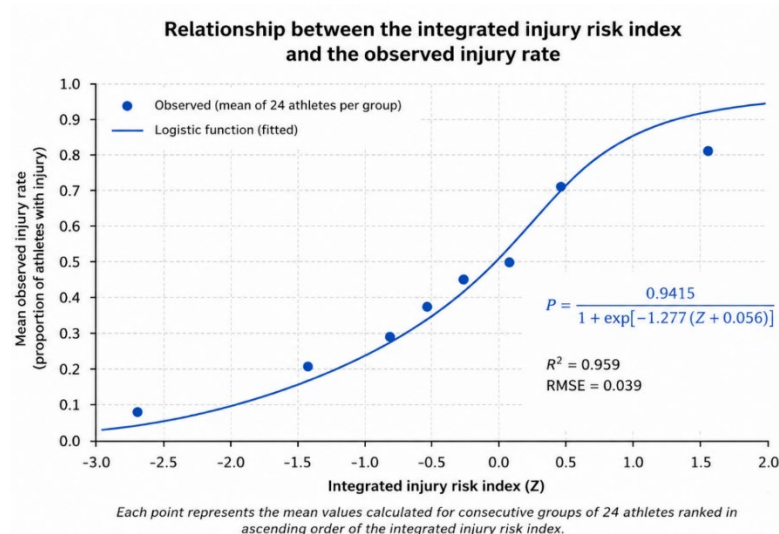


Figure 2. Logistic relationship between the integrated injury risk index and the observed injury probability (10 independent groups).

The grouped descriptive analysis showed an increasing observed injury rate across increasing values of the integrated risk index. This analysis is presented as an illustrative description of the relationship between the fitted index and observed injury occurrence and does not constitute independent calibration validation.

Based on the grouped empirical data, an illustrative logistic relationship between the integrated injury risk index and observed injury probability was described by the following equation:

$$P = \frac{0.9415}{1 + e^{-1.277(Z+0.056)}}$$

Where:

P – observed probability of injury;

Z – integrated injury risk index.

This equation represents an empirical descriptive relationship derived from the grouped development data and was subsequently used to illustrate the calculation of individualized injury probabilities. It should not be interpreted as evidence of independent calibration validation.

This empirical equation represents an illustrative implementation of the general conceptual model and was subsequently used to demonstrate the calculation of individualized injury probabilities presented in Table 6.

Table 6. An example of calculating the predicted injury rate using the coefficients of the logistic model for a specific athlete

Indicators	Coefficients	The value of an indicator for a specific athlete	The value of the indicator multiplied by the coefficient
Age	0.005	17.00	0.085
Sex	-0.483	2.00	-0.966
Level	0.248	3.00	0.744
Fatigue	-0.208	4.00	-0.832
Sleep	0.119	5.00	0.595
Recovery	0.167	5.00	0.835
Pain	0.379	2.00	0.758
Stress	0.096	5.00	0.48
Anxiety	0.148	5.00	0.74
Burnout	-0.097	5	-0.485
Technique	0.041	4.00	0.164
Coordination	0.2	4.00	0.8
TechFatigue	-0.163	4.00	-0.652
SelfRisk	0.339	4.00	1.356
BMI	-0.295	19.72	-5.8174
Uncertainty	-0.177	5.00	-0.885
Constant	4.504		4.504
Integrated index (Z)			1.4236
General logistic model	$P_{injury} = \frac{1}{1 + e^{-Z}}$		0.8059
calibrated injury probability (Empirical logistic model)	$P = \frac{0.9415}{1 + e^{-1.277(Z+0.056)}}$		0,8179
Observed injury (previous 12 months)		-	Yes

Several individual predictors showed limited independent associations, whereas the multivariable additive model demonstrated apparent discrimination in the development sample.

The calculated injury probability for this athlete was 0.806, indicating a high predicted injury risk. The individual example is provided solely to demonstrate the calculation of the integrated index and the transformation of Z into a predicted probability. It is not presented as evidence of predictive accuracy or model validation. Although a single case cannot validate the model, it demonstrates the practical interpretation of the proposed individualized risk assessment approach.

3.2. Practical Application Scheme

For practical application, the logistic regression curve can be partitioned into distinct risk zones (Figure 1, Table 4). For instance, an integrated risk factor index (Z) below zero indicates a low risk of injury, reflecting the dominance of protective factors. Values of Z near or equal to zero characterize a moderate risk level, signaling a system in threshold equilibrium. Conversely, Z values greater than zero denote the dominance of variables that amplify injury probability. Highly positive Z values represent a critical state wherein the probability of an athlete sustaining an injury becomes exceedingly high (Table 7, Figure 1). The risk thresholds ($P < 0.10$, $P \approx 0.50$, $P > 0.90$) and Z -score cut-offs are designated strictly as illustrative conceptual decision boundaries for proposed monitoring architectures. They represent theoretical target zones and require prospective clinical utility validation before being applied to mandatory training-load adjustments.

Table 7. Interpretation of the integrated risk factor index (Z)

Z value	Conceptual Interpretation	Expected Risk Level
$Z < 0$	Protective factors dominate	Low
$Z \approx 0$	System at threshold / unstable balance	Moderate
$Z > 0$	Risk factors dominate	Elevated
High positive Z	Critical overload state	High

In summary, the proposed framework provides a conceptual integration of multidimensional physiological, technical, psychological, situational, and individual factors into a non-linear, individualized injury risk architecture specifically tailored for situational sports. Unlike traditional predictor-based regression studies, this model conceptualizes injury risk as a systemic, threshold-driven process emerging from dynamic factor interactions, thereby establishing a structural foundation for future research into individualized decision-support systems for sports training and competition management.

These findings indicate that the integrated logistic index contains substantially more information than any individual predictor considered separately.

At its current stage, the framework should not be used as a stand-alone basis for mandatory training-load modification or clinical decision-making. Its practical value is presently conceptual and hypothesis-generating, providing a structure for the future development and validation of sport-specific monitoring systems.

4. Discussion

4.1. Rationale for the Logistic Function in Injury Risk Modeling

The selection of the logistic function was based on its ability to describe logistic adaptive processes commonly observed in biological systems [20, 21]. Unlike linear models, which assume a constant rate of change, logistic models capture the transition

from physiological compensation to accelerated deterioration and, ultimately, to functional saturation. Similar logistic dynamics have been described in population biology, epidemiology, ecology, physiology, and systems medicine, where adaptive reserves initially buffer external stressors before a threshold is reached, leading to rapid system destabilization [20, 21, 23, 24].

Sports injury development appears to follow a comparable biological pattern. During the early stages of training, physiological and psychological compensatory mechanisms maintain functional stability despite accumulating stress [3, 6, 7, 9]. However, as multiple risk factors progressively interact, adaptive capacity declines and injury probability increases disproportionately rather than linearly. The logistic function naturally constrains predicted probabilities to the biologically meaningful interval between 0 and 1, avoiding unrealistic extrapolations that may occur with polynomial regression models [18, 23, 24, 50].

The proposed framework therefore uses logistic regression not merely as a statistical classification technique but as a mathematical representation of progressive biological adaptation and loss of compensation. This biological interpretation forms the basis for the structural phases described below.

4.2. Methodological Novelty and Distinctive Dimensions

The principal methodological contribution of the proposed framework is the transition from independent evaluation of individual predictors to an integrated logistic representation of injury risk. Most existing models estimate the influence of separate variables or combine predictors additively, implicitly assuming that each factor contributes independently to the final outcome.

In contrast, the present framework assumes that physiological, psychological, technical, situational, and individual characteristics interact dynamically within a common adaptive system. Injury risk is therefore interpreted as an emergent property arising from cumulative interactions rather than from isolated predictors.

This conceptual transition is consistent with contemporary systems biology, where complex outcomes emerge from logistic interactions among multiple components instead of simple additive effects. Consequently, the integrated injury risk index (Z) provides a more informative representation of athlete status than any individual predictor alone. The preliminary empirical illustration supports this assumption, demonstrating that although individual predictors showed relatively weak effects, their logistic integration produced substantially stronger agreement with observed injury occurrence.

4.3. Proof-of-concept role of the pilot empirical illustration

The empirical analyses presented in this study were explicitly conceived as a proof-of-concept test of the proposed framework rather than a definitive validation of a ready-to-use prediction model. The retrospective design, reliance on self-reported questionnaire data, and the absence of prospective longitudinal follow-up inherently limit the generalizability and clinical applicability of the derived coefficients. However, the core objective of the pilot illustration was not to estimate sport-specific threshold values or to provide final decision rules, but to examine whether an integrated, logistic risk index shows a coherent and monotonic relationship with actual injury occurrence.

In this respect, the findings are encouraging: while most individual predictors demonstrated relatively weak associations with injury status, their integration into the composite index Z produced a clear logistic pattern with good calibration across risk strata. This supports the underlying systems-based assumption that injury risk emerges from the cumulative interaction of multiple domains, and that a non-linear probabilistic transformation can capture this emergent behaviour more effectively than

isolated linear predictors. Future prospective studies with objective biomechanical and physiological measures will be required to refine and externally validate the model coefficients, but the present proof-of-concept results provide an important first empirical step.

4.4. Structural Phases of Non-Linear Risk Growth

The proposed framework conceptualizes injury development as a gradual transition through three biologically meaningful phases (Figure 1). Rather than representing discrete clinical states, these phases describe successive stages of adaptation, loss of compensation, and functional saturation within a continuous logistic process.

When operationalized via the critical parameters of the logistic curve, the proposed non-linear injury risk model can be structurally partitioned into three distinct phases (Figure 1):

Latent Risk Phase (Initial Lower Plateau): At this stage, adverse variables (e.g., micro-fatigue, minor sleep disturbances, sub-clinical dehydration, subtle technical errors) accumulate latently. Injury probability increases at a minimal rate due to the robust compensatory capacity of the organism. As cumulative exposure intensifies, the system converges toward the first critical point—the compensation threshold—beyond which adaptive stability begins to decay.

Non-Linear Risk Acceleration Phase (Steep Ascending Segment): Once the compensation threshold is breached, a rapid, non-linear escalation in injury probability is observed, driven by the mutual, synergistic amplification of risk variables. During this phase, the system progressively loses stability, and the inflection point of the logistic curve marks the maximum velocity of injury risk acceleration.

Critical Risk Saturation Phase (Upper Asymptotic Plateau): With the continued accumulation of uncompensated adverse factors, injury probability approaches its maximum value and exits onto a plateau. This state is characterized by critically high system vulnerability resulting from severe exhaustion of compensatory mechanisms and compromised neuromuscular stability (Kozin et al., 2026b). The deceleration of curve growth in this phase is governed by the mathematical constraint of probability values bounded between 0 and 1.

Thus, in our work, a theoretical framework detailing the non-linear accumulation of sports injury risks has been developed based on the dynamics of the S-shaped logistic function. The proposed model characterizes the system's transition from a compensated state to a phase of accelerated non-linear risk expansion through critical threshold states of adaptation. Furthermore, the model formalizes the phenomenon of "critical risk saturation," wherein injury probability plateaus at a critically high level, rendering the specific characteristics of the final external trigger irrelevant.

The model achieves a conceptual integration of multidimensional physiological, technical, psychological, situational, and individual risk factors into a non-linear, individualized injury risk architecture for situational sports. In contrast to traditional predictor-based linear regression analyses, this framework treats injury risk as an emergent, threshold-driven system process resulting from dynamic factor interactions, thereby establishing a structural blueprint for future research into individualized decision-support systems for athletic training and competition management [50].

4.5. Practical Implications

The practical value of the proposed framework lies in its ability to transform multidimensional athlete information into an individualized estimate of injury probability. Instead of evaluating isolated predictors, coaches and sports medicine specialists obtain an integrated representation of cumulative injury risk based on measurable physiological, psychological, technical, situational, and individual variables.

An important practical consequence is the identification of the "Safety Window" — the adaptive interval preceding the rapid acceleration of injury probability. Monitoring an athlete's position relative to this transition zone may support timely modification of training loads, individualized recovery planning, and preventive interventions before irreversible functional deterioration occurs.

Because the proposed model is based on routinely collected variables and standard logistic regression, it can be incorporated into digital athlete-monitoring platforms and future artificial intelligence decision-support systems. Such systems could automatically estimate individualized injury risk, identify emerging high-risk states, and assist coaches in optimizing training while reducing injury incidence.

4.5. Practical application pathway for the proposed framework

Although the present model is conceptual and requires sport-specific calibration, it already offers a structured pathway for practical implementation in athlete monitoring systems. A possible application workflow can be outlined as follows. First, practitioners define a set of measurable indicators representing the proposed conceptual domains (physiological, technical, psychological, anthropometric/individual, history-related, situational, and recovery), using either subjective (questionnaires) or objective (wearable sensors, laboratory tests, biomechanical assessments) measures depending on available resources. Second, these indicators are standardized and combined into an integrated risk index Z using preliminary or context-specific weight coefficients derived from pilot data or expert judgement. Third, the index Z is transformed into a bounded injury probability using the logistic function, and the resulting values are interpreted within individualized low-, moderate-, and high-risk zones as suggested by the structural phases of the logistic curve.

In this stage, the framework does not prescribe universal cut-off values, but rather provides a coherent structure for integrating heterogeneous information and monitoring temporal shifts in an athlete's position along the risk curve. Coaches, sports scientists, and medical staff can use this structure to identify when an athlete is approaching the safety window boundary and to adjust training load, recovery strategies, or technical and psychological interventions before entering the phase of accelerated risk growth. As empirical evidence accumulates, this same framework can be populated with more precise coefficients and sport-specific thresholds, ultimately supporting the development of automated decision-support tools.

4.6. Future Research Directions

This conceptual framework establishes a rigorous methodological foundation for interdisciplinary research linking mathematical modeling, psychophysiological monitoring, and sports biomechanics.

Future investigative pathways should focus on executing pilot validation studies, calibrating weight coefficients to accommodate sport-specific demands, integrating wearable monitoring technology for real-time data streaming, conducting longitudinal injury tracking, and developing automated risk-monitoring architectures driven by artificial intelligence (AI) algorithms.

Future prospective multicenter studies involving different sports and competitive levels will be necessary to refine model coefficients, evaluate longitudinal stability, and determine the generalizability of the proposed logistic framework.

Further research should evaluate content validity, test-retest reliability, construct validity, and the dimensional structure of sport-specific versions of the instrument.

4.7. Limitations

Several methodological limitations must be noted:

Retrospective Design and Reverse Causation: The 12-month retrospective survey structure introduces potential reverse causation. Current ratings of pain, fatigue, or altered technique may reflect lingering consequences of past injuries rather than antecedent causal predictors.

Outcome and Sport Heterogeneity: Pooling diverse situational sports (team, combat, racket, and nature-based sports) and combining acute, overuse, contact, and non-contact injuries creates outcome heterogeneity, assuming a single underlying co-efficient structure.

Statistical Implementation vs. Complex Systems: While the theoretical framework is motivated by a systems-based view of multifactorial and potentially non-linear processes, the empirical model is an additive binary logistic regression. Non-linearity in the empirical implementation is restricted to the logistic sigmoid probability transformation.

Illustrative Case Example: The individual athlete calculation (Table 6) serves solely as a mathematical demonstration of formula execution, not cohort-level predictive validation.

Model Complexity and Internal Validation: With 107 injury events and 16 predictors, the pilot model may be vulnerable to coefficient instability and overfitting. No resampling-based internal validation or shrinkage procedure was performed; therefore, the reported AUC and other apparent performance estimates may be optimistic and should not be interpreted as validated predictive performance.

The absence of prospective injury surveillance and standardized clinical verification represents an additional limitation of the retrospective self-reported injury assessment.

5. Conclusions

1. This study presents a non-linear conceptual framework for organizing multidimensional injury risk parameters in situational sports, utilizing a logistic sigmoid function to represent the transition from compensated functional states to threshold-dependent risk growth.
2. A retrospective pilot illustration (n=237) demonstrated internal feasibility for calibrating the framework via additive logistic regression (AUC=0.740). These empirical findings provide preliminary proof-of-concept rather than validation of a dynamic causal prediction engine.
3. The proposed framework integrates physiological, technical, psychological, anthropometric or individual, injury-history, recovery-related, and situational factors into a unified individualized architecture for injury-risk assessment in situational sports. The logistic curve provides a theoretical basis for identifying the region in which injury probability increases most rapidly and for introducing the concept of a "Safety Window" as a potential tool for individualized monitoring and training-load management.
4. The present study establishes a systems-based, non-linear architecture that may support the future development of athlete-monitoring and decision-support systems for injury prevention. Further research is required to estimate sport-specific coefficients, validate the framework prospectively in diverse athletic populations, incorporate objective longitudinal measurements, and translate the model into user-friendly digital tools for real-time decision support.

Supplementary Materials: The following supporting information can be downloaded with this article: Research_Data_Pack.zip (containing Raw_data.xlsx, Data1.sav, Logistic.1.spv, Questionnaire.docx, and Readme.docx).

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “Conceptualization, Z.K. and S.K.; methodology, O.K. and R.P.; software, V.P.; validation, I.M., N.R. and R.P.; formal analysis, Z.K.; investigation, S.K.; resources, O.K.; data curation, Z.K.; writing—original draft preparation, Z.K.; writing—review and editing, O.K.; visualization, R.P.; supervision, Z.K.; project administration, Z.K.; funding acquisition, I.M, R.P., N.R. All authors have read and agreed to the published version of the manuscript.”

Funding: The research was funded by the Provincial Secretariat for Higher Education and Scientific Research (Grant No. 003878792 2025 09418 003 000 000 001).

Institutional Review Board Statement: This study was reviewed and approved by the Ethics Committee of H.S. Skovoroda Kharkiv National Pedagogical University (approval No. KhNPU/PhES/EC/7/5/2026). The study was conducted in accordance with the ethical principles of the Declaration of Helsinki of the World Medical Association.

Informed Consent Statement was obtained from all participants before completion of the questionnaire.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy/ethical restrictions.

Preprint No: An earlier conceptual version of this work was deposited as a preprint; however, the present manuscript substantially expands that version by incorporating a preliminary empirical illustration, quantitative model performance evaluation, practical implementation, and an extended methodological discussion: Kozin, S.; Potop, V.; Kozina, Z.; Kozin, O.; Pavlovic, R.; Mihajlovic, I.; Radulovic, N. A Non-Linear Conceptual Framework for Individualized Injury Risk Assessment in Situational Sports, *Preprints* 2026, 2026060975. <https://doi.org/10.20944/preprints202606.0975.v1>

Acknowledgments: The authors express their deep gratitude to all participants in the pilot study. The research was carried out in the current scientific research work on the topic of the Department of Olympic and Professional Sports, Sports Games and Tourism of the H.S. Skovoroda Kharkiv National Pedagogical University for the year 2021-2026: “Development and development of technology for the improvement of health and harmonious development of people of various centuries and social groups” (registration number: 0121U110053).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Appendix A.1

Table A1. Results of calibration calculations for predicted probability and observed injury risk

Group	Predicted probability	Observed injury rate
Low	0,219	0,228
Moderate	0,451	0,418
High	0,681	0,709

Table A2. Observed and predicted injury probability according to the integrated injury risk index

Risk group	Mean of the integrated injury risk index (Z)	Mean predicted probability	Observed injury rate	n
1	-2,66778	0,113488208	0,083333	24
2	-1,23042	0,225322167	0,208333	24
3	-0,82696	0,30199925	0,258333	24
4	-0,54675	0,364153833	0,291667	24
5	-0,29075	0,425457833	0,375	24
6	-0,0615	0,4823245	0,45	24
7	0,142267	0,533549875	0,5	24
8	0,429125	0,60200475	0,608333	24
9	0,825346	0,689512833	0,785	24
10	1,54411	0,813196095	0,809524	21

References

- Hidayat, R.A.; Sumaryanti, S.; Nugroho, S.; Ihsan, F. Injury prevention and rehabilitation in badminton: an evidence-based approach to player wellbeing - a systematic review. *Health Sport Rehabil.* 2025. 11(4). 79–99. <https://doi.org/10.58962/HSR.2025.955>
- Arboix-Alió, J.; Aguilera-Castells, J.; Buscà, B.; Miró, A.; Hilenó, R.; Trabal, G.; Peña, J. Situational variables in elite rink hockey: effect of match location, team level, scoring first and match status at halftime on the competitive outcome. *Int. J. Perform. Anal. Sport* 2021. 21(6). 1101–1116. <https://doi.org/10.1080/24748668.2021.1976057>
- Kozin, S.; Cretu, M.; Kozina, Z.; Boychuk, Y.; Pavlovic, R.; Korobeinik, V.; Batyuk, L. Pedagogical and biomechanical aspects of injury prevention in sports with changing circumstances and coach training: a systematic review with bibliometric analysis. *Health Sport Rehabil.* 2026. 12(1). 128–150. <https://doi.org/10.58962/HSR.2026.1328>
- Fazackerley, L.; Hickey, J.; Johnston, R.; Tofari, P.; Timmins, R.; Roelands, B.; Russell, S. Practitioner Perspectives on the Association Between Mental Fatigue and Injury Risk in High-Performance Sport: A Mixed Methods Study. *Eur. J. Sport Sci.* 2025. 25(8). ejsc.70028. <https://doi.org/10.1002/ejsc.70028>
- Prayudho, S.; Nasrulloh, A.; Skaliy, A. Risk factor of pickleball injury: systematic review and meta-analysis. *Health Sport Rehabil.* 2024. 10(3). 115–124. <https://doi.org/10.58962/HSR.2024.10.3.115-124>
- Lundgren, L.; Tran, T.; Nimphius, S.; Raymond, E.; Secomb, J.; Farley, O.; Sheppard, J. Development and Evaluation of a Simple, Multifactorial Model Based on Landing Performance to Indicate Injury Risk in Surfing Athletes. *Int. J. Sports Physiol. Perform.* 2015. 10(8). 1029–1035. <https://doi.org/10.1123/ijsp.2014-0591>
- Lahti, J.; Mendiguchia, J.; Ahtiainen, J.; Anula, L.; Kononen, T.; Kujala, M.; Morin, J. Multifactorial individualised programme for hamstring muscle injury risk reduction in professional football: protocol for a prospective cohort study. *BMJ Open Sport Exerc. Med.* 2020. 6(1). bmjsem-2020-000758. <https://doi.org/10.1136/bmjsem-2020-000758>

8. Edouard, P.; Lahti, J.; Fleres, L.; Ahtiainen, J.; Ulvila, J.; Lehtinen, T.; Mendiguchia, J. A musculoskeletal multifactorial individualised programme for hamstring muscle injury risk reduction in professional football: results of a prospective cohort study. *BMJ Open Sport Exerc. Med.* 2024. 10(1). bmjsem-2023-001866. <https://doi.org/10.1136/bmjsem-2023-001866>
9. Eckart, A.; Ghimire, P.; Stavitz, J. Predictive Validity of Multifactorial Injury Risk Models and Associated Clinical Measures in the U.S. Population, *Sports* 2024. 12(5). 123. <https://doi.org/10.3390/sports12050123>
10. Neledva, I.; Yachsie, B.T.P.W.B. Correlation between Psychophysical Indicators and Motor Skills of 15-16-Year-Old Football Players: Review article. *Health Technol.* 2024. 2(4). 17–27. <https://doi.org/10.58962/HT.2024.2.4.17-27>
11. Suhadaq, T.A.; Sugiyanto, S.; Nugroho, H.; Riyadi, S. The effect of the interaction between the exercise method and the level of ankle sprain injury in athletes on ankle stability. *Health Technol.* 2024. 2(1). 24–34. <https://doi.org/10.58962/HT.2024.2.1.24-34>
12. Khasanah, F.N.S.; Sugiyanto, S.; Riyadi, S. Prone plank test base core muscle strength contribution to anticipate the risk of ankle injury for soccer player. *Health Technol.* 2023. 1(3). 46–53. <https://doi.org/10.58962/HT.2023.1.3.46-53>
13. Kozin, S.; Kozina, Z.; Korobeinik, V.; Cieřlicka, M.; Radosław, M.; Ryepko, O.; Boychuk, Y.; Evtifieva, I.; Bejtka, M. Neuro-muscular training for injury prevention of students-rock climbers studying in the specialty "physical education and sports": A randomized study. *J. Phys. Educ. Sport* 2021. 21. 1251–1259. <https://doi.org/10.7752/jpes.2021.s2159>
14. Milic, V.; Radenkovic, O.; Capric, I.; Mekic, R.; Trajkovic, N.; Spirtovic, O.; Kahrovic, I. Sports Injuries in Basketball, Handball. and Volleyball Players: Systematic Review, *Life* 2025. 15(4). 529. <https://doi.org/10.3390/life15040529>
15. Schampheleer, E.; Roelands, B. Mental Fatigue in Sport-From Impaired Performance to Increased Injury Risk, *Int. J. Sports Physiol. Perform.* 2024. 19(10). 1158–1166. <https://doi.org/10.1123/ijsp.2023-0527>
16. Shitara, H.; Kobayashi, T.; Yamamoto, A.; Shimoyama, D.; Ichinose, T.; Tajika, T.; Osawa, T.; Iizuka, H.; Takagishi, K. Prospective multifactorial analysis of preseason risk factors for shoulder and elbow injuries in high school baseball pitchers. *Knee Surg, Sports Traumatol, Arthrosc.* 2017. 25(10). 3303–3310. <https://doi.org/10.1007/s00167-015-3731-4>
17. Perera, J.; Miller, M.; Danahy, P. Case Report Demonstrating Multifactorial Risks of Anterior Cruciate Ligament Re-tear Injuries and Appropriate Response Among Those With High Chance of Recurrence, *Cureus* 2022. 14(5). e24965. <https://doi.org/10.7759/cureus.24965>
18. Zhan, X.H.; Li, Y.H.; Liu, Y.Z.; Domel, A.G.; Alizadeh, H.V.; Zhou, Z.; et al. Predictive Factors of Kinematics in Traumatic Brain Injury from Head Impacts Based on Statistical Interpretation, *Ann. Biomed. Eng.* 2021. 49(10). 2901–2913. <https://doi.org/10.1007/s10439-021-02813-z>
19. Audini, V.A.; Doewes, M.; Sabarini, S.S.; Riyadi, S. Effect of training methods and body mass index on ankle injury in futsal players. *Health Technol.* 2023. 1(3). 38–45. <https://doi.org/10.58962/HT.2023.1.3.38-45>
20. Yuan, J.; Zeng, Q.; Wang, A.; Zhang, Y.; Li, J. Machine Learning Applications in Non-Contact Lower Limb Sports Injury Prediction: A Systematic Review, *J. Sports Sci, Med.* 2026. 25(1). 172–194. <https://doi.org/10.52082/jssm.2026.172>
21. Buldú, J.; Gómez, M.; Herrera-Diestra, J.; Martínez, J. Editorial: Nonlinear dynamics and networks in sports. *Chaos Solitons Fractals* 2021. 142*. 110518. <https://doi.org/10.1016/j.chaos.2020.110518>
22. Oosterhoff, J.H.F.; Gouttebarger, V.; Moen, M.; Staal, J.B.; Kerkhoffs, G.M.M.J.; Tol, J.L.; Pluim, B.M. Risk factors for musculoskeletal injuries in elite junior tennis players: a systematic review. *J. Sports Sci.* 2019. 37(2). 131–137. <https://doi.org/10.1080/02640414.2018.1485620>
23. Colby, M.J.; Dawson, B.; Peeling, P.; Heasman, J.; Rogalski, B.; Drew, M.K.; et al. Multivariate modelling of subjective and objective monitoring data improve the detection of non-contact injury risk in elite Australian footballers. *J. Sci, Med. Sport* 2017. 20(12). 1068–1074. <https://doi.org/10.1016/j.jsams.2017.03.022>
24. Lu, Y.; Eilen, H.; Pareek, A.; Varano, M.; Wilbur, R.; Lavoie-Gagné, O.; Krych, A.J.; Camp, C.L.; Okoroha, K.; Forsythe, B. Comparisons of machine learning models to logistic regression in orthopedic sports medicine are confounded by methodological heterogeneity: a systematic review and meta-analysis. *J. ISAKOS* 2026. 17. 1–11. <https://doi.org/10.1016/j.jisako.2026.101088>
25. Wang, J.; Ying, Y.; Lu, B.; et al. Injury risk reduction programs including balance training reduce the incidence of anterior cruciate ligament injuries in soccer players: A systematic review and meta-analysis. *J. Orthop, Surg. Res.* 2025. 20(1). 56. <https://doi.org/10.1186/s13018-025-05639-w>
26. Olivares-Jabalera, J.; Filter-Ruger, A.; Dos'Santos, T.; et al. Exercise-based training strategies to reduce the incidence or mitigate the risk factors of anterior cruciate ligament injury in adult football (soccer) players: A systematic review. *Int. J. Environ. Res. Public Health* 2021. 18(24). 13351. <https://doi.org/10.3390/ijerph182413351>
27. Grimm, N.L.; Jacobs, J.C.; Kim, J.; et al. Anterior cruciate ligament and knee injury prevention programs for soccer players: A systematic review and meta-analysis. *Am. J. Sports Med.* 2015. 43(8). 2049–2056. <https://doi.org/10.1177/0363546514556737>
28. García-Luna, M.A.; Cortell-Tormo, J.M.; García-Jaén, M. Acute effects of ACL injury-prevention warm-up and soccer-specific fatigue protocol on dynamic knee valgus in youth male soccer players. *Int. J. Environ. Res. Public Health* 2020. 17(15). 5608. <https://doi.org/10.3390/IJERPH17155608>

29. Andersson, S.H.; Bahr, R.; Clarsen, B.; Myklebust, G. Risk factors for overuse shoulder injuries in a mixed-sex cohort of 329 elite handball players: previous findings could not be confirmed. *Br. J. Sports Med.* 2018. 52(18). 1161–1167. <https://doi.org/10.1136/bjsports-2017-097648>
30. Emery, C.A.; Eliason, P.; Warriyar, V.; Palacios-Derflingher, L.; Black, A.M.; Krolikowski, M.; et al. Body checking in non-elite adolescent ice hockey leagues: it is never too late for policy change aiming to protect the health of adolescents. *Br. J. Sports Med.* 2022. 56(1). 12–18. <https://doi.org/10.1136/bjsports-2020-103757>
31. Emery, C.A.; Meeuwisse, W.H. Risk factors for groin injuries in hockey. *Med. Sci. Sports Exerc.* 2001. 33(9). 1423–1433. <https://doi.org/10.1097/00005768-200109000-00002>
32. Chandran, A.; DiPietro, L.; Young, H.; Elmi, A. Modeling time loss from sports-related injuries using random effects models: an illustration using soccer-related injury observations. *J. Quant. Anal. Sports* 2020. 16(3). 221–235. <https://doi.org/10.1515/jqas-2018-0104>
33. Bittencourt, N.F.N.; Meeuwisse, W.H.; Mendonça, L.D.; Nettel-Aguirre, A.; Ocarino, J.M.; Fonseca, S.T. Complex systems approach for sports injuries: moving from risk factor identification to injury pattern recognition-narrative review and new concept. *Br. J. Sports Med.* 2016. 50(21). 1309–1314. <https://doi.org/10.1136/bjsports-2015-095850>
34. García-Visual, I.; Pradas, F.; Ortega-Zayas, M.; Castellar-Otín, C.; García-Giménez, A.; Lecina, M. Muscle, Neuromuscular, and Cardiac Damage in Trail Running: A Systematic Review, *Muscles* 2026. 5(1). 9. <https://doi.org/10.3390/muscles5010009>
35. Chandran, A.; Morris, S.N.; Boltz, A.J.; Robison, H.J.; Collins, C.L. Epidemiology of Injuries in National Collegiate Athletic Association Women's Soccer: 2014-2015 Through 2018-2019. *J. Athl. Train.* 2021. 56(7). 651–658. <https://doi.org/10.4085/1062-6050-372-20>
36. Chandran, A.; Rao, N.; Boltz, A.J.; Garcia, R.E.; Collins, C.L.; Shafik, A.; et al. Knee and ACL injury rates in NCAA soccer players: an epidemiological study of 10 consecutive seasons. *Sci. Med. Footb.* 2025. 9(4). 412–421. <https://doi.org/10.1080/24733938.2025.2476479>
37. Kozina, Z.L.; Iermakov, S.S.; Kuzmin, V.A.; Kudryavtsev, M.D.; Galimov, G.J. Change of Cortisol and Insulin Content in Blood under Influence of Special Workability Recreation System for Students with High Motor Functioning Level, *Res. J. Pharm. Biol. Chem. Sci.* 2016. 7(2). 1068–1077.
38. Jagiello, W.; Kozina, Z.L.; Marina, J. Somatic aspects of sports championship in Taekwon-Do ITF, *Phys. Educ. Stud.* 2015. 19(4). 51–55. <https://doi.org/10.15561/20755279.2015.0408>
39. Kozina, Z. Recovery functional condition of sportsmen using individual non-traditional means of rehabilitation. *J. Phys. Educ. Sport* 2015. 15(4). 634–639.
40. Kozina, Z.; Safronov, D.; Kozin, S.; Bugayets, N.; Peretyaha, L.; Shepelenko, T.; Grinchenko, I. Use of non-traditional recovery means to improve performance of 11-12-year-old athletes specializing in rowing and canoeing. *J. Phys. Educ. Sport* 2019. 19(1). 756–764. <https://doi.org/10.7752/jpes.2019.01108>
41. Joksimovic, M.; Pavlovic, R.; Koprivica, V.; Plevnik, M. Dynamic strength index in athletic performance: a comprehensive analysis of theory, measurement and practical application. *Health Sport Rehabil.* 2025. 11(4). 17–32. <https://doi.org/10.58962/HSR.2025.1324>
42. Ihsan, F.; Nasrulloh, A.; Nugroho, S.; Kozina, Z. Optimizing Physical Conditioning Programs for Badminton Athletes: A Comprehensive Review of Training Strategies - A Systematic Review, *Retos* 2024. 54. 488–498. <https://doi.org/10.47197/retos.v54.103208>
43. Yabroudi, M.A.; Bashaireh, K.; Nawasreh, Z.H.; Snyder-Mackler, L.; Logerstedt, D.; Maayah, M. Rehabilitation duration and time of starting sport-related activities associated with return to the previous level of sports after anterior cruciate ligament reconstruction. *Phys. Ther. Sport* 2021. 49. 164–170. <https://doi.org/10.1016/j.ptsp.2021.02.014>
44. von Rosen, P.; Heijne, A. Previous and current injury and not training and competition factors were associated with future injury prevalence across a season in adolescent elite athletes. *Physiother. Theory Pract.* 2022. 38(3). 448–455. <https://doi.org/10.1080/09593985.2020.1762266>
45. Lopes, T.J.A.; Simic, M.; Chia, L.E.; Terra, B.D.; Alves, D.D.; Bunn, P.D.; et al. Trunk endurance, posterior chain flexibility, and previous history of musculoskeletal pain predict overuse low back and lower extremity injury: a prospective cohort study of 545 Navy Cadets. *J. Sci. Med. Sport* 2021. 24(6). 555–560. <https://doi.org/10.1016/j.jsams.2020.11.020>
46. Jönsson, F.; von Rosen, P. Is there a strong association between substantial injuries and previous injuries in adolescent elite athletes? A 1-year prospective cohort study. *Physiother. Theory Pract.* 2023. 39(7). 1528–1535. <https://doi.org/10.1080/09593985.2022.2042756>
47. Tesliuk, M.; Adamcak, S. Subjective method of control and regulation of intensity of physical activity (the rate of perceived exertion) in the training process of young basketball players aged 12-13. *Health Technol.* 2025. 3(3). 6–14. <https://doi.org/10.58962/HT.2025.3.3.6-14>
48. Batalla-Gavaldà, A.; Beltran-Garrido, J.; Garrosa-Martín, G.; Cecilia-Gallego, P.; Montoliu-Colás, R.; Corbi, F. Long-Term Analyses of the Rate of Perceived Exertion as an Indicator of Intensity in Women's Basketball during a Relegation Play-off, *Biology* 2022. 11(11). 1592. <https://doi.org/10.3390/biology11111592>

49. Pustomelnik, O.; Kozina, Z. The impact of regulating physical activity of mixed martial arts (MMA) fighters of different fighting styles on the competitive performance of athletes. *Health Technol.* 2025. 3(3). 15–25. <https://doi.org/10.58962/HT.2025.3.3.15-25>
50. Kozin, S.; Potop, V.; Kozina, Z.; Kozin, O.; Pavlovic, R.; Mihajlovic, I.; Radulovic, N. A Non-Linear Conceptual Framework for Individualized Injury Risk Assessment in Situational Sports, *Preprints* 2026, 2026060975. <https://doi.org/10.20944/preprints202606.0975.v1>.