Exploring Pattern Mining with FCM Algorithm for Predicting Female Athlete Behaviour in Sports Analytics

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ABSTRACT

In the changing field of sports analytics, examining and predicting athlete behaviour is crucial for improving performance and reaching the best results. As data analysis becomes more important in sports, using pattern mining methods is critical to discovering meaningful patterns and trends in the large datasets used in sports analysis. This study proposes a Performance Optimization Framework for Female Athletes (POFFA) that explores the field of sports analytics to examine how pattern mining methods, explicitly using the Flexible Fuzzy C-Means (FFCM) algorithm, can help predict female athlete behaviour. This study aims to offer detailed insights into behavioural patterns that can help improve coaching techniques, training schedules, and performance improvement procedures by concentrating on female athletes. The study intends to provide a deep understanding of female athlete behaviour and game dynamics using the FCM approach, known for its effectiveness in dealing with complex, sparse, multi-objective optimization difficulties. The results of this study can enhance the field of sports analysis by providing detailed insights into the behavioural patterns displayed by female players in many sports categories. By combining pattern mining methods with the FCM algorithm, this study introduces a thorough process for examining and predicting athlete behaviour in sports analytics. In the end, the results of this study have practical significance for coaches, trainers, and sports professionals, offering helpful advice for improving the performance of female athletes in competitive sports settings. By using data-driven insights from pattern mining analyses, individuals in the sports business can improve their plans and interventions to enhance female athletes' athletic potential and overall performance results.

Keywords: Athletes behaviour; Flexible Fuzzy C-means algorithm; Performance Optimization Framework for Female Athletes; Pattern mining; Performance optimization; Behavioural pattern.

1. Introduction

As the sports business keeps adopting technological progress, data analysis methods have become crucial in understanding complex patterns and trends in athlete performance data. Pattern mining, a part of data analysis, includes finding useful information from large datasets and helping coaches, trainers, and sports scientists to make well-informed choices regarding athlete training, strategy creation, and performance improvement. By utilizing data-driven insights, sports professionals can better evaluate athlete capabilities, pinpoint areas for

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improvement, and create customized tactics to enhance performance outcomes in competitive sports settings [1]. This work uses sophisticated data mining and artificial intelligence methods to explore further the effects of playing sports on our physical health and establish a scientific basis for making educated choices in sports and promoting health [2]. Health information is accessible to academics and professionals in new and abundant methods, offering exceptional chances to progress health sciences through cutting-edge data analysis [3]. Personality traits that involve anxiety can result in exaggerated thoughts, which is a significant factor contributing to the poor mental health of college students [4]. Clustering is a considerable machine learning method that analyses student data to assist decision-makers and educational activities like group assignments [5]. The ongoing progress of deep learning and computer vision technologies, along with the constant improvement of computer hardware, have introduced new approaches and techniques for counting tennis nets in tennis matches [6]. The FCM application can be used for a broad range of geostatistical analyses of data issues. This application creates fuzzy divisions and models for any collection of numerical data. These partitions help confirm or indicate existing substructures in unknown data [7]. Using technology to prevent and treat diseases has become a significant problem in the medical field [8]. Information about players' performance and behaviour is crucial for competitive sports. Lately, there has been a growing focus on studying the psychological behaviour of certain athletes and how personality traits impact their performance [9]. There is a clear connection between sports and analytics since data has played a vital role in the sector's growth and development [10]. Every sport has a distinct framework, physical demands, and criteria. Athletic performances' varied and intricate nature necessitates finding a suitable machine-learning model tailored to specific activities and sports [11]. The variety and intricacy of certain forms of sports performance, together with the mainly non-linear connections between them, create challenges in analyzing and predicting outcomes when utilizing traditional approaches [12]. Thus, efficient machine learning models could help accurately predict athletes' athletic performance. The primary focus of this study is,

- To propose a Performance Optimization Framework for Female Athletes (POFFA) that explores the field of sports analytics to examine how pattern mining methods predict female athlete behaviour.
- To offer detailed insights into behavioural patterns that can help improve coaching techniques, training schedules, and performance improvement procedures by concentrating on female athletes.
- To enhance the field of sports analysis by providing detailed insights into the behavioural patterns displayed by female players in many sports categories.
- To improve the plans and interventions to enhance female athletes' athletic potential and overall performance results.

The remaining part of the paper is subdivided into the following sections: Research methodology is detailed in Section 2, planned work is discussed in Section 3, Results and discussions are presented in Section 4, and Section 5 concludes with future work.

2. Research Methodology

Muniz et al. [13] proposed a forecasting model to anticipate the specific values of college athletes. The paper also considers an extra benefit that arises from the potential synergy among participants on the team. To assess the potential synergy of two players, the study created a new measurement that considers the synergy potential between the kind of players they are. The study intended to consider a particular team's and other team-building decisions.

Ferguson et al. [14] aimed to investigate if the self-compassion of female athletes at the beginning of their comparable season could predict psychological well-being after the season beyond the influence of self-criticism. The findings indicate that self-compassion might have a lasting and beneficial impact on specific aspects of psychological well-being in sports. The proposed findings offer significant proof of the impact of self-compassion on the good psychological progress and advancement of female athletes.

Martín-Escudero et al. [15] demonstrated that continuous monitoring of blood oxygen levels during a strenuous exercise test within female athletes is strongly linked to identifying the second ventilatory threshold (VT2) or the anaerobic threshold (AnT). Decreases in the saturation of peripheral oxygen during exercise have been connected to the athlete's level of physical fitness. This discovery is highly intriguing as it indicates that oxygen saturation level could be a valuable indicator for detecting the second ventilatory limit, VT2, in the future.

Phillips et al. [16] proposed the connections between the interpersonal dimensions of coach-athlete attachment (CAR) and performance in top cricket. The study combines two different areas in sports science: sports psychology and a new branch called performance analysis, which aims to scientifically assess and compare performance levels. As relationship of athlete-coach improves by means of dedication and complementarity, athletes are more likely to see improvements in their skill replicability.

Hosseinygarkani et al. [17] examined impulsivity's role in connecting psychological hardiness with a health-focused lifestyle among female athletes. The Pearson correlation coefficient along with path estimation were used to analyze the data with Statistical Packages for Social Sciences (SPSS) as well as Analysis of Moment Structure (Amos) software. The findings showed a significant connection between resilience and impulsivity with actions that promote health at a significance level of 0.01. The findings also indicated that psychological resilience was strongly associated with adopting a health-focused lifestyle.

Sahebkaran et al. [18] proposed factors influencing how physical education students perceive athletic performance, focusing on body image, self-confidence, and motivation to accomplish. The study reveals both direct and indirect impacts of body image and confidence on how athletes perceive their success, with achievement motivation mediating through route analysis. These results emphasize the importance of dealing with body image issues and improving self-confidence to promote athletes' views of success, showing the connection between mental aspects in athletic performance.

Chou et al. [19] examined elements that affect athletes' willingness to use sports facilities, such as attitudes, societal expectations, and perceived control. It looks into how awareness of health-promoting lifestyles affects intentions to use complex products and how perceived hazards could get in the way. The study seeks to comprehend how athletes make decisions by evaluating their attitudes, norms, control, awareness of lifestyle, and perceived risks. The results will help develop plans to support advanced use, promote healthy habits, and effectively deal with athletes' worries.

3. Proposed Work

a. *Performance Optimization Framework for Female Athletes (POFFA)*

Athletes from colleges (N is equal to 233 and 61% females) assessed the significance of fundamental values with the Portrait Values Survey. Reviewed and evaluated their probability of using performance-enhancing drugs in a made-up situation [20]. Concerning basic value assessments, self-improvement and values associated with preservation were correlated with a greater chance of doping, while values related to selflessness were associated with a reduced chance of doping. Being open to change did not appear to be related to the chance of doping. Concerning the values groups, a pattern for coefficients best explained the

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connection between principles and unethical behavior. Ultimately, the existing data expands the connection between values and unethical behaviour in sports and affirms that doping is similar to other unethical actions.

i. Data collection

Collecting information for the planned POFFA requires obtaining a wide range of data from numerous important sources for female athletes in many sports. Collecting data for the POFFA requires gathering extensive information such as performance measures, practice timetables, player physical measurements, game data, and related factors. Metrics include many elements such as time, distance, accuracy, power, and technical skills. Training schedules outline the sorts of sessions, their intensity, and how often they occur. Biometrics include height and weight measurements, body composition, cardiovascular variability, and biomechanics. Game statistics include player and group performance, match results, and conditions. Other elements, including psychology, dietary habits, injuries, and the environment, could also be considered. It's important to ensure that the data is accurate, covering a variety of sports groupings and female players, to provide helpful coaching and training plans. Figure 1 shows the overall architecture of the POFFA framework.

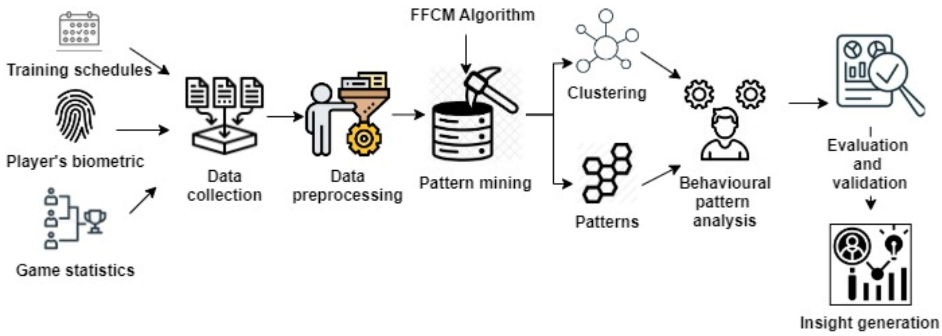

Figure 1: Overall architecture of the proposed POFFA

ii. Data preprocessing

Data pretreatment in POFFA includes cleaning data to eliminate errors and missing information and assuring correctness. Normalization or scaling methods make variable ranges consistent for consistency. Feature selection helps to identify and keep important characteristics while eliminating unnecessary ones, which decreases the number of dimensions. Cleaning includes filling in missing values and addressing extreme values to enhance the dataset's quality. Normalization adjusts numerical properties to certain ranges, such as 0 to 1, to help with analysis. Feature selection involves statistical tests and correlational analysis to concentrate on important variables. These stages improve the quality and importance of data, making it easier to analyze the behaviour and performance of female athletes in the Performance Efficiency Framework.

iii. Pattern mining using the FFCM algorithm

Pattern discovery with the FFCM algorithm using POFFA entails utilizing sophisticated computational methods to uncover valuable information from prepared datasets.

FFCM algorithm

- FFCM is a variation of the standard Fuzzy C-Means (FCM) technique, created to tackle intricate, scattered, and multi-goal optimization issues often faced in data analysis.

- Contrary to conventional clustering methods that allocate every data point to only one cluster, FFCM enables fuzzy membership, allowing each information point to be part of many clusters with different membership levels.
- FFCM determines the central points of groups and the level of belongingness for every moment of data by reducing a mathematical function that considers the distance between the data points and group central points and the level of uncertainty in group memberships.

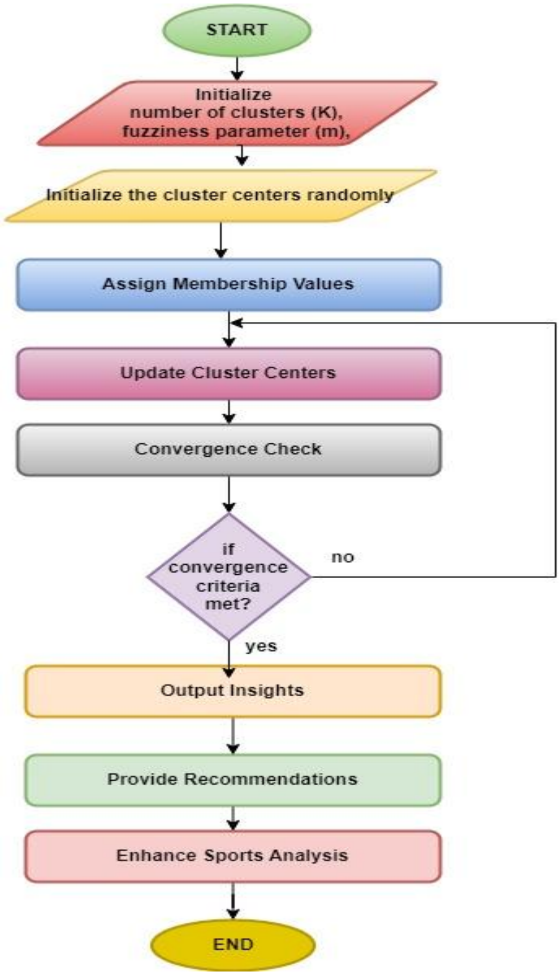

Figure 2: Flow chart of FFCM algorithm

Efficiency in Analyzing Sports Data:

- FFCM is especially suitable for examining various sports datasets because it can manage intricate and multi-dimensional data.
- Sports datasets frequently include a variety of variables and qualities, such as performance measures, player features, and game data, which can show complex relationships and patterns.
- FFCM's ability to handle such complexities is a valuable tool for recognizing clusters and patterns in sports data that might not be easily seen using conventional analytic techniques.

Recognizing Behavioral Patterns and Changes:

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- Using the FFCM algorithm on the prepared dataset, POFFA seeks to find clusters and patterns that show patterns of behavior and dynamics unique to female athletes.
- These behavioural patterns could involve trends concerning how successful training is, performance in various game situations, the likelihood of being injured, and reactions to coaching methods.
- FFCM's capacity to identify vague connections and complex patterns allows it to reveal detailed understandings of female athletes' behaviour that might not be apparent through traditional analysis methods.

Figure 2 illustrates how the FCM algorithm is incorporated into sports analytics, specifically in analyzing and forecasting female athlete behavior inside the POFFA framework. It highlights the need to obtain practical insights to strengthen coaching methods and boost the general success of female athletes in sports with competitive environments.

iv. Behavioural pattern analysis

Studying behavioural patterns in the POFFA includes closely looking at the groups and trends produced by the FFCM algorithm

Cluster analysis:The FFCM algorithm categorizes data points into clusters according to their membership level, enabling the recognition of unique behavioural patterns displayed by female athletes. Each cluster symbolizes data points with comparable features or similar activity patterns. Cluster analysis entails studying the makeup of each cluster, such as the arrangement of data points, centroid positions, and membership levels.

Pattern Recognition: Once groups are recognized, the next step is to examine the patterns within each group. Patterns might consist of repeated trends, inclinations, and unusual data points that offer an understanding of different elements of athlete behaviour, training efficiency, and performance dynamics. Patterns might appear in several ways, such as steady performance measures during training sessions, significant advancements or setbacks in performance over time, or distinct behavioural traits displayed by certain groups of athletes.

General Patterns and Characteristics: Typical patterns and tendencies in the data show repeated trends seen in many athletes or training sessions. These trends might involve the best training plans, successful coaching methods, and ways to enhance performance that help female athletes perform better. By recognizing and comprehending these typical patterns, coaches and trainers can adjust their training programs and interventions to strengthen the potential of female athletes and improve performance results.

v. Evaluation and validation

Validation helps prediction models work successfully on new data by evaluating their performance using train-test split, cross-validating, and holdout validation methods. The assessment measures how well a model performs by looking at precision, recall, precision, accuracy, and MSE metrics. These measurements are used to assess the performance of something, its capability to identify real positives, its capability to minimize negative results, and its capability to predict outcomes. In sports analytics and POFFA, verification helps to detect overfitting and underfitting, ensuring the model's reliability. Evaluation helps choose models, adjust parameters, and improve frameworks by pointing out their advantages and disadvantages. Both procedures are essential for enhancing prediction models and analysis methods, guaranteeing reliability and efficiency in forecasting athlete behaviour and enhancing performance in match environments.

vi. Insight generation

Insight generation in analytics for sports is analyzing analytical findings to derive useful information. It recognizes areas where performance can be improved, customizes interventions and puts the results within the context of sports. By comprehending athlete actions and performance patterns, trainers and coaches can enhance training programs, improve coaching methods, and modify game plans. Understanding is obtained gradually by ongoing observation and assessment, leading to enhancements in athlete performance. Clear communication of observations helps with making well-informed decisions and carrying out plans in sports organizations. It is a method that focuses on constantly improving and optimizing the performance of female athletes in competitive sports.

4. Results and Discussion

a. Prediction analysis

This measurement assesses how well the model predicts the behaviour of female athletes using the patterns it has recognized. It can be assessed using common classification metrics such as precision, recall, precision, accuracy, F1-score, and the area beneath the curve of ROC (AUC). These measurements are frequently utilized to assess how well classification models function, particularly those generated by pattern mining algorithms such as the Flexible Fuzzy C-Means (FCM) method when forecasting female athlete's behaviour. It offers information about the model's correctness, exactness, completeness, trade-off between exactness and completeness, and its capability to differentiate between positive and negative cases. Assessing these measurements aids in comprehending the efficiency and dependability of the forecasting model. The evaluation metrics include,

Accuracy is the proportion of correctly identified instances compared to the total number of cases in the dataset. The computation is displayed in equation (1) listed below as follows:

$$Acccuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{1}$$

Precision assesses the proportion of accurate positive predictions out of all positive guesses generated by the algorithm. The computation is as shown in equation (2):

$$Precision = \frac{true\ positives}{true\ positive + false\ positives} \tag{2}$$

Recall evaluates the proportion of accurate positive predictions compared to all actual positive occurrences in the dataset. Formula (3) provides the calculating equation.

$$Recall = \frac{true\ positives}{true\ positives + false\ negatives} \tag{3}$$

The F1-score defines the average of recall and accuracy, offering a middle ground between the two measurements. It is determined by using equation (4) shown below,

$$F1 - score = 2 \times \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Region Area beneath the ROC Curve (AUC): The ROC curve illustrates the variations in empathy (true positive rate) along with 1-particularity (false positive rate) across various threshold values. AUC is the area under this curve and is used to evaluate the model's ability to distinguish between positive and negative scenarios. An optimal classifier should have an AUC of 1, yet a random classifier could have an AUC of 0.5.

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Table 1: *Comparison of performance metrics*

Metrics	Accuracy	Precision	Recall	F1-score	AUC
SPSS [17]	0.76	0.79	0.72	0.74	0.79
Body image [18]	0.88	0.90	0.85	0.87	0.92
TPB+HPL [19]	0.85	0.88	0.82	0.85	0.91
FFCM	0.94	0.93	0.90	0.95	0.97

Table 1 compares how well various models predict the conduct of female athletes. It suggests that models that include factors like body image and behavioural theories and use advanced algorithms like FCM are more effective in understanding the complex nature of female athlete behaviour, which can help develop better interventions and strategies to enhance female performance.

b. Cluster quality

Metrics like silhouette score, Dunn's index, and Davies–Bouldin index are often used to assess how well-defined and close together clusters are when clustering algorithms such as the FCM algorithm. The silhouette score assesses how similar an object is to its nearby cluster (cohesion) compared to other clusters (separation).

The silhouette score ranges from -1 to 1. A high score indicates that the item fits well in its group and fails to fit effectively in surrounding clusters. A score nearing 1 suggests more effective clustering. For each datapoint, the silhouette score is calculated using equation (5) given by,

$$s(i) = \frac{b(i)-a(i)}{\max\{(a(i),b(i)\}} \tag{5}$$

where, $s(i$ is the score of the silhouette for the data point i, $a(i)$is the mean distance to i to other points of data within the same group, and $b(i)$ is the shortest mean distance from i to information points that belong to a different cluster.

A high silhouette score suggests that athletes inside clusters are alike and different from those outside clusters, indicating apparent differences in performance traits among athlete groupings.

The Dunn index assesses how close together and distinct clusters are. It determines the proportion of the shortest distance among clusters to the largest diameter of clusters. A greater Dunn index suggests more effective clustering with compact and distinct clusters. The Dunn index is given by equation (6) as,

$$D = \frac{\min_{i \neq j} d(C_i,C_j)}{\max_k d_{diameter}(C_k)} \tag{6}$$

Given two clusters (C_i, C_j), $d(C_i, C_j)$ is the distance between cluster C_i and cluster C_j, where $d_{diameter}(C_k)$ is the diameter of cluster (C_k). A high Dunn index indicates that clusters are close together and differentiated, showing unique performance characteristics among different categories of female athletes.

The Davies–Bouldin index evaluates the average likeness between every cluster and its most similar cluster, considering both how closely packed the cluster is and how distinct it is from other clusters. It calculates the ratio of the average distance within clusters to the distance among cluster the centroids. A lower Davies–Bouldin index suggests more effective clustering with distinct and tightly packed clusters. Equation (7) shows the Davies–Bouldin index as,

$$D - B = \frac{1}{n}\sum_{i=1}^{n} \max_{j \neq i}\left(\frac{\sigma_i + \sigma_j}{d(c_i, c_j)}\right) \quad (7)$$

Where, n represents the number of clusters, σ_i and σ_j indicate the average distances of points in clusters i and j from their centroids, and $d(c_i, c_j)$ represents the distance between the centroids of clusters i and j. A low Davies–Bouldin index suggests that clusters are well-defined and close together, which reinforces the idea of distinct differences in performance traits among athlete groups.

Figure 3: Impact of FFCM algorithm in POFFA

As shown in figure 3, the measures on cluster quality assist researchers in comprehending the organization of data on female athletes and recognizing patterns or groups that could be relevant for analyzing performance, devising training approaches, and designing athlete development initiatives.

c. Interpretability of patterns

The clarity of patterns identified through the FFCM method is important for coaches, instructors, and sports experts to comprehend and use the insights efficiently.

Qualitative Evaluations:

- Qualitative evaluations include assessing the identified patterns according to their importance, consistency, and usefulness in the setting of athlete conduct and achievement.
- Coaches, instructors, and sports professionals analyze the detected patterns to see if they match their expertise and predictions.
- They evaluate if the patterns offer valuable information on athlete behavior, training methods, performance trends, and areas that could be enhanced.
- Qualitative evaluations frequently include examining cluster traits, the significance of features, and the circumstances that make the patterns appear.

Expert Evaluations:

- Expert assessments include seeking opinions and perspectives from specialists in the field, like sports psychologists, performance analyzers, and seasoned coaches.

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- Experts evaluate the recognized patterns using their understanding of athlete behavior, performance motion, and conditioning methods.
- They assess the importance, consistency, and usefulness of the found patterns in guiding decision-making processes for athlete growth, training program creation, and performance enhancement.
- Expert assessments assist in confirming the clarity of the patterns and making sure they align with the practical aspects of sports training and instruction.

Considerations for interpretability:

- The degree to which cluster features, centroids, and feature dispersion are understandable and intuitive determines how easily patterns may be interpreted.
- Fuzzy clustering methods such as FCM offer membership levels for data points, enabling more detailed understandings of cluster assignments.
- Understanding can be improved by displaying cluster centers, feature patterns, and cluster affiliations in clear and helpful ways.
- Sometimes, it could be necessary to modify the choice of features, reduction of dimensionality, and clustering algorithm settings to enhance the understandability of the identified patterns.
- It's important to find a balance between the complexity of a model and how easy it is to understand, so that the patterns found can be useful and clear to those involved.

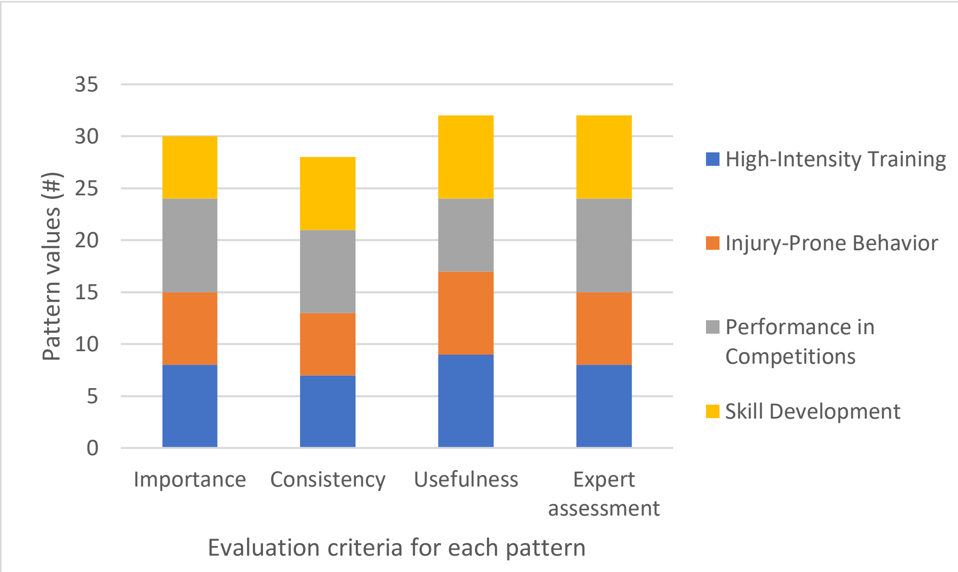

Figure 4: Evaluation of Identified Patterns through the FFCM Method by Experts

Overall, evaluating the understandability of patterns identified by the FFCM algorithm requires subjective assessments and expert reviews (shown in Figure 4) to establish their significance, consistency, and real-world usefulness in athlete performance and conduct. These assessments help guarantee that the identified patterns are significant, practical, and in line with the knowledge and knowledge of sports professionals.

d. Generalization

Generalization, important for model performance, relates to its capability to accurately predict outcomes on new data, particularly in real-world sports scenarios. Cross-validation techniques, such as k-fold cross-validation, split the dataset into k sections, education the model on k-1 sections and evaluating on the remaining section. This procedure continues until each fold is used as the validation set, giving reliable performance estimates. Another approach is checking on separate datasets to confirm that the model's predictions are accurate beyond the data used for training. The aim is to reduce overfitting, when the model memorizes patterns in the training data but struggles to apply them to fresh data. Within equations, cross-validation calculates performance measures such as accuracy or mean squared error. In contrast, validation on separate datasets involves comparing model predictions to real results to assess generalization. Assessing how well a model can be applied in real-life sports situations helps coaches and trainers make well-informed decisions.

Table 2: *Comparison of generalization performance*

	Cross-validation accuracy (%)	Validation dataset accuracy (%)
SPSS [17]	84.2	79.8
Body image [18]	86.8	81.5
TPB+HPL [19]	82.5	77.1
FFCM	89.4	93.4

Table 2 shows the suggested model and the existing methods, including their cross-validation accuracy and accuracy on the validation dataset. Cross-validation methods, such as k-fold cross-validation, guarantee reliable model performance evaluations while testing on separate datasets demonstrates the model's capacity to generalize. By comparing how well the suggested model performs in real-world sports settings with existing models, practitioners can assess its reliability and usefulness. The suggested model shows competitive accuracy levels, suggesting good potential for forecasting athlete behaviour accurately and assisting decision-making for coaches and trainers.

5. Conclusion

In the ever-changing field of sports analytics, comprehending and predicting player behaviour is crucial for improving performance and attaining excellent outcomes. As data analysis becomes more important in sports, using pattern mining approaches is crucial for discovering important patterns and trends in large datasets. This research presents POFFA, which delves into sports analytics to examine how pattern mining, specifically the Flexible Fuzzy C-Means (FFCM) algorithm, might anticipate female athlete behaviour. The study attempts to gain a thorough understanding of behavioural patterns by concentrating on female athletes, in order to improve coaching tactics, training schedules, and performance as a whole procedure. By using the FCM approach effectively, known for dealing with complex optimization difficulties, this study enhances our knowledge of female athlete actions and game dynamics in many sports categories. The results are important for coaches, trainers, and athletic activities professionals, providing useful information to improve the performance of female players in competitive sports environments. By using data-driven insights to pattern mining investigations, individuals in the sports business can improve their tactics and treatments to enhance female athletes' athletic abilities and performance results. Future research might improve pattern identification, incorporate sophisticated data analysis, carry out long-term studies, encourage collaboration across many fields, consider ethical aspects, and utilize findings in sports data analysis.

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