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Research Article

Team Performance Indicators That Predict Match Outcome in Rugby Union

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ABSTRACT

The aim of the study is to identify the most significant indicators of the national team's performance at the European Rugby Championships 15 and to design a model for predicting the outcomes of matches. Data was collected from teams' performance at the European Rugby 15 Championships 2021, 2022 and 2023 for the analysis. The total number of matches was 41. All indicators presented in the official reports were taken: 22 for the home and away teams. The analysis of the team results was carried out according to all indicators: mean value, standard deviation, and test were used to compare the performance indicators of the winning and losing teams. Machine learning techniques were utilized to develop a predictive model for match outcomes. On one hand, 15 indicators (68.2%) are higher for teams that won (winning teams). On the other hand, 7 (31.8%) indicators are higher for teams that lost. The difference between the teams' means varies from -56.46% (the minus indicates that this indicator is higher for the teams that lost) to 273.68%. Based on the results, the Random Forest Classifier and Extra Trees Classifier algorithms have the best prediction accuracy (0.92). The most significant indicators of team performance that affect the final result of the match are tries (196.3% – the difference between the average values of winning and losing teams), conversions (176.7%), missed tackles (-56.46%), offload (126.3%). Based on the data obtained, refining the team training process in Rugby 15 is possible.

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INTRODUCTION

Today, in the world of sports and sports games, the achievement of a competitive edge has become synonymous with understanding and harnessing the power of scientific prognostication and prediction. Managers, coaches, administrators, athletes, and analysts find themselves delving deeper into scientific methodologies to gain actionable insights and make data-driven decisions (Bompa & Buzzichelli, 2015; Veal & Darcy, 2014). Science has paved the way for precise analysis and prediction models. Currently, using science to predict outcomes in sports games and rugby, in particular, is common and typical for the scientific community (Bunker & Thabtah, 2019; Richter et al., 2021).

A sufficient number of studies are aimed at the analysis of data that are focused on various aspects of sports science (Travassos et al., 2013): anthropometric (Toselli et al., 2019) and physiological qualities (Jones et al., 2014; Romanenko et al., 2022); performance indicators of motor activity (Xu et al., 2023; Paolini et al., 2023); aspects of players selection (Till et al., 2011; Gabbett et al., 2011); relative age effect (Latyshev et al., 2022); predicting occurrence of injury during the game (Rizi et al., 2017), pre-season training as a factor in the occurrence of injuries during the season (Tee et al., 2016), predicting the development trajectory of athletes in rugby (Fontana et al., 2017).

As the review of publications shows, specialists are quite interested in various aspects of performance analysis, predicting and modeling in sports games (Hopkins et al., 1999; Latyshev et al., 2020; McGarry, 2009; Sampaio & Leite, 2013;). At present, predicting the outcomes of matches is one of the main areas among sports analysts. For many sports, such studies have been conducted (Bunker & Susnjak, 2022; Horvat & Job, 2020; Stekler et al., 2010; Wunderlich & Memmert, 2021), while for rugby, a limited number of publications has been observed. It is also essential that in rugby, there is a list of popular forms, which may have their peculiarities: Rugby union (rugby fifteens), Rugby sevens and Rugby league.

An effective approach to determining significant indicators for predicting match outcomes is the comparison of performance metrics between winning and losing teams (Jones et al., 2004; Ortega et al., 2009). Such analyses have been systematically carried out across diverse championships, spanning various years and competition tiers (Bennett et al., 2019; Bremner et al., 2013; Watson et al., 2017). The research underscores the pivotal role played by distinct indicators, their significance varying in accordance with the nature of the competition (Colomer et al., 2020).

At the present stage, another significant direction for sports forecasting involves harnessing the capabilities of Artificial Intelligence and Machine Learning (Dindorf et al., 2022). Currently, there is a sufficient number of publications related to this field, spanning both specialized sports journals (Richter et al., 2021) and computer science publications (Bunker & Susnjak, 2022), underscoring the timeliness and relevance of this burgeoning field.

The history of attempts to predict the outcome of rugby matches goes a long way. For instance, in papers by (O'Donoghue & Williams, 2004; Reed & O'Donoghue, 2005) accuracy of human and computer-based methods of predicting have been compared. The first advances in predicting the outcome of the match for Rugby union have been presented, which amounted to an average of half of the matches predicted successfully. However, the authors state that the results suggested that the ability of machine learning methods to predict the outcome of matches has, for the first time, surpassed that of humans.

The results obtained in modern studies have a higher prediction accuracy (over 80%). The paper (Parmar et al., 2017) analyzes the 2012, 2013, and 2014 European Super League seasons and has achieved a prediction accuracy of 85.5% on the test data set. Also, a study by Bennett et al. (2019) examines the 2016-17 English Premiership rugby season, its aim was to identify the most effective method of data analysis (the method of data analysis), which has the highest accuracy, and based on it to design a prediction model.

Most research in analyzing and forecasting rugby outcomes are associated with national club championships or World Cup (Vahed et al., 2016). At the same time, there is a scarcity of analyses concerning continental-level competitions among national teams. Furthermore, there is a limited number of studies utilizing machine learning methods in rugby, especially for the analysis of the most significant performance indicators of team. Conducting such research will provide a broader insight into the significance of performance indicators of national team in the contemporary era for achieving success at the European level. This justifies the relevance of the study. The aim of the study is to identify the most significant indicators of the national team’s performance at the European Rugby Championships 15 and to design a model for predicting the outcomes of matches.

METHODS

Data was collected from teams’ performance at the European Men’s Rugby 15 Championships 2021, 2022 and 2023 for the analysis. The selection was made based on the latest three championships to discern and analyze current trends in the field. Data were taken from the official website of Rugby Europe. Rugby Europe is a Regional Association of World Rugby. As the association's website states, "Rugby Europe is the governing body responsible for the promotion, development, administration and management of international competitions for the 48 member unions across Europe". The overall number of analyzed matches amounted to 41 out of 44. The absence of official statistics for three matches is likely associated with the disqualification proceedings involving a specific team.

This study only used the utilized publicly available data from official sources without involving human participants or any form of personal data. However, the research was conducted in accordance with the ethical standards of the Khmelnytskyi National University and adhered to the principles outlined in the Declaration of Helsinki concerning ethical conduct in research. The authors took consideration to ensure that all data used from official sites, such as protocols of matches, were obtained and handled in a manner that respects the integrity of the data sources and the entities involved.

We of all the teams' indicators (22 in total) available on the official website of Rugby Europe. The data were sourced from official match protocols and statistical information provided on the federation's official website. The authors did not perform the initial collection of statistical data for each match but utilized ready-made official data for each match. The final collection of official statistics from the website was executed through an automated Python script, followed by the authors' manual verification of the data. No missing data were identified. In total, 22 indicators for the home and away teams were analyzed each (Table 1). The outcome yielded a data table comprising 41 rows (representing the number of matches) and 44 indicators. Additionally, such data as team names, match timing, and competition stage were collected; however, these particulars were excluded from the analytical framework. It is worth noting that different terminologies (indicators and features) are employed based on the industry context (the field of machine learning), while these are essentially the same team attributes.

Data Analysis

The mean value and standard deviation (SD) of the winning and losing teams indicators were measured. Also, a t-test was used to compare the performance indicators of the winning and losing teams' indices. The significance level has been taken to be equal to 0.05 (Thomas et al., 2022). Before employing the t-test, a normality check of the data distribution was conducted using two tests (Normality Test and Equal Variance Test). The majority of indicators met the specified criteria; however, the Mann-Whitney U test was employed in cases where this was not observed. For statistical data processing, visualization, and machine learning model training, the Python programming language was used.

Machine Learning Models

Machine learning techniques were utilized to develop a predictive model for match outcomes, followed by a comprehensive analysis. The resulting model successfully forecasted match outcomes in two potential scenarios (victory for the home or away team) based on team performance indicators, essentially accomplishing a binary classification task. According to the plan, the final model construction unfolded in two sequential stages. The first stage aimed to identify a more accurate algorithm for forecasting match results. The first stage involved the following sequential steps. The dataset was partitioned into two segments: one for training the model and the other for testing the pre-trained model (to assess accuracy and prevent overfitting). The training sample was 78% of all data (32 matches), and the test sample was 22% (9 matches). The training dataset comprised 44 features (22 for each home and away team) across 32 matches. In the next step, we employed the PyCaret library to develop machine-learning models for comparison. Utilizing this library, we deployed 15 well-established machine learning algorithms to the dataset and compared the prediction accuracy for each algorithm. The following metrics of machine learning models were evaluated: accuracy, precision, and recall. In the concluding phase of this stage, an algorithm and learning hyperparameters with the highest accuracy were chosen for further construction of the predictive model.

Table 1
The List of Teams' Indicators and Their Brief Characteristics

Indicator	Description
Possession	ball possession by the team during the game, measured in percents
Passes	the number of passes made by a team during the game
Tries	the number of tries made by a team during the game
Defenders beaten	the number of insignificant defensive line breaks by opponents during the game
Clean breaks	the number of significant team's defensive line breaks
Offloads	the number of short passes made by a player after he was grabbed (one of the most spectacular components in modern rugby)
Turnovers conceded	the number of losses of the ball in an open game due to active play by the defenders (ball turnover, counter-attack, interception, etc.)
Tackles	the number of tackles aimed at stopping the opponent's forward progression
Missed tackles	the number of unsuccessful plays on defense against the opponent
Turnovers taken	the number of losses of ball possession due to active play by defenders
Kicks in play	the number of ball kicks
Conversions	the number of tries and their conversion (a shot on goal that results in 2 points)

Table 1 (Continues)

Indicator	Description
Conversions missed	the number of successful tries and a missed shot on goal
Penalty goals	the number of penalty shots (if successfully executed from the spot the rules were violated on, the team earns 3 points)
Penalty goals missed	the number of missed penalty shots
Drop goals	the number of successful plays (a player must shoot the ball bouncing off the ground) that results in 3 points
Drop goals missed	the number of successful plays by the opponents that results in their 3 points
Rucks won	the number of rucks standard play won
Rucks lost	the number of rucks standard play lost
Line outs lost	the number of bringing the ball back to play using a line of players after the ball has crossed the sideline
Scrums won	the number of scrums standard play won (formed at the pitch to resume the game after rules violation or game stoppage)
Scrums lost	the number of scrums standard play lost

The second stage involves constructing a predictive model for match outcomes and identifying key performance indicators. It is important to emphasize that the central aim of the study is to determine the more significant team's performance indicators rather than seek and construct a more accurate prediction model. The training of the final model involved using the complete dataset (41 matches) with hyperparameters that were determined in the previous stage. Following this, the contribution of each indicator to match outcome prediction was quantified in percentages.

RESULTS

The analysis of the team performance indicators has been carried out; the results of the calculations are presented in Table 2.

Table 2
Statistical Value of Team Performance Indicators

Indicators	Statistical indicators					
	Winning teams		Losing teams		Percentage difference, %	p-value
	Mean	SD	Mean	SD		
Possession	53.95	6.6	46.05	6.6	17.16	7.0e-07 *
Passes	125.12	43.2	95.95	28.0	30.40	5.4e-04 *
Tries	5.78	2.8	1.95	1.2	196.25	5.5e-11 *
Defenders beaten	17.93	11.8	8.24	5.8	117.46	1.6e-05 *
Clean breaks	6.56	5.4	2.46	2.1	166.34	3.5e-05 *
Offloads	8.83	4.8	3.90	2.7	126.25	3.3e-07 *
Turnovers conceded	14.39	6.8	12.76	4.7	12.81	2.1e-01
Tackles	102.51	29.4	111.63	34.1	-8.17	2.0e-01
Missed tackles	10.02	5.5	23.02	12.9	-56.46	2.1e-07 *
Turnovers taken	5.95	2.7	5.90	2.9	0.83	9.4e-01
Kicks in play	18.68	6.1	18.93	6.4	-1.29	8.6e-01

Table 2 (Continues)

Indicators	Statistical indicators					
	Winning teams		Losing teams		Percentage difference, %	p-value
	Mean	SD	Mean	SD		
Conversions	4.05	2.3	1.46	1.2	176.67	3.3e-08 *
Conversions missed	1.73	2.0	0.46	0.6	273.68	2.5e-04 *
Penalty goals	1.24	1.4	1.22	1.2	2.00	9.3e-01
Penalty goals missed	0.34	0.6	0.44	0.7	-22.22	5.1e-01
Drop goals	0.10	0.3	0.05	0.2	100.00	4.0e-01
Drop goals missed	0.05	0.2	0.05	0.2	0.00	1.0e+00
Rucks won	72.98	21.7	63.66	20.1	14.64	4.7e-02 *
Rucks lost	2.71	2.2	2.44	2.0	11.00	5.7e-01
Line outs lost	2.17	2.2	3.22	2.2	-32.58	3.2e-02 *
Scrums won	5.44	1.9	6.10	2.6	-10.80	2.0e-01
Scrums lost	0.49	0.6	0.68	0.8	-28.57	2.1e-01

Note. * – statistically significant differences between parameters of the losing and winning teams ($p< 0.05$) have been revealed.

The analysis of the team results was carried out according to 22 indicators. On one hand, 15 indicators (68.2%) are higher for teams that won (winning teams). On the other hand, 7 (31.8%) indicators are higher for teams that lost. The difference between the teams' means varies from -56.46% (the minus indicates that this indicator is higher for the teams that lost) to 273.68%. It should be noted that four (18.2%) indicators have differences of less than two percent, and only the mean results of one indicator (Drop goals missed) are equal for the losing and winning teams.

The analysis of statistical differences between the indicators of the teams showed that 11 (50.0%) indicators significantly differed statistically ($p<0.05$): nine of them were higher for the team that won and two for the team that lost. Also, eleven (50.0%) indicators did not have statistically significant differences ($p>0.05$): of these, six indicators were higher for the team that won, and five – for the team that lost.

Based on the training data, several models were designed for various machine learning algorithms. The PyCaret Python library was used to compare the accuracy of various machine learning algorithms. Table 3 lists ten algorithms and their metrics (accuracy, recall, precision) for the test sample. In total, over 15 machine-learning algorithms were tested.

Table 3
The List of Models of Machine Learning and the Accuracy of Their Predictions

Model (algorithm)	Abbreviation	Accuracy	Recall	Precision
Random Forest Classifier	rf	0.92	1.0	0.92
Extra Trees Classifier	et	0.92	1.0	0.92
K Neighbors Classifier	knn	0.87	0.85	0.87
Ridge Classifier	ridge	0.87	0.9	0.82
Extreme Gradient Boosting	xgboost	0.83	0.95	0.87
Gradient Boosting Classifier	gbc	0.83	0.95	0.87
Decision Tree Classifier	dt	0.82	0.85	0.82
Naive Bayes	nb	0.82	0.85	0.82
Ada Boost Classifier	ada	0.73	0.85	0.77
Light Gradient Boosting Machine	light gbm	0.55	1.0	0.55

Based on the results, the Random Forest Classifier and Extra Trees Classifier algorithms have the best prediction accuracy (0.92). Consequently, the resulting model gives the accurate outcome of the match in 92% of cases (win or loss of the team) in terms of the team performance at the end of the match.

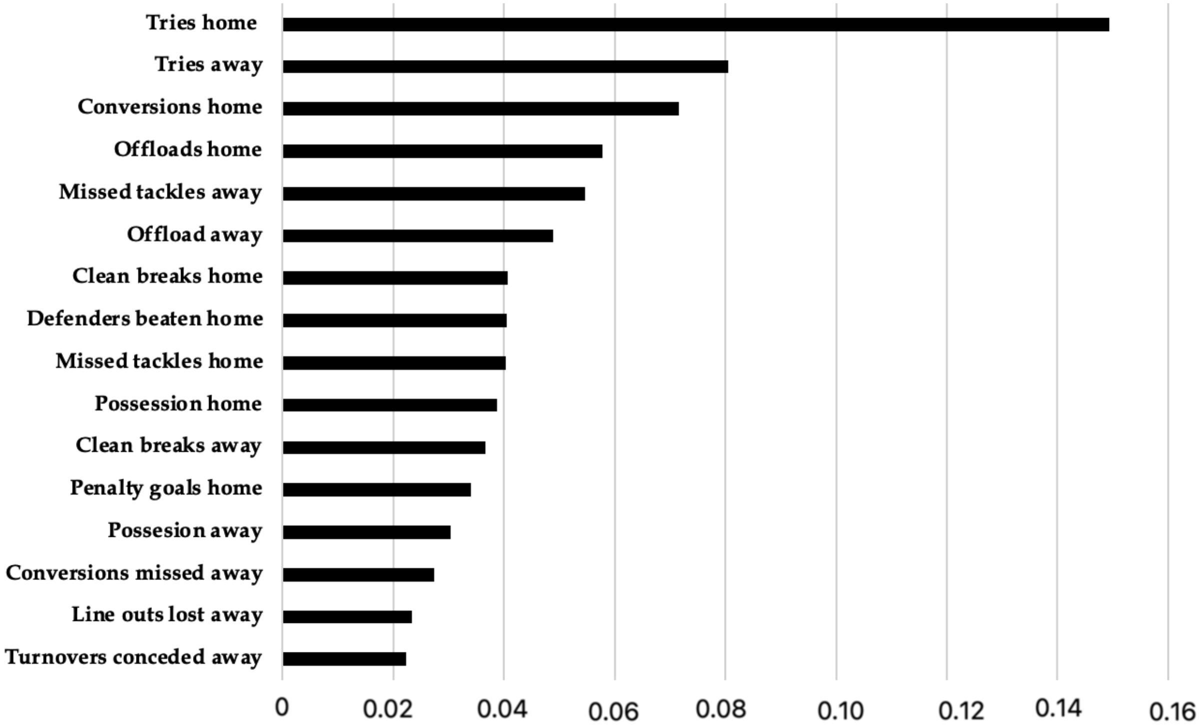
It should be noted that algorithms based on decision trees showed promising results. For further analysis and construction of the final model, the Random Forest Classifier algorithm was chosen. The model was designed based on all the data and the obtained hyperparameters.

The following important stage of the study is to determine the impact of each feature on the final prediction model. Based on the obtained machine learning model for predicting match outcomes, the features with the most significant impact have been identified. Figure 1 shows feature with more significant impact than 2% (0.02) in the final match prediction model. The words home and away characterize the features belonging to the home and away teams, respectively –44 features, 22 features each for the home and away teams.

Sixteen (36.4%) features in the model weight more than 2% (they account for 79.8% of the model's input). Also, 16 (36.4%) features contribute from 0.5% to 2%, and the remaining 12 (27.2%) parameters are less than 0.5%.

The following features have the largest impact (more than 5%) on the model: tries of home (14.9%) and away (8.1%) teams, conversions of home team (7.2%), offloads of home (5.8%) and missed tackles of away team (5.5%). The following features do not contribute to the model: the drop goals of the away team, the drop goals missed by the away team, and the drop goals missed by the away team.

Figure 1
Contribution of Team Performance Indicators to the Model of Match Outcome Prediction



DISCUSSION

The most significant aspect of the study for the practical coaching activity and training process is the analysis of the significance of indicators. Similar research for rugby has been conducted for various competition levels and temporal scopes (Colomer et.al., 2020; Sasaki et.al., 2007). Key performance indicators encompassed tries, conversions, possessions, tackles, and other indicators. Notably, experts examined indicators extending beyond the confines of our study (from the results of their research, it was evident that these indicators are important for achieving victory); for example, the first team scored quick rucks or average carry meters (Jones et al., 2004; Ortega et al., 2009; Parmar et al., 2017; Schoeman & Schall, 2019; Watson et al., 2017).

The obtained results, indicators such as tries (196.3% – the difference between the means of winning and losing teams), conversions (176.7%), missed tackles (-56.46%), offload (126.3%) are in the top five in terms of significance in the final model. The difference between the means of winning and losing teams on these five indicators is over 100%, except for one indicator (missed tackles). This indicator has the largest difference, with higher mean values for the losing team. Among the indicators in the top 10, the possession indicator should be pointed out: the difference between the mean values for this indicator is only 17.2% (all other indicators have values above 100%, except for the one mentioned above). All of the previously mentioned indicators are statistically significantly different for winning and losing teams. The Conversions missed indicator stands out, having the largest difference (273.7%) between the means and a statistically significant difference, but at the same time, it is ranked 14th in terms of significance in the model. It should be noted that most of the indicators are important for both home and away teams, indicating the equivalence of these indicators. Based on these data, it is possible to refine the team training process in Rugby 15. The acquired data demonstrate contemporary trends within the performance indicators of national teams in the European Championships. Also, these data allow us to identify more significant indicators of competition activity during the season/game and pay more attention to these indicators during the game (as the opposing team during the analysis).

The accuracy of predictions obtained using our model exceeds the results obtained earlier. We obtained an accuracy of 91.7%, while in the study by Parmar et al. (2017) the accuracy of the prediction on the test set was 86.5% (the algorithms employed in the study included Logistic and Linear regression), and in the study by Bennet et al. (2019) – about 80% (Random Forest). In our study, Random Forest demonstrates the most superior result among machine learning algorithms. However, our study analyzed the team performance indicators obtained at the end of the match. These indicators characterize the completed match when the match's outcome is already clear and do not consider the dynamics of indicators during the match. Therefore, it is earlier incorrect to compare it with earlier studies – there, the prediction was made for future matches with no given information about them. This is due to the relatively high degree of accuracy (more than 90%) obtained in our study.

Additionally, the model can be used at certain points during the match, but the accuracy of such predictions is currently unclear. We did not conduct research during the match. It should also be noted that we conducted research for Rugby 15, while most of the research has been conducted for other types of rugby, and other indicators of competition activity have been used.

CONCLUSION

The analysis of the team performance at the European Rugby Championships 15 was done. Based on the indicators of the teams, a model for predicting the outcome of the match was designed. As shown by machine learning model design results, the most successful algorithms are Random Forest Classifier and Extra Trees Classifier. They have the best prediction accuracy (over 90%), higher than some indicators obtained in earlier research.

However, they have certain limitations in prediction. The most significant indicators of team performance that affect the final result of the match are tries of home and away teams, conversions, missed tackles, and offload. On the other hand, the indicators of least significance include penalty goals, penalty goals missed, drop goals missed, scrums won, and kicks in play. The obtained results overall confirm and expand upon the insights gleaned by experts in previous studies. Based on the data obtained, it is possible to refine the team training process in Rugby 15.

Authors' contribution

The first and second authors took responsibility for the research design, conceptualization, and referencing. All other authors contributed to the implementation of the research, data collection, data analysis, and the writing and editing processes.

Declaration of conflict interest

No conflict of interest is declared by the authors.

REFERENCES

Bennett, M., Bezodis, N., Shearer, D. A., Locke, D., & Kilduff, L. P. (2019). Descriptive conversion of performance indicators in rugby union. *Journal of science and medicine in sport*, *22(3)*, 330-334. https://doi.org/10.1016/j.jsams.2018.08.008

Bompa, T., & Buzzichelli, C. (2015). *Periodization training for sports, 3e*. Human kinetics.

Bremner, S., Robinson, G., & Williams, M. D. (2013). A retrospective evaluation of team performance indicators in rugby union. *International Journal of Performance Analysis in Sport, 13(2)*, 461-473. https://doi.org/10.1080/24748668.2013.11868662

Bunker, R. P., & Thabtah, F. (2019). A machine learning framework for sport result prediction. *Applied computing and informatics*, *15(1),* 27-33. https://doi.org/10.1016/j.aci.2017.09.00

Bunker, R., & Susnjak, T. (2022). The application of machine learning techniques for predicting match results in team sport: A review. *Journal of Artificial Intelligence Research*, *73,* 1285-1322. https://doi.org/10.48550/arXiv.1912.11762

Colomer, C. M., Pyne, D. B., Mooney, M., McKune, A., & Serpell, B. G. (2020). Performance analysis in rugby union: a critical systematic review. *Sports Medicine-Open, 6,* 1-15. https://doi.org/10.1186/s40798-019-0232-x

Dindorf, C., Bartaguiz, E., Gassmann, F., & Fröhlich, M. (2022). Conceptual structure and current trends in Artificial Intelligence, Machine Learning, and Deep Learning research in sports: A bibliometric review. *International Journal of Environmental Research and Public Health*, *20(1),* 173. https://doi.org/10.3390/ijerph20010173

Fontana, F. Y., Colosio, A. L., Da Lozzo, G., & Pogliaghi, S. (2017). Player's success prediction in rugby union: From youth performance to senior level placing. *Journal of science and medicine in sport*, *20(4),* 409-414. https://doi.org/10.1016/j.jsams.2016.08.017

Gabbett, T. J., Jenkins, D. G., & Abernethy, B. (2011). Relative importance of physiological, anthropometric, and skill qualities to team selection in professional rugby league.

Journal of Sports Sciences, *29(13)*, 1453-1461 https://doi.org/10.1080/02640414.2011.603348

Hopkins, W. G., Hawley, J. A., & Burke, L. M. (1999). Design and analysis of research on sport performance enhancement. *Medicine and science in sports and exercise, 31(3),* 472-485. https://doi.org/10.1097/00005768-199903000-00018

Horvat, T., & Job, J. (2020). The use of machine learning in sport outcome prediction: A review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(5),* e1380. https://doi.org/10.1002/widm.1380

Jones, M. R., West, D. J., Harrington, B. J., Cook, C. J., Bracken, R. M., Shearer, D. A., & Kilduff, L. P. (2014). Match play performance characteristics that predict post-match creatine kinase responses in professional rugby union players. *BMC sports science, medicine and rehabilitation, 6(1),* 1-7. https://doi.org/10.1186/2052-1847-6-38

Jones, N. M., Mellalieu, S. D., & James, N. (2004). Team performance indicators as a function of winning and losing in rugby union. *International Journal of Performance Analysis in Sport, 4(1),* 61-71. https://doi.org/10.1080/24748668.2004.11868292

Latyshev, M., Latyshev, S., Korobeynikov, G. Kvasnytsya, O., Shandrygos, V., & Dutchak, Y. (2020). The analysis of the results of the Olympic free-style wrestling champions. *Journal of Human Sport and Exercise, 15 (2),* 400-410. https://doi.org/10.14198/jhse.2020.152.14

Latyshev, M., Tropin, Y., Podrigalo, L., & Boychenko, N. (2022). Analysis of the Relative Age Effect in Elite Wrestlers. *Ido movement for culture. Journal of Martial Arts Anthropology, 22(3),* 28-32. https://doi.org/10.15391/ed.2023-3.10

McGarry, T. (2009). Applied and theoretical perspectives of performance analysis in sport: Scientific issues and challenges. *International Journal of Performance Analysis in Sport, 9(1),* 128-140. https://doi.org/10.1080/24748668.2009.11868469

O'Donoghue, P., & Williams, J. (2004). An evaluation of human and computer-based predictions of the 2003 rugby union world cup. *International Journal of Computer Science in Sport, 3(1),* 5-22 https://doi.org/10.1515/ijcss-2016-0003.

Ortega, E., Villarejo, D., & Palao, J. M. (2009). Differences in game statistics between winning and losing rugby teams in the Six Nations Tournament. *Journal of sports science & medicine, 8(4),* 523. PMID: 24149592

Paolini, S., Bazzini, M. C., Rossini, M., De Marco, D., Nuara, A., Presti, P., ... & Fabbri-Destro, M. (2023). Kicking in or kicking out? The role of the individual motor expertise in predicting the outcome of rugby actions. *Frontiers in Psychology, 14,* 797. https://doi.org/10.3389/fpsyg.2023.1122236

Parmar, N., James, N., Hughes, M., Jones, H., & Hearne, G. (2017). Team performance indicators that predict match outcome and points difference in professional rugby league. *International Journal of Performance Analysis in Sport, 17(6),* 1044-1056. https://doi.org/10.1080/24748668.2017.1419409

Reed, D., & O'Donoghue, P. (2005). Development and application of computer-based prediction methods. *International Journal of Performance Analysis in Sport, 5(3),* 12-28. https://doi.org/10.1080/24748668.2005.11868334

Richter, C., O'Reilly, M., & Delahunt, E. (2021). Machine learning in sports science: challenges and opportunities. Sports Biomechanics, 1-7. https://doi.org/10.1080/14763141.2021.1910334

Rizi, R. M., Yeung, S. S., Stewart, N. J., & Yeung, E. W. (2017). Risk factors that predict severe injuries in university rugby sevens players. *Journal of science and medicine in sport*, *20(7),* 648-652. https://doi.org/10.1016/j.jsams.2016.11.022

Romanenko, V., Piatysotska, S., Tropin, Y., Rydzik, Ł., Holokha, V., & Boychenko, N. (2022). Study of the reaction of the choice of combat athletes using computer technology. *Slobozhanskyi Herald of Science & Sport*, *(4),* 97-103. https://doi.org/10.15391/snsv.2022-4.001

Sampaio, J., & Leite, N. (2013). Performance indicators in game sports. In *Routledge handbook of sports performance analysis* (pp. 115-126). Routledge.

Sasaki, K., Furukawa, T., Murakami, J., Shimozono, H., Nagamatsu, M., Miyao, M., Yamamoto, T., Watanabe, I., Yasugahira, H., Saito T., Ueno, Y., Katsuta, T.& Kono, I. (2007). Scoring profiles and defense performance analysis in Rugby Union. *International Journal of Performance Analysis in Sport*, *7(3),* 46-53. https://doi.org/10.1080/24748668.2007.11868409

Schoeman, R., & Schall, R. (2019). Comparison of match-related performance indicators between major professional rugby competitions. *International Journal of Sports Science & Coaching*, *14(3),* 344-354. https://doi.org/10.1177/1747954119848419

Stekler, H. O., Sendor, D., & Verlander, R. (2010). Issues in sports forecasting. *International Journal of Forecasting, 26(3),* 606-621. https://doi.org/10.1016/j.ijforecast.2010.01.003

Tee, J. C., Klingbiel, J. F., Collins, R., Lambert, M. I., & Coopoo, Y. (2016). Preseason Functional Movement Screen component tests predict severe contact injuries in professional rugby union players. *Journal of strength and conditioning research*, *30(11),* 3194-3203. https://doi.org/10.1519/JSC.0000000000001422

Thomas, J. R., Martin, P., Etnier, J. L., & Silverman, S. J. (2022). *Research methods in physical activity*. Human kinetics.

Till, K., Cobley, S., O'Hara, J., Brightmore, A., Cooke, C., & Chapman, C. (2011). Using anthropometric and performance characteristics to predict selection in junior UK Rugby League players. *Journal of Science and Medicine in Sport*, *14(3),* 264-269. https://doi.org/10.1016/j.jsams.2011.01.006

Toselli, S., Merni, F., & Campa, F. (2019). Height prediction in elite Italian rugby players: A prospective study. *American Journal of Human Biology*, *31(5),* e23288. https://doi.org/10.1002/ajhb.23288 .

Travassos, B., Davids, K., Araújo, D., & Esteves, T. P. (2013). Performance analysis in team sports: Advances from an Ecological Dynamics approach. *International journal of performance analysis in sport*, *13*(1), 83-95. https://doi.org/10.1080/24748668.2013.11868633

Vahed, Y., Kraak, W., & Venter, R. (2016). Changes on the match profile of the South African Currie Cup tournament during 2007 and 2013. *International Journal of Sports Science & Coaching*, *11(1),* 85-97. https://doi.org/10.1177/1747954115624826.

Veal, A. J., & Darcy, S. (2014). *Research methods in sport studies and sport management: A practical guide*. Routledge. https://doi.org/10.4324/9781315776668

Watson, N., Durbach, I., Hendricks, S., & Stewart, T. (2017). On the validity of team performance indicators in rugby union. *International Journal of Performance Analysis in Sport*, *17(4)*, 609-621. https://doi.org/10.1080/24748668.2017.1376998

Wunderlich, F., & Memmert, D. (2021). Forecasting the outcomes of sports events: A review. *European Journal of Sport Science*, *21(7)*, 944-957. https://doi.org/10.1080/17461391.2020.1793002

Xu, X. Q., Korobeynikov, G., Han, W., Dutchak, M., Nikonorov, D., Zhao, M., & Mischenko, V. (2023). Analysis of phases and medalists to women's singles matches in badminton at the Tokyo 2020 Olympic Games. *Slobozhanskyi Herald of Science and Sport, 27(2),* 64-69 https://doi.org/10.15391/snsv.2023-2.002