Longitudinal study of match load zones and performance in elite football: a multivariate analysis and machine learning technique

Estudio longitudinal de las zonas de carga y el rendimiento en el fútbol de élite: análisis multivariante y aprendizaje automático

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Abstract

Introduction: Recent technological advancements have revolutionized athlete monitoring, with football clubs worldwide leveraging embedded sensors to track player performance. However, interpreting the vast and complex data from these sensors remains a challenge for coaches and analysts.
Objective: This study aims to identify the most significant match loads influencing player performance.
Methodology: Data were collected from Terengganu Football Club (TFC) during the 2022 Malaysia Super League season. The Louvain clustering algorithm was employed to classify player performance levels, while logistic regression (logit model) identified key load zones linked to different performance tiers. The Kruskal-Wallis test was used to validate distinctions among these clusters.
Results: Data were collected from Terengganu Football Club (TFC) during the 2022 Malaysia Super League season. The Louvain clustering algorithm was employed to classify player performance levels, while logistic regression (logit model) identified key load zones linked to different performance tiers. The Kruskal-Wallis test was used to validate distinctions among these clusters.
Discussion: The findings provide insights into key load-related metrics, helping coaches understand their impact on player performance. These insights can guide workload management and training adjustments to enhance player efficiency and reduce injury risks.
Conclusions: This study offers valuable guidance for refining training programs and developing more effective strategies to optimize team performance in modern football.

Keywords

Football; global positioning system (GPS); performance analysis; team sport; team sport; wearable tracking system.

Resumen

Introducción: Los avances tecnológicos recientes han revolucionado el monitoreo de los atletas, permitiendo que los clubes de fútbol de todo el mundo utilicen sensores integrados para rastrear el rendimiento de los jugadores. Sin embargo, la interpretación de los vastos y complejos datos generados por estos sensores sigue siendo un desafío para entrenadores y analistas.
Objetivo: Este estudio tiene como objetivo identificar las cargas de partido más significativas que influyen en el rendimiento de los jugadores.
Metodología: Se recopilaron datos del Terengganu Football Club (TFC) durante la temporada 2022 de la Superliga de Malasia. Se empleó el algoritmo de agrupamiento Louvain para clasificar los niveles de rendimiento de los jugadores, mientras que la regresión logística (modelo logit) identificó las zonas de carga clave asociadas con diferentes niveles de rendimiento. La prueba de Kruskal-Wallis se utilizó para validar las diferencias entre estos grupos.
Resultados: Los datos recopilados permitieron identificar tres grupos de rendimiento: moderado (10 partidos), alto (7 partidos) y bajo (5 partidos). De las 20 zonas de carga analizadas, 15 fueron significativas, logrando una precisión inicial de clasificación del 72,7%. Tras aplicar la prueba de Kruskal-Wallis, se aislaron siete métricas de carga clave, mejorando la precisión de clasificación al 86,4%.
Discusión: Los hallazgos proporcionan información sobre métricas clave relacionadas con la carga, ayudando a los entrenadores a comprender su impacto en el rendimiento de los jugadores. Estos conocimientos pueden orientar la gestión de la carga de trabajo y los ajustes en el entrenamiento para mejorar la eficiencia de los jugadores y reducir el riesgo de lesiones.
Conclusiones: Este estudio ofrece una guía valiosa para la optimización de los programas de entrenamiento y el desarrollo de estrategias más efectivas para mejorar el rendimiento de los equipos en el fútbol moderno.

Palabras clave

Fútbol; sistema de posicionamiento global (GPS); análisis del rendimiento; deporte de equipo; sistema de seguimiento portáti.

Introduction

Football, recognised as one of the most popular and lucrative sports worldwide, boasts a staggering participation rate of approximately 265 million players globally (Kang et al., 2022). As a dynamic team sport, football is characterized by frequent transitions in action patterns that range from low to moderate-intensity movements such as jogging, walking, and positioning, to high-intensity actions, including sprinting, shooting, and rapid directional changes (Póvoas et al., 2023; Abdullah et al., 2016). The increasing demands of contemporary football necessitate that players not only exhibit high levels of physical capability but also possess advanced technical and tactical skills (Mamytko & Hadyko, 2024; Martín-García et al., 2022). The outcomes of matches hinge upon the continuous interplay between teammates and opponents (Plakias et al., 2024), as player strategically adjust their positions based on the evolving dynamics of the game, whether to initiate an attack, score or maintain defensive integrity (Brandão et al., 2024; Forcher et al., 2022).

The advent of technology has revolutionized the analysis of sports performance, particularly in football, where the physical and metabolic demands have escalated significantly (Beygmohammadloo et al., 2024; Nikić et al., 2024). The introduction of global positioning system (GPS)-based has facilitated real-time tracking of players' loads, activity profiles, and positional data (Kelly, 2021; Maher, 2022; Oladele, 2022). These compact systems, often integrated with user-friendly applications, enable coaches and managers to derive valuable metrics that inform decision-making regarding training regimes, tactical strategies as well as overall player's performance metrics such as loads and other physiological indicators (Gu et al., 2024; Padrón-Cabo et al., 2024).

Athletes' loads can be classified into internal and external measures. Internal loads reflect the physiological and psychological stresses placed on athletes during training and competition, including metrics such as heart rate (HR), blood lactate (BLa), and ratings of perceived exertion (RPE). In contrast, external load represents objective performance metrics, such as distance covered, speed, and power output (Lechner et al., 2023a; Pinheiro et al., 2023). Recent studies underscore the importance of integrating both internal and external load metrics, providing coaches and athletes with comprehensive insights that guide performance enhancement (Helwig et al., 2023; Lechner et al., 2023b). Nevertheless, the effective utilization of these metrics can be complex, suggesting that focusing on a selected few key variables may facilitate better performance monitoring (Stieler et al., 2023).

Research indicates that systematic monitoring of athletes can elucidate their responses to training regimens and tactical approaches. For instance, athletes displaying insufficient internal load relative to standardized external load may be deemed unfit, prompting coaches to adjust their training plans accordingly (Akubat et al., 2018; Lechner et al., 2023c). Conversely, excessive internal load can lead to fatigue, necessitating careful management of training intensity (Ammann et al., 2023; Costa et al., 2022; Silva et al., 2023). Given these considerations, this study seeks to leverage GPS-based technology to identify and prioritize the most significant load metrics influencing player performance within the context of the Terengganu Football Club (TFC) during the 2022 Malaysia Super League season.

Method

Participants

Data was collected from all matches (22 in total) played by the Malaysian professional team, TFC, in the 2022 Malaysia Super League. The study focused on outfield players, who were all registered members of the squad aged between 21 and 35 years. The data collection spanned the duration of the league season, from January to December 2022.

Ethical approval for this research was granted by TFC Sdn Bhd, with reference number TFC/14/2020. Participants were informed about the study's purpose, its potential risks and benefits, and the measures taken to ensure confidentiality and anonymity of their data. Consent was obtained through a formal letter, which was explained to participants in person for clarity and transparency. A copy of the consent letter was also provided to each member of the club's management for record-keeping purposes. No adverse events were recorded during the data collection period. All ethical procedures, including participant consent, were adhered to according to the approved protocol.

Procedure

Instrument

The Sport Performance Tracking (SPT) system developed by SPT Group Pty Ltd (United States of America), was employed for tracking the athletes' loads during matches. The SPT system is widely recognized for being a robust, user-friendly, and cost-effective GPS solution for performance tracking. The device, worn by the players, integrates various advanced sensors, including a 10 Hz GPS module, battery, Bluetooth connectivity, magnetometer, accelerometer, gyroscope, and Global Navigation Satellite System (GNSS) for location tracking. The compact device is housed in a water-resistant, form-fitted half-vest, ensuring comfort during use. The vest is equipped with docking features and supports multi-unit charging, allowing for efficient management of multiple devices during data collection. The SPT system has gained popularity across more than 100 countries, with users ranging from professional football clubs to rugby associations and health professionals (Prather et al., 2020). Figure 1 visualized the SPT device with a half vest.

Figure 1. SPT system (Sports Performance Tracking | GPS Tracking for Contact Sports | SPT – SportsPerformanceTracking, n.d.)

Data Treatment

Data from the SPT devices were transmitted via the Bluetooth module to the GameTraka software (SPT Group Pty Ltd, USA), a performance analysis system designed for soccer. The process of data capture and transmission through SPT device is illustrated in Figure 2. The collected parameters included a wide array of athlete performance metrics such as performance duration, total distance covered, distances for different intensity levels (walking, jogging, running, and sprinting), sprint efforts, sprinting rate, hard running, work rate, and top speed. Additionally, session-specific metrics were gathered, including 2D and 3D loads, intensity, impact count, mean and maximum heart rate, and efficiency index.

Figure 2. Signal capturing and transmitting via SPT device (Hernandez-Martin et al., 2020)

Data Treatment

Upon extracting the raw data from the GameTraka software, the information was pre-processed and compiled into a master dataset. A total of 396 data points were systematically gathered from the 22 matches of the 2022 Malaysia Super League season. Data transformation techniques were applied to standardize all feature values between 0 and 1, ensuring consistent distribution and representation across the different metrics. This normalization was necessary because the raw data spanned various ranges, potentially affecting the comparability of the features. Standardizing the features before feeding them into the model improved classification performance by ensuring that each metric had equal influence on the analysis (H. Li et al., 2024; Yang et al., 2022).

Data Analysis

Louvain Clustering

The Louvain clustering algorithm, a widely used technique for classifying large datasets, was applied to group the different performance zones based on the collected metrics. This algorithm was chosen due to its ability to produce significant classifications from complex data. The clustering analysis was carried out in two distinct phases. Initially, the algorithm identified smaller clusters through the maximization of modularity. Subsequently, the algorithm grouped related nodes into larger populations until a final modularity condition was achieved. This process resulted in a hierarchical fragmentation of the data, producing clusters based on the density of their boundaries (Musa et al., 2022).

Logistic Regression

Logistic regression, specifically with L1 regularization (Lasso), was used to perform feature selection by eliminating less significant parameters (Wilke et al., 2022). L1 regularization reduces the coefficients of irrelevant features to zero, effectively removing them from the dataset. This process reduced the dimensionality of the data, ensuring that only the most critical performance metrics were retained for further analysis (Browne et al., 2022). All statistical analyses, including data preprocessing, clustering, and feature selection, were conducted using XLSTAT 2021.2.2 (Addinsoft, Paris, France) and Orange 3.34.0 (University of Ljubljana, Slovenia).

Kruskal-Wallis Test

The Kruskal-Wallis H test, a non-parametric rank-based test also referred to as a one-way ANOVA on ranks, was employed to determine statistically significant differences between the performance clusters identified in the clustering analysis (Bhavani & Ponnusamy, 2024). This test was chosen due to its robustness in dealing with non-normally distributed data.

Results

Descriptive Statistics

The descriptive statistics of the parameter metrics are provided in Table 1, which details the variables, number of observations, minimum and maximum values, means, and standard deviations. This table offers a comprehensive overview of the dataset used in the analysis.

Table 1. Descriptive statistics of the parameter metrics

Variable	Observations	Minimum	Maximum	Mean	Std. dev
Performance Duration [min]	22	-2.480	2.527	0.000	1.024
Total Distance [m]	22	-2.273	2.101	0.000	1.024
Walk Distance [m]	22	-1.987	2.405	0.000	1.024
Jog Distance [m]	22	-2.375	2.700	0.000	1.024
Run Distance [m]	22	-1.542	3.059	0.000	1.024
Sprint Distance [m]	22	-0.527	3.976	0.000	1.024
Sprint Efforts	22	-1.362	1.989	0.000	1.024
Sprinting Rate [m/min]	22	-0.518	3.968	0.000	1.024
Hard Running [m]	22	-1.590	3.313	0.000	1.024
Hard Running Rate [m/min]	22	-0.584	4.433	0.000	1.024
Hard Running Efforts	22	-3.404	1.332	0.000	1.024
Work Rate [m/min]	22	-1.570	2.161	0.000	1.024
Top Speed [m/s]	22	-2.601	1.523	0.000	1.024
Intensity	22	-2.624	1.865	0.000	1.024
Total Impacts	22	-2.948	1.571	0.000	1.024
Load 2D	22	-3.613	1.784	0.000	1.024
Load 3D	22	-3.587	1.777	0.000	1.024
HR Mean [bpm]	22	-2.537	1.672	0.000	1.024
HR Max [bpm]	22	-2.044	2.206	0.000	1.024
HR Efficiency [m/beat]	22	-1.368	2.108	0.000	1.024

Clustering Analysis

Figure 3 illustrates the clusters of the team's performance based on the measured parameters. Three distinct clusters were identified using Louvain clustering: HP (High Performance, 7 matches), MP (Moderate Performance, 10 matches), and LP (Low Performance, 5 matches). The clustering was derived from the external and internal load variables, and these clusters represent the team's varying performance levels across different matches.

Figure 3. Clusters obtained via Louvain Clustering

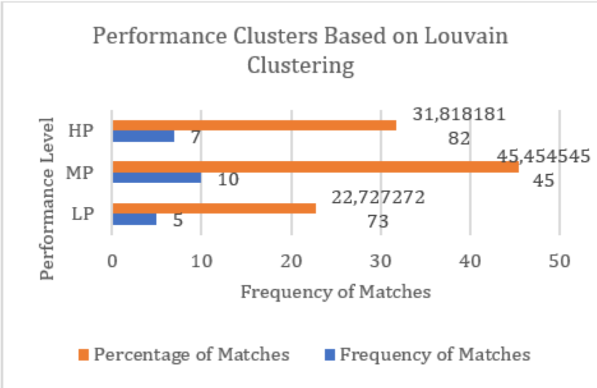


Figure 4 visualized the performance analysis of TFC across clusters revealing distinct patterns in various parameters which also determined by the 2022 MSL final standings (Table 2).

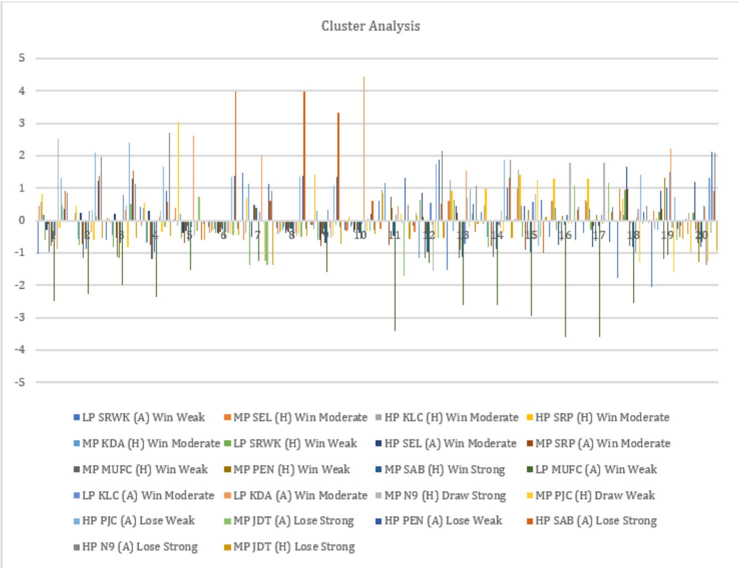
Table 2. 2022 MSL Standings

No	Club	Match Played	Win	Draw	Lose	Points
1	Johor Darul Takzim	22	17	5	0	56
2	Terengganu	22	14	2	6	44
3	Sabah	22	13	3	6	42
4	Negeri Sembilan	22	12	5	5	41
5	Selangor	22	8	6	8	30
6	Kuala Lumpur	22	8	5	9	29
7	Pahang	22	8	4	10	28
8	Kedah	22	8	3	11	27
9	PJ City	22	6	8	8	26
10	Melaka United	22	4	6	12	18
11	Sarawak United	22	5	2	15	17
12	Penang	22	2	5	15	11

Figure 4. Cluster analysis referring to the match load zones

Figure 4 visualised the performance analysis of Terengganu Football Club (TFC) across clusters revealing distinct patterns in various parameters. The High Performance (HP) cluster had mixed results, with shorter distances covered in wins against moderate teams and longer distances in losses to both weak and strong opponents. Sprint efforts in HP were moderate, while the sprinting rate peaked during losses to strong teams. In contrast, the Low Performance (LP) cluster, despite winning all matches, showed the highest sprint efforts and sprinting rates, especially against weaker teams, along with the highest hard running rate and efforts. The work rate was consistent in LP, whereas HP exhibited higher work rates in losses. Top speed and intensity levels were also highest in LP, correlating with their victories. Load metrics (both 2D and 3D) followed a trend where HP recorded the highest values, although one LP match showed an unusually high 2D load. Lastly, heart rate metrics revealed that LP had higher HR Mean and HR Max in winning matches, whereas HP exhibited superior cardiovascular efficiency with the highest HR Efficiency across clusters. Overall, LP displayed more intense physical efforts, while HP showed more efficiency in both cardiovascular and workload management.

Figure 5. Cluster analysis referring to the match load zones



Features Extraction – Logistic Regression

In this study, LR was applied to the extracted data for feature selection. LR is a robust statistical technique commonly employed to identify the most significant features in datasets by analyzing the model's coefficients (Fávero et al., 2023; Lasek & Gagolewski, 2021). Specifically, L1 regularization was utilized in this analysis, introducing sparsity to the dataset, which allows for efficient feature selection by eliminating non-influential variables (L. Li & Liu, 2022; Schroeder, 2021). Table 3 outlines the logistic regression coefficients for various match load zones, categorized by HP, MP, and LP clusters.

Table 3. Logistic Regression Coefficients

Name	HP	LP	MP
Intercept	-0.39701	0.004287	0.392725
Performance Duration [min]	0.257591	-0.55536	0.297772
Total Distance [m]	0.350613	-0.08279	-0.26782
Walk Distance [m]	0.159262	-0.02297	-0.13629
Jog Distance [m]	0.412677	-0.04224	-0.37043
Run Distance [m]	0.141311	0.066952	-0.20826
Sprint Distance [m]	0.16064	-0.12858	-0.03206
Sprint Efforts	0.026393	-0.07068	0.044283
Sprinting Rate [m/min]	0.142231	-0.0473	-0.09494
Hard Running [m]	0.19248	0.013272	-0.20575
Hard Running Rate [m/min]	-0.16036	0.356571	-0.19621
Hard Running Efforts	0.310497	-0.07282	-0.23768
Work Rate [m/min]	0.392617	0.461319	-0.85394
Top Speed [m/s]	0.388259	-0.13716	-0.2511
Intensity	0.434272	-0.1934	-0.24087
Total Impacts	0.364447	-0.32729	-0.03716
Load 2D	-0.0574	-0.2706	0.327993
Load 3D	-0.08247	-0.22885	0.311316
HR Mean [bpm]	0.465302	-0.5901	0.124797
HR Max [bpm]	-0.07697	0.082024	-0.00505
HR Efficiency [m/beat]	0.356435	0.377231	-0.73367

The bolded variables in Table 3 represent the features with the highest coefficient values, suggesting they are the most influential for each cluster.

Performance Duration stands out as a key factor across all three clusters, with HP = 0.257591 min, LP = |-0.55536| min, and MP = 0.297772 min, highlighting its importance in distinguishing player performances.

Total Distance, Jog Distance, and Run Distance also exhibit higher coefficient values compared to Walk Distance and Sprint Distance, underscoring their greater relevance in performance analysis. For instance, Jog Distance has the highest coefficient for HP = 0.412677 m, while Walk Distance shows smaller influence.

Sprint Efforts and Sprinting Rate are less significant with lower coefficients, indicating they play a smaller role in distinguishing performances between clusters.

Interestingly, Hard Running metrics (including Hard Running Distance, Hard Running Rate, and Hard Running Efforts) display relatively high coefficients, suggesting these are valuable indicators of performance, especially in HP and MP clusters. Work Rate, Top Speed, Intensity, and Total Impacts further highlight key differences between the clusters, with high coefficients in HP and LP.

For Load 2D and Load 3D, the MP cluster presents notably higher coefficients compared to HP and LP, implying a unique pattern of external load in moderate-performing players.

The Heart Rate (HR) zones reveal that HR Max contributes the least to the model across all clusters, whereas HR Mean and HR Efficiency show stronger correlations with performance, particularly in HP and LP clusters. Negative values were disregarded due to their emergence from standardized data transformation.

Model Evaluation – Logistic Regression

Table 4 presents the performance metrics of the logistic regression model, evaluating its classification accuracy, precision, recall, and F1 score.

Table 4. Logistic Regression Model Evaluation

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	0.819	0.727	0.650	0.588	0.727

The model's Area Under the Curve (AUC) is 0.819, which is considered a strong indicator of the model's performance across different threshold values. Since 0.5 is the base threshold, this score demonstrates the models' ability to classify between the performance clusters effectively. Similarly, the Classification Accuracy (CA) of 72.7% indicates a high overall accuracy of the model in classifying players into the respective performance clusters. The F1 Score of 0.650, along with the Precision (0.588) and Recall (0.727), demonstrate a balanced model, though the slightly lower precision suggests there may be some room for improvement in minimizing false positives.

Kruskal-Wallis

To further validate the differentiation between clusters, a Kruskal-Wallis test was performed on the extracted match load zones using the H statistic. This non-parametric test further confirmed significant differences between the HP, MP, and LP clusters for various external load metrics.

Figure 6. Kruskal-Wallis Test displaying the significant metrics: Performance Duration, Total Distance, Jog Distance, Work Rate, Intensity, HR Mean, and HR Efficiency

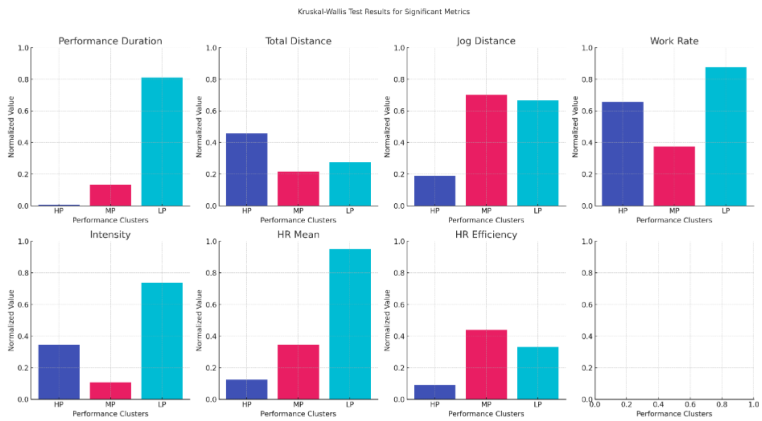


Figure 5 highlight the metrics that exhibited p-values below the alpha threshold of 0.05, demonstrating statistically significant differences between the clusters which emphasized how these metrics distinguish player performance across the HP, MP, and LP groups.

Performance Duration and Total Distance show significant differences across clusters showing that HP players sustain longer periods of play and cover more ground than MP and LP, reinforcing endurance as a key differentiator. Although jogging is less intense than running or sprinting, the HP cluster still shows a considerable amount of jogging, reflecting balanced movement in different phases of the game. Work Rate, on the other hand, displayed significant differences across clusters suggesting that higher work rates directly correlate with superior match outcomes. For load zones such as intensity, is statistically significant, exhibiting differences that HP players exert higher intensity, driving successful match outcomes. Finally, the Heart Rate (HR) metrics, demonstrate significant differences in HR Mean and HR Efficiency indicating that more efficient cardiovascular performance (i.e., covering more distance per heartbeat) is a hallmark of high-performing players.

Table 5. Summary p-values of Kruskal-Wallis

Variable	Kruskal-Wallis
Performance Duration [min]	0.005
Total Distance [m]	0.003
Jog Distance [m]	0.002
Run Distance [m]	0.736
Hard Running [m]	0.097
Hard Running Rate [m/min]	0.067
Hard Running Efforts	0.285
Work Rate [m/min]	0.001
Top Speed [m/s]	0.085
Intensity	0.002
Total Impacts	0.475
Load 2D	0.241
Load 3D	0.210
HR Mean [bpm]	0.048
HR Efficiency [m/beat]	0.004

Table 5 summarizes the p-values from the Kruskal-Wallis test, which identified significant differences among the three clusters for 7 out of 15 match load variables: Performance Duration, Total Distance, Jog Distance, Work Rate, Intensity, HR Mean, and HR Efficiency. These variables exhibited p-values below the alpha threshold (0.05), suggesting statistically significant differences across the clusters. A visual representation of these p-values is provided in Figure 11. Additionally, the Kruskal-Wallis model's evaluation can be observed in Table 6. The Area Under the Curve (AUC) for the 7 selected match loads is 0.948, notably higher than the AUC for all 15 loads (0.819). The Classification Accuracy (CA) of the reduced model is also 13.7% higher than the 15-match load model, with corresponding improvements in F-Score, Precision, and Recall, which stand at 0.859, 0.865, and 0.864, respectively.

Figure 7. Kruskal-Wallis p-values

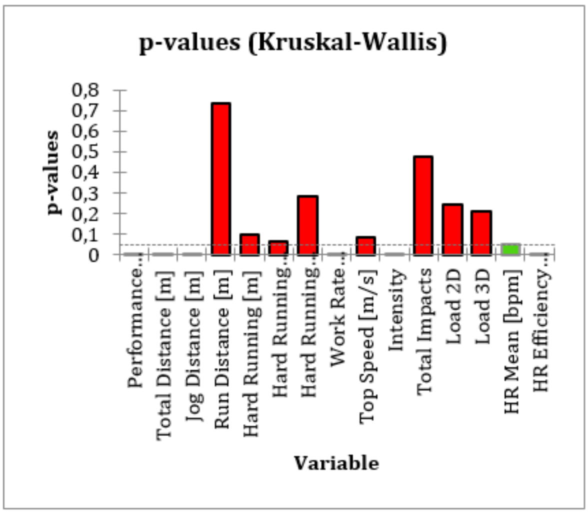


Table 6. Kruskal-Wallis Evaluation Model

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	0.948	0.864	0.859	0.865	0.864

Table 6 evaluates the logistic regression model using key metrics such as AUC, CA, F1 score, Precision, and Recall, showing strong performance across all measures. The model's AUC of 0.948 indicates near-perfect classification ability, while the CA of 86.4% reflects significant improvement in categorizing performance clusters (HP, MP, LP) following feature reduction using the Kruskal-Wallis H test. The balanced F1 score (0.859), along with high Precision (0.865) and Recall (0.864), demonstrates the model's effectiveness in predicting both high- and low-performing clusters without overfitting. These enhancements highlight the value of combining logistic regression with non-parametric testing for identifying key performance indicators, offering practical applications in match analysis and strategic planning for coaching staff.

Discussion

This study has elucidated critical match load zones in a Malaysian football club's performance during the 2022 Malaysia Super League (MSL) season, employing a range of statistical analyses to derive meaningful insights. By categorizing the team's performance into three distinct clusters—High Performance (HP), Medium Performance (MP), and Low Performance (LP)—we observed how various match loads influenced the team's outcomes against different levels of opposition. The findings illustrate a nuanced interplay between performance metrics and opponent strength, with TFC achieving notable victories against moderately ranked opponents during HP performances while struggling against both weaker and stronger teams. This trend suggests that the team's capacity to secure wins is not solely contingent on individual metrics but is significantly influenced by psychological and tactical dynamics. Such insights align with existing literature positing that motivation, confidence level, and team strategies can profoundly impact match outcomes (Catalá & Vich, 2022; Schei et al., 2022),(Castillo-Rodríguez et al., 2023; Kaminski, 2022; Wang et al., 2022).

Moreover, the analysis of Total Distance, Sprint Efforts, and Heart Rate metrics highlights the complexity of performance dynamics within the clusters. Variability in distance covered during HP performances underscores a potential correlation between match outcomes and the physical demands placed on players, while the LP cluster's consistent sprinting metrics suggest a tactical approach focused on energy conservation against weaker teams. Additionally, the highest heart rates recorded in the LP cluster during victories may indicate greater exertion against lower-ranked opponents, potentially compromising energy management for more competitive matches. These findings invite further investigation into the interplay of physical load, psychological factors, and match outcomes, emphasizing the need for TFC to refine its training and match preparation strategies. By fostering adaptability to varying opponent strengths, the club can enhance its competitive edge in the Malaysia Super League.

Further, the logistic regression analysis (Table 3) identified 15 out of 20 match loads as significant, with higher coefficients observed in the HP cluster despite negative values. These loads were extracted as the most influential features, underscoring their relevance to team performance. In contrast, variables such as Walk Distance, Sprint Distance, and HR Max were not deemed significant. The findings align with prior studies, such as (Modric et al., 2021) which suggests that walking distance contributes minimally to match performance, and Sprint Distance, though essential in other contexts, played a lesser role in TFC's performance during the 2022 season.

Model performance, as outlined in Table 4, shows an AUC of 0.819, indicating solid classification accuracy. The CA of the logistic regression model is 72.7%, while the F-Score and Precision reveal that the model accurately predicts about 60% of positive cases. Moreover, the Kruskal-Wallis H test identified 7 key match loads that further improved model accuracy, yielding an AUC of 0.948 and CA of 86.4%. These findings suggest that refining the match load features enhances predictive accuracy.

Conclusions

This study successfully extracted the most influential match load features affecting team performance in the Terengganu Football Club (TFC) during the 2022 MSL season. Logistic regression, coupled with the Kruskal-Wallis H test, proved to be an effective method for identifying these features, which could assist coaches in improving training regimens and refining tactical strategies. The final model, based on 7 key features, demonstrated a significant improvement in classification accuracy, indicating its potential as a robust tool for performance analysis and strategic planning in football.

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