



INTERNATIONAL JOURNAL OF
SUPPLY CHAIN, OPERATION
MANAGEMENT AND LOGISTICS
(IJSCOL)

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SUPERVISED LOGIC MINING FOR ATHLETE INJURY DATA WITH RANDOM 3-SATISFIABILITY

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Article Info:

Article history:

Received date: 15.01.2026

Revised date: 05.02.2026

Accepted date: 03.03.2026

Published date: 31.03.2026

To cite this document:

Hamidi, N. H., Zamri, N. E., Fadil, N. K. M., Mansor, F. H., Rusli, N. H. A., & Abdul Ghafar, A. A. (2026). Supervised Logic Mining for Athlete Injury Data with Random 3-Satisfiability. *International Journal of Supply Chain, Operation Management and Logistic*, 6(11), 01-19.

Abstract:

Nowadays, athletes are exposed to high performance demands and intense training loads, increasing their risk of injury. The absence of early detection systems often leads to late interventions, longer recovery periods and performance decline. This project addresses the need for an interpretable early detection model for athlete injury prevention. The proposed solution is built using Random 3-Satisfiability Reverse Analysis (RAN3SATRA) model enhanced through correlation-based attribute selection. By implementing logic mining, the systems able to extract human-readable rules that explain relationships between injury and performance factors, allowing domain experts to make transparent, data-driven decisions. The model was tested using the Athlete Injury and Performance Dataset and demonstrated strong and consistent performance across multiple metrics including accuracy, sensitivity, specificity, Matthews Correlation Coefficient and Negative Predictive Value. These results indicate that the proposed logic-based framework is affective in identifying injury risk patterns while maintaining interpretability. The logic mining process successfully identified key injury-related factors such as training load balance, ACL injury risk level, fatigue level, weekly recovery days and weekly training duration.

These findings offer direct insight into injury prevention and enable the development of actionable monitoring systems for coaches, physiotherapists and sports scientists. This project reflects the potential of explainable AI in sports analytics, combining data science and logic reasoning to protect athlete health and optimise performance.

DOI: 10.35631/IJSCOL.611001 **Keyword:**

Athlete Injury, Artificial Intelligence, Logic Mining, Random 3-Satisfiability Reverse Analysis, Discrete Hopfield Neural Network



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Introduction

Sport has always played a major role in human life, shaping physical development, emotional growth and social connection. From early forms of physical competition to the highly organised sports we see today, people across all cultures have been drawn to the challenges and excitement of athletic performance. Sports encourage discipline, teamwork and resilience. Then, continue to inspire individuals and communities around the world. Despite the many advantages of participating in sports, there are also potential risks involved. One of the common issues faced by athletes at all levels is injury. According to Verhagen et al. (2010), understanding the patterns and factors that lead to injuries is essential for protecting athletes and optimising their performance. This includes studying things like training intensity, recovery time, physical conditions and previous injury history.

Today, the use of data has made it possible to study these factors in a more accurate and detailed way. By collecting and analysing athlete data, I can identify hidden patterns that are not easily seen through observation alone. In this study, a real dataset about athlete injuries and performance is used to explore these connections. The goal is not only to understand how injuries happen but also to find out how they affect performance over time. With the help of Artificial Intelligence (AI), this research aims to reveal useful insights that could support better prevention strategies, smarter training plans and safer environments for athletes. By combining human knowledge with intelligent data analysis, it contributes to the growing effort of keeping athletes both healthy and high performing.

AI has become an influential tool across numerous fields, including healthcare, finance, education, and sports science. Within the context of athlete performance and injury prediction, AI allows for the efficient processing of complex and high-volume datasets, uncovering hidden relationships among variables and facilitating early detection of potential risks. However, many AI models particularly those based on deep learning are often viewed as “black boxes” because

they produce results without offering clear explanations for their predictions (Zamri et al., 2024). This lack of interpretability presents a challenge in sports analytics, where coaches, trainers, and medical professionals must be able to understand and trust AI-generated insights before making data-driven decisions.

To address this issue, logic mining has emerged as a promising approach. Logic mining is a branch of AI focused on discovering interpretable patterns and decision rules expressed in human-understandable logic. Rather than only providing predictions, it explains how and why certain outcomes occur, which makes it highly valuable for sports science applications. By using structured logical representations, logic mining extracts clear, rule-based relationships from data, offering transparency and interpretability in injury prediction models. A key computational foundation for logic mining is the Artificial Neural Network (ANN), particularly the Discrete Hopfield Neural Network (DHNN), which models symbolic logic using a network of binary neurons. The DHNN, first proposed by Hopfield and Tank (1985) and later extended by Abdullah (1992), links logical clauses with synaptic weights, allowing the network to represent and retrieve logical relationships based on input-output dynamics. Building on these foundations, Kasihmuddin et al. (2017) introduced the 2-Satisfiability (2SAT) logical rule, followed by Mansor et al. (2017) who proposed the 3-Satisfiability (3SAT) model for more complex clause structures. These frameworks use Boolean satisfiability to represent relationships between variables contributing to specific outcomes such as injury likelihood or performance change.

Despite their success, fixed clause structures 2SAT or 3SAT may not fully capture the complexity of real-world data. Rusdi et al. (2023) emphasized the need for more adaptable frameworks that can manage varied clause configurations while maintaining interpretability and practical relevance. This motivates the development of the Random 3-Satisfiability Reverse Analysis (RAN3SATRA) model in the current study, which aims to enhance flexibility and explainability in logic mining for athlete injury prediction.

Literature Review

Foundations Of Satisfiability Logic

Satisfiability logic represents one of the earliest bridges between symbolic reasoning and neural computation. The foundation was laid by Hopfield and Tank (1985), who introduced the Hopfield Neural Network (HNN) to model optimisation and logical problems through energy minimisation. Their model demonstrated that logical relationships could be represented using interconnected neuron states that converge toward stable solutions. Building on this foundation, Abdullah (1992) incorporated the HornSAT logical structure into neural networks, establishing a theoretical link between satisfiability and computational intelligence. This allowed logical clauses to be represented through synaptic weights, enabling neural systems to simulate logical reasoning and decision processes. The integration of satisfiability into neural computation evolved with the introduction of clause-based logic frameworks. Kasihmuddin et al. (2017) proposed the 2SAT model, which encoded binary logical relationships within a discrete Hopfield network. This model enhanced interpretability and facilitated logic rule extraction. Later, Mansor et al. (2017) extended this approach through the 3SAT model, allowing the inclusion of three-variable logical clauses. The transition from 2SAT to 3SAT represented an important step in improving the complexity and expressiveness of logical reasoning within neural networks. Recent advancements have explored hardware-based approaches to solving satisfiability problems. Pedretti et al., 2025 introduced a method for

solving Boolean satisfiability using resistive content addressable memories (ReCAMs), providing faster and more energy-efficient computation. Their work demonstrates that satisfiability can be efficiently implemented within neuromorphic systems, bridging symbolic logic and physical computing. This innovation reinforces satisfiability logic as a crucial component in the development of interpretable and high-performance artificial intelligence frameworks.

Advancements In Logic Mining for Interpretable AI

Logic mining has evolved as an advanced extension of satisfiability logic, focusing on extracting interpretable and rule-based knowledge from data. Unlike conventional black-box models, logic mining produces transparent reasoning patterns that can be easily understood by humans. Karim et al. (2021) introduced the Random 3-Satisfiability Reverse Analysis (RAN3SATRA) framework, which incorporates random clause generation ($k = 1, 2, 3$) to construct diverse and adaptable logical structures. This framework improved flexibility and generalisation while maintaining interpretability in supervised learning environments. Further developments have enhanced the robustness of logic mining models. Roslan et al. (2023) proposed a logic mining framework based on major 3-satisfiability logic combined with a multi-objective selection algorithm, improving classification performance and rule diversity. Rusdi et al. (2023) later enhanced the SATRA model by implementing the Hebbian Threshold Activation Function (HTAF), which strengthened logical stability and reduced susceptibility to noise. These advancements signify the evolution of logic mining from traditional satisfiability-based reasoning into adaptive, data-driven frameworks that maintain interpretability.

Research Gap in Sports Injury Prediction Models

Although satisfiability and logic mining frameworks have achieved significant progress in producing interpretable reasoning, most existing studies remain limited to theoretical analyses or experiments on synthetic datasets. There is still a lack of research that applies these models to real-world, domain-specific problems such as athlete injury prediction, where multiple interacting variables influence outcomes. Current AI techniques in sports science, particularly deep learning-based models, often deliver strong predictive accuracy but lack transparency in explaining the causal relationships behind injuries (Zamri et al., 2024). This limits their adoption by coaches, trainers, and sports scientists who require interpretable models for data-driven decision-making. Furthermore, traditional satisfiability frameworks such as 2SAT and 3SAT rely on fixed clause structures, reducing their ability to model complex, heterogeneous data. As highlighted by Rusdi et al. (2023), there is a growing need for flexible logical frameworks capable of handling varied clause configurations while maintaining interpretability. To address these limitations, the current study adopts the RAN3SATRA model, which combines satisfiability logic with logic mining to generate interpretable logical rules from athlete injury data. This integration aims to enhance both flexibility and explainability, offering a novel and transparent approach to understanding how physical, workload, and performance attributes contribute to injury risk in sports.

Methodology

This study proposed the development of a logic-based classification method using RAN3SATRA embedded within the DHNN. The study introduces a supervised learning approach that applies higher-order satisfiability logic to identify logical rules from structured

data, particularly in the context of athlete injury and performance analysis. Key processes such as data preprocessing, clause construction, training, and testing are discussed, along with techniques for weight optimisation and logic evaluation. The goal is to produce interpretable logic rules that support accurate and explainable decision-making.

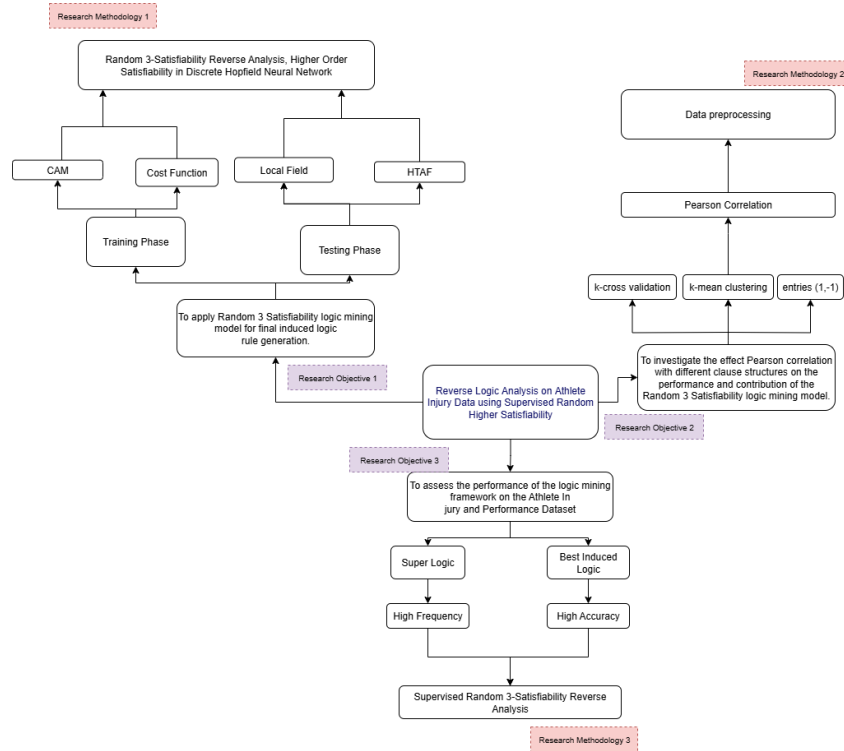


Figure 1: Overview Methodology of RAN3SATRA

Higher Order Satisfiability Representation

Satisfiability (SAT) refers to the process of identifying a combination of truth values that satisfies a given logical rule. In this study, we focus on RAN3SATRA, which is a higher-order form of SAT logic. It serves as the symbolic structure for the proposed logic mining model. The 3SAT structure can be described based on the following definitions provided by Zamri et al. (2020) and Zhu et al. (2022).

1. A set of logical rules consists of n variables, such as q_1, q_2, \dots, q_n , where each clause contains exactly three literals.
2. All variables are represented in bipolar format, where 1 indicates true and -1 indicates false.
3. Literals within clauses may be either positive or negative, meaning each literal belongs to the set $\{q_i, -q_i\}$.
4. A group of x definite clauses, denoted M_1, M_2, \dots, M_x , is formed. Each clause connects literals using logical OR (\vee), while the clauses themselves are joined using logical AND (\wedge).

Combining these properties, the general form of a RAN3SATRA logical rule is defined as:

$$Q_{RAN3SATRA} = \bigwedge_{i=1}^x M_i^{(3)} \bigwedge_{i=1}^y M_i^{(2)} \bigwedge_{i=1}^z M_i^{(1)}$$

where x is total number of 3SAT clause, y is total number of 2SAT clause and z is total number of 1SAT. Each clause M_i contains exactly three literals and is expressed as:

$$M_i^{(k)} = \left\{ (A_i \vee B_i \vee C_i), \text{ if } M_i^{(3)}, (D_i \vee E_i), \text{ if } M_i^{(2)}, F_i, \text{ if } M_i^{(1)} \right\}$$

However, in extended variants (e.g., combinations of clause sizes 1, 2, and 3), the form can include mixed-length clauses:

$$Q_{(1,2,3)RAN3SATRA} = (A \vee B \vee C) \wedge (D \vee E \vee F) \wedge (G \vee H) \wedge I \wedge J$$

$$Q_{(1,3)RAN3SATRA} = (A \vee B \vee C) \wedge (D \vee E \vee F) \wedge (G \vee H \vee I) \wedge J$$

$$Q_{(2,3)RAN3SATRA} = (A \vee B \vee C) \wedge (D \vee E \vee F) \wedge (G \vee H) \wedge (I \vee J)$$

In this proposed method, redundant attributes are not considered. All clauses (M_1, M_2, M_3, \dots) must evaluate to true for the overall expression $Q_{RAN3SATRA}$ to be satisfied. If any single clause evaluates to false under a given truth assignment, the entire expression becomes false. For example, if $M_1 = (A \vee B \vee -C)$ and the values are $A = 0, B = 0,$ and $C = 1$, then the clause becomes $0 \vee 0 \vee 0 = 0$, making $Q_{RAN3SATRA}$ unsatisfiable.

Higher Order Satisfiability in Discrete Hopfield Neural Network

The Discrete Hopfield Neural Network (DHNN) comprises a finite set of neurons S_i , where $1 < i < N$, each assuming a bipolar state from the set $\{-1, 1\}$. The neuron state is updated according to

$$S_i = \begin{cases} 1, & \text{if } \sum_{j=1}^N W_{ij} S_j \geq h \\ -1, & \text{otherwise} \end{cases}$$

where W_{ij} denotes the synaptic weight between neurons i and j , and h is a predefined threshold, typically set to zero ($h = 0$) to ensure consistent energy minimization (Sathasivam, 2010). The weight matrix is symmetric ($W_{ij} = W_{ji}$), and self-connections are prohibited ($W_{ii} = 0$).

In this study, the RAN3SATRA logical formulation, denoted $Q_{RAN3SATRA}$, is embedded within the DHNN to guide the learning process. The objective is to determine optimal synaptic weights W_{ij} stored in the Content-Addressable Memory (CAM) for reliable retrieval.

The cost function for the RAN3SATRA logic is expressed as

$$E_{Q_{RAN3SATRA}} = \sum_{i=1}^{NC} \prod_{j=1}^3 Z_{ij}$$

where N_c is the total number of clauses and Z_{ij} depends on the literal polarity:

$$Z_{ij} = \begin{cases} \frac{1}{2}(1 - S_X), & \text{if the literal is negative} \\ \frac{1}{2}(1 + S_X), & \text{otherwise} \end{cases}$$

To obtain optimal synaptic weights, the cost function is compared with the Lyapunov energy function $H_{QRAN3SATRA}$

$$H_{QRAN3SATRA} = \frac{1}{3} \sum_i \sum_j \sum_k W_{ijk}^{(3)} S_i S_j S_k - \frac{1}{2} \sum_i \sum_j W_{ij}^{(2)} S_i S_j - \sum_i W_i S_i$$

During the recall phase, neuron states are updated based on stored synaptic weights, with the local field of neuron i defined as

$$h_i = \sum_j W_{ijk}^{(3)} S_j S_k + \sum_j W_{ij}^{(2)} S_j + W_i$$

The Hebbian Threshold Activation Function (HTAF) determines the updated state:

$$S_i = \begin{cases} +1, & \text{if } h_i > 0 \\ -1, & \text{otherwise} \end{cases}$$

Network stability is achieved when global energy satisfies:

$$H_{QRAN3SATRA} - H_{min} \leq \text{Tolerance}$$

Following Hopfield and Tank (1985), the symmetric structure and absence of self-connections ensure convergence to a stable energy minimum. Once this condition is met, the induced logic of the DHNN corresponds to the expected output Q_i^{test} , allowing accurate differentiation between true and false states. Embedding higher-order satisfiability within DHNN therefore enables logic-based classification through interpretable and energy-efficient reasoning.

Proposed Supervised Higher Order Reverse Analysis Method

In the preprocessing phase, each attribute in the dataset is represented as a neuron S_i , where $i = 1, 2, \dots, N$. Based on the Abdullah (1992) method, all neuron states are converted into bipolar form such that:

$$S_i \in \{-1, 1\}$$

This transformation allows DHNN to work with binary logic states, representing false and true respectively. To ensure that only relevant attributes are used, Pearson correlation analysis is applied to measure the strength of the relationship between each attribute and the target class. Attributes are selected based on correlation values that are closest to 1, either positively or negatively. This approach ensures that the most influential features are chosen for clause construction. From the correlation results, the top 11 attributes are selected. Ten of them serve as input neurons, while the eleventh is used as the output class which is injured.

During training, multiple candidate logical structures are created using combinations of selected attributes. The objective is to identify the best logic rule that maximises classification performance. This is done by selecting the structure with the highest total of *true positives* (TP) and *true negatives* (TN):

$$Q_{RAN3SATRA}^{best} = \max \left[\sum_{i=1}^n S_i \right] \text{ where } S_i \in \{ 1 (TP \text{ or } TN) \}$$

Once the best rule is selected, it is embedded into the DHNN. The synaptic weight values $W_{ijk}^{(3)}$ are calculated by minimising the difference between the logic cost function and the Lyapunov energy function. These weights are stored in the CAM of the network. To increase robustness, multiple variations of the selected rule are generated by changing the neuron combinations. Each rule is trained independently to improve diversity in logic retrieval and enhance generalization. In the testing phase, the trained synaptic weights are used to evaluate new data. The local field for each neuron is computed as:

$$h_i = \sum_j W_{ijk}^{(3)} S_j S_k + \sum_j W_{ij}^{(2)} S_j + W_i$$

The neuron state is updated using the HTAF:

$$S_i = \begin{cases} +1, & \text{if } h_i > 0 \\ -1, & \text{otherwise} \end{cases}$$

The final neuron states are converted into the induced logic output Q_A^i , which is then compared with the actual test labels Q_i^{test} to evaluate the model's performance. The key evaluation metrics used include:

- *True Positives (TP)*
- *True Negatives (TN)*
- *False Positives (FP)*
- *False Negatives (FN)*

To further investigate the effectiveness of different logical clause configurations within the RAN3SATRA framework, this study performs a comparative analysis by testing several clause sizes. The clause sizes tested are $k = 1$, $k = 2$, and $k = 3$, each evaluated independently to observe their individual impact on classification performance. In addition to testing individual clause sizes, two pairwise combinations are also considered, which are $(k = 1,3)$ and $(k = 2,3)$. These combinations aim to explore whether using a mix of short and long clauses can improve generalization and produce more expressive logical rules. Each configuration uses the same training and testing process and is based on the same selected attributes. Model performance for each clause size and clause combination is compared using evaluation metrics such as accuracy, sensitivity, specificity, negative predictive value (NPV), and Matthews Correlation Coefficient (MCC). The purpose is to identify which clause structure gives the best balance between logical interpretability and predictive accuracy in the injury classification task. This testing process is repeated for all ten logical structures generated during training. The final model performance is reported based on the induced logic rule that matches the test data and achieves the highest accuracy.

Benchmark Dataset

The dataset used in this study was sourced from the Kaggle machine learning repository (<https://www.kaggle.com/datasets>). Two main criteria guided the selection process. First, only datasets with more than 150 instances were considered, as dataset size significantly affects model accuracy and generalisability. As noted by Ajiboye et al. (2015), larger datasets help reduce overfitting, improve generalisation to unseen data, and minimise sampling bias. Second, the number of attributes was considered. Too many attributes may lead to overfitting, while too few may cause underfitting. According to Sugumaran and Ramachandran (2011), high-dimensional datasets complicate feature selection and may obscure meaningful patterns. Following the recommendations of Kasihmuddin et al. (2017) and Jamaludin et al. (2022), this study focuses on datasets with 16 attributes to achieve a balance between model complexity and classification performance.

All attributes were converted into bipolar format (1 and -1) prior to modelling. Quantitative attributes were binarised using k-means clustering to determine attribute means, while qualitative attributes were transformed using frequency distribution tables. To ensure fair and consistent evaluation, multiple train-test splits were employed, namely 60%–40%, 70%–30%, 80%–20%, and 90%–10%. In addition, 5-fold cross-validation was applied to enhance robustness and reduce sampling bias, allowing the performance of the proposed model to be assessed across different data partitions.

Data Information

The Athlete Injury and Performance Dataset obtained from Kaggle provides a practical foundation for analysing the relationship between physical performance indicators and injury outcomes in athletes. The dataset consists of 200 instances, with each instance representing an individual athlete, and includes 16 attributes covering demographic, physical, workload, and performance-related factors. These attributes include age, gender, height, weight, playing position, training intensity, training hours per week, recovery days per week, match count per week, rest days between events, fatigue score, performance score, team contribution score, load balance score, ACL risk score, and an injury indicator. Most attributes are numerical, enabling quantitative analysis, while categorical variables were appropriately encoded during preprocessing. The final attribute, labelled *injury*, serves as the target variable and is represented in bipolar form, where 1 denotes an injured athlete and -1 denotes a non-injured athlete. The dataset exhibits a moderately imbalanced class distribution, reflecting real-world injury occurrences, which further motivates the use of interpretable logic-based classification rather than purely accuracy-driven models. This dataset provides a compact yet realistic representation of athlete injury data, making it suitable for logic mining and satisfiability-based classification. Its structure supports the investigation of how individual and combined attributes contribute to injury risk, aligning closely with the objectives of this study and the application of the proposed RAN3SATRA framework for rule discovery.

Table 1: Information Of Dataset Employed in The Simulation.

Dataset Name	Instances	Attributes	Attribute Type	Field Area
Athletes Injury and Performance	200	16	Mixed	Sports Science

Table 2: List Of Details Attributes.

No.	Names Of Attributes	Detail Of Attributes
1	Age	Age Of The Athlete (Between 18 To 25 Years)
2	Gender	Gender Of The Athlete (Male Or Female)
3	Height	Height Of The Athlete In Centimeters (160–200 Cm)
4	Weight	Weight Of The Athlete In Kilograms (55–100 Kg)
5	Position	Playing Position In The Team (Guard, Forward, Center)
6	Training Intensity	Average Training Intensity On A Scale From 1 (Low) To 10 (High)
7	Training Hours Per Week	Total Weekly Training Hours (5–20 Hours)
8	Recovery Days Per Week	Number Of Recovery Days Per Week (1–3 Days)
9	Match Count Per Week	Number Of Matches Played Per Week (1–4 Matches)
10	Rest Between Events Days	Average Rest Days Between Events (1–3 Days)
11	Load Balance Score	Score (0–100) Representing The Balance Between Training Load And Recovery
12	ACL Risk Score	Predicted ACL Injury Risk Score (0–100), With Higher Values Indicating Higher Risk
13	Fatigue Score	Athlete’s Subjective Fatigue Level (Scale Of 1 To 10)
14	Performance Score	Composite Performance Rating (Range 50–100)
15	Team Contribution Score	Score Indicating Overall Team Contribution (Scale Of 50 To 100)
16	Injury Indicator	Target Variable Indicating ACL Injury Occurrence (1 = Yes, 0 = No)

Table 3: List Of Binary Attributes

No.	Attribute Name	Data Type	Description
1	Age	Numerical	$k_{mean_1} = \begin{cases} 1, & \text{if } k > 21.17 \\ -1, & \text{otherwise} \end{cases}$
2	Gender	Categorical	Male = 1 And Female = -1
3	Height	Numerical	$k_{mean_3} = \begin{cases} 1, & \text{if } k > 180.81 \\ -1, & \text{otherwise} \end{cases}$
4	Weight	Numerical	$k_{mean_4} = \begin{cases} 1, & \text{if } k > 77.48 \\ -1, & \text{otherwise} \end{cases}$
5	Position	Categorical	Guard = 1, Center = -1, Forward = -1
6	Training Intensity	Numerical	$k_{mean_6} = \begin{cases} 1, & \text{if } k > 5.11 \\ -1, & \text{otherwise} \end{cases}$
7	Training Hours/Week	Numerical	$k_{mean_7} = \begin{cases} 1, & \text{if } k > 11.32 \\ -1, & \text{otherwise} \end{cases}$
8	Recovery Days/Week	Numerical	$k_{mean_8} = \begin{cases} 1, & \text{if } k > 1.99 \\ -1, & \text{otherwise} \end{cases}$
9	Match Count/Week	Numerical	$k_{mean_9} = \begin{cases} 1, & \text{if } k > 2.39 \\ -1, & \text{otherwise} \end{cases}$
10	Rest Between Events Days	Numerical	$k_{mean_{10}} = \begin{cases} 1, & \text{if } k > 1.98 \\ -1, & \text{otherwise} \end{cases}$
11	Fatigue Score	Numerical	$k_{mean_{11}} = \begin{cases} 1, & \text{if } k > 4.92 \\ -1, & \text{otherwise} \end{cases}$
12	Performance Score	Numerical	$k_{mean_{12}} = \begin{cases} 1, & \text{if } k > 74.47 \\ -1, & \text{otherwise} \end{cases}$
13	Team Contribution Score	Numerical	$k_{mean_{13}} = \begin{cases} 1, & \text{if } k > 72.63 \\ -1, & \text{otherwise} \end{cases}$
14	Load Balance Score	Numerical	$k_{mean_{14}} = \begin{cases} 1, & \text{if } k > 93.40 \\ -1, & \text{otherwise} \end{cases}$
15	ACL Risk Score	Numerical	$k_{mean_{15}} = \begin{cases} 1, & \text{if } k > 46.47 \\ -1, & \text{otherwise} \end{cases}$
16	Injury Indicator	Numerical	$k_{mean_{16}} = \begin{cases} 1, & \text{if } k > 0.07 \\ -1, & \text{otherwise} \end{cases}$

Baseline Method

This study focuses on comparing the performance of different clause structures within the RAN3SATRA model. The aim is to understand how the size and combination of clauses affect the quality of the logic rules produced by the model. Rather than comparing RAN3SATRA with external models, this research evaluates the model's internal performance using three different clause settings. The model is tested using three setups. The first uses all clause sizes together, including one-variable, two-variable, and three-variable clauses. The second uses only one-variable and three-variable clauses, and the third uses two-variable and three-variable clauses. This approach allows us to explore whether the mix of simpler or more complex logic rules influences the model's ability to detect patterns. All three experiments use the same dataset, which contains information about athlete injuries and performance. To make sure the comparison is fair, the same preprocessing method is used. This involves selecting the most relevant features using correlation analysis, where attributes with the strongest relationships to the injury outcome are chosen. No random feature selection is applied. Each model setup follows the same training and testing method. During training, logic rules are created based on neuron interactions, and synaptic weights are calculated using the Wan Abdullah method. The model then uses energy-based logic induction to store and retrieve rules. During testing, the model performance is measured using accuracy, sensitivity, specificity, the Matthews Correlation Coefficient, and negative predictive value. This structured comparison helps identify how different clause setups influence both the clarity and performance of logic rules applied to athlete data.

Table 4: List Of Parameters in RAN3SATRA

Parameter	Parameter Value
Number Of Attributes	10
Number Of Clauses	(4,5)
Q_{best}	$Q_i^{learn} = (1,1)$
Logical Rule	$Q_{RAN3SATRA}$
Attribute Selection	Correlation
Tolerance Value	0.001
Number Of Trials	100
Neuron Combination	100
Maximum Permutation	100
Activation Function	Hyperbolic Tangent Activation Function (HTAF)

Results & Discussion

Preprocessing Result

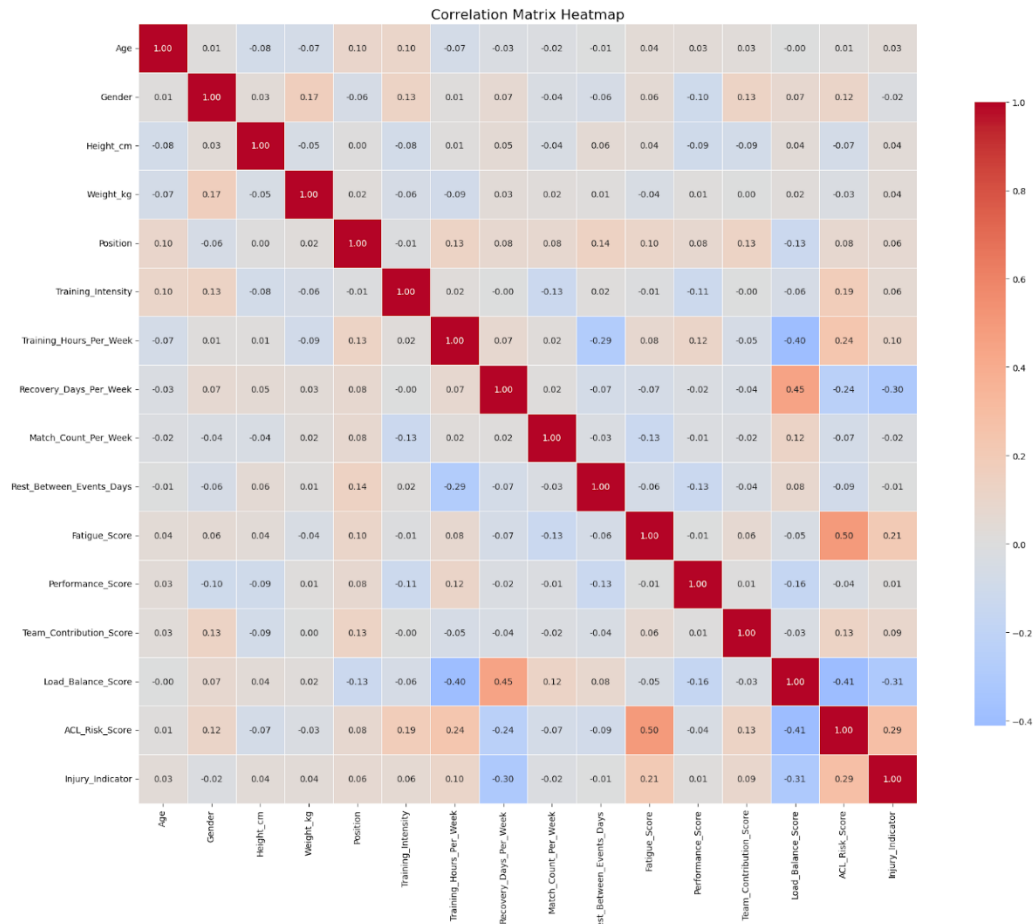


Figure 2: Correlation Heatmap of Selected Features with Injury Indicator

Table 5: Top Ten Attributes Selected.

Variables	Attributes
A	Height
B	Weight
C	Position
D	Training Intensity
E	Training Hours Per Week
F	Training Days Per Week
G	Fatigue Score
H	Team Contribution Score

I	Load Balance
J	ACL Risk Score

Discussion On Preprocessing Result

In this study, attribute selection was conducted using correlation analysis to determine the most influential factors related to athlete injuries. The Pearson correlation coefficient was applied to evaluate the linear relationships between each attribute and the target output which is the injury class. Figure 2 presents the correlation heatmap that visualised these relationships. Attributes with stronger positive or negative correlations were prioritised, as they indicate a more substantial influence on injury outcomes.

Based on this correlation analysis, ten attributes were selected as shown in table 5 for further processing and logic clause construction. The attributes represent a balanced combination of physical, workload and performance-based factors. Physical characteristics like height, weight and position may influence biomechanics and injury susceptibility, while workload measures like training hours, training intensity and recovery days capture the athlete’s physical strain. Additionally, performance and physiological indicators like fatigue, team contribution, load balance and ACL risk provide deeper insight into the athlete’s condition and coordination efficiency. Together, these attributes ensure that the generated logic rules are both data-driven and contextually meaningful in understanding injury risk. This correlation-based selection process establishes a strong foundation for the next stage of the study, where the RAN3SATRA model utilises these refined attributes to generate logical clauses and evaluate classification performance.

Performance Metrics Result

Table 6: Performance Metrics For k = 1, 2, 3

Train: Test Split	Acc	Sen	Spe	MCC	NPV
60:40	0.9625	0.5179	0.9863	0.7034	0.9735
70:30	0.9708	0.6111	0.9907	0.6953	0.9778
80:20	0.9750	0.9333	0.9791	0.8361	0.9931
90:10	1.0000	1.0000	1.0000	1.0000	1.0000

Table 7: Performance Metrics For k = 2, 3

Train: Test Split	Acc	Sen	Spe	MCC	NPV
60:40	0.8594	0.6786	0.8698	0.3612	0.9731

70:30	0.8875	0.8889	0.8890	0.5486	0.9898
80:20	0.8813	0.6333	0.8992	0.4452	0.9701
90:10	0.9625	1.0000	0.9612	0.7731	1.0000

Table 8: Performance Metrics For k = 1, 3

Train: Test Split	Acc	Sen	Spe	MCC	NPV
60:40	0.9031	0.6830	0.9092	0.4211	0.9858
70:30	0.9333	0.7222	0.9466	0.5838	0.9811
80:20	0.9375	0.9333	0.9383	0.6933	0.9929
90:10	0.9750	1.0000	0.9721	0.7642	1.0000

Discussion On Performance Metrics Results

After the attribute selection process, the model’s performance was evaluated using multiple training–testing ratios (60%–40%, 70%–30%, 80%–20%, and 90%–10%) to assess its consistency, robustness, and generalisation behaviour. The analysis primarily focused on the clause configuration $k = 1, 2, 3$, while $k = 1, 3$ and $k = 2, 3$ were included for comparative evaluation. For each configuration, confusion matrices were generated and standard performance metrics including accuracy, sensitivity, specificity, MCC, and NPV were computed.

For the $k = 1, 2, 3$ configurations, the model demonstrated consistently strong performance across all evaluation ratios, with accuracy values ranging from 0.9625 to 1.0000 and specificity consistently exceeding 0.97. Sensitivity increased with larger training proportions, indicating improved detection of injury cases as more training data became available. The MCC values also remained comparatively high, reflecting balanced classification across both classes. The variation observed across different data splits was limited, suggesting stable model behaviour and reliable generalisation. In contrast, the $k = 1, 3$ and $k = 2, 3$ configurations exhibited greater variability across training–testing ratios. While $k = 1, 3$ achieved acceptable accuracy and specificity, its lower MCC values indicate weaker agreement between predicted and actual classifications. The $k = 2, 3$ configurations showed the lowest overall performance, particularly in sensitivity at smaller training ratios, suggesting insufficient logical coverage when intermediate clause sizes are excluded. Therefore, the inclusion of all clause sizes ($k = 1, 2, 3$) provides the best balance between expressive logical representation and classification stability, resulting in more consistent performance across different data partitions. This highlights the importance of combining short and higher-order clauses to effectively capture complex injury-related relationships within the dataset.

Best Induced Logic

The RAN3SATRA model produced an optimal logical rule that differentiates between injured and non-injured athletes based on the selected attributes. This best induced logic was obtained through correlation-guided attribute selection followed by clause construction and evaluation under the 90:10 train–test split (Fold 5). The resulting rule represents the most consistent logical pattern identified from the dataset, capturing key relationships among physical, workload, and injury-risk-related variables that contribute to classification performance.

Best Induced Logic:

$$(A \vee E \vee C) \wedge (H \vee D \vee F) \wedge (B \vee J) \wedge I \wedge G$$

The variables represented in the logic expression correspond to the attribute definitions listed in the table 5.

Discussion On Best Induced Logic

The induced logic reveals several meaningful interactions among attributes associated with injury outcomes. The clause $(A \vee E \vee C)$ suggests that physical characteristics and training exposure jointly contribute to injury susceptibility, where height, playing position, or extended training duration may increase physical strain. Similarly, the clause $(H \vee D \vee F)$ reflects the combined influence of team contribution, training intensity, and training frequency on overall workload exposure. The clause $(B \vee J)$ captures the association between body weight and ACL risk, which is commonly linked to biomechanical stress on lower limbs. The inclusion of the conjunctive literals I and G indicates that these factors play a critical role in injury classification within the proposed framework. Their presence as standalone conditions increase the model's sensitivity to workload imbalance and accumulated fatigue, which helps reduce misclassification of injured cases. This structural characteristic of the induced logic aligns with the higher MCC, and sensitivity values observed for the $k = 1, 2, 3$ configurations, as it enables the model to capture both individual risk indicators and their interactions. Overall, the induced logic supports the interpretation that injury risk arises from multidimensional interactions between physical attributes, training load, and physiological risk factors. The ability to represent these relationships explicitly demonstrates the interpretability and analytical strength of the RAN3SATRA model, while maintaining competitive classification performance.

Conclusion

This study introduced the Random 3-Satisfiability Reverse Analysis (RAN3SATRA) model as an interpretable framework for athlete injury analysis. By integrating satisfiability-based logic mining with supervised learning, the proposed approach addresses a key limitation of conventional artificial intelligence models by providing transparent and human-interpretable reasoning for injury-risk classification. Correlation-based attribute selection identified ten influential factors related to injury risk, and experimental results showed that the clause configuration $k = 1, 2, 3$ achieved the most consistent and stable performance across different training–testing ratios. The best induced logic explicitly captured meaningful interactions between physical characteristics, training load, fatigue, and injury risk, demonstrating how logical rule structures contribute to improved classification performance while remaining interpretable. The core contribution of this study lies in demonstrating the feasibility of explainable injury-risk modelling using satisfiability logic on real athlete data, offering a practical balance between predictive accuracy and model transparency. From an applied

perspective, the findings provide actionable insights that may support coaches and sports professionals in designing balanced training programmes and injury prevention strategies. Future work may extend this framework by incorporating time-series workload or fatigue data to capture temporal injury patterns, evaluating performance on larger and multi-sport datasets, or conducting comparative studies with explainable machine learning techniques such as SHAP-based models to further assess interpretability and generalisation capabilities.

Acknowledgements: The authors would like to express their sincere gratitude to Universiti Putra Malaysia for providing the necessary resources and support throughout the course of this research. Special appreciation is extended to colleagues and peers who contributed valuable insights and constructive feedback, which greatly enhanced the quality of this paper.

Funding Statement: This research received financial support from IPM Putra Grant under Grant Number GP-IPM/2024/9806600. The funding body had no role in the design of the study, data collection, analysis, interpretation of results, or the decision to publish this manuscript.

Conflict of Interest Statement: The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission to the International Journal of Supply Chain, Operation Management and Logistics (IJSCOL).

Ethics Statement: This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.

Author Contribution Statement: All authors contributed significantly to the development of this manuscript. Nurin Hazwani Hamidi and Nur Ezlin Zamri was responsible for the conceptualization, methodology, and overall supervision of the study. Nurin Kamalin Mohd Fadil and Nurul Huda Ahmad Rusli handled data collection, analysis, and interpretation of results. Farisyah Husna Mansor and Ameer Azamuddin Abdul Ghafar contributed to the literature review, drafting, and critical revision of the manuscript. All authors read and approved the final version of the manuscript prior to submission.

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