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Classifying Winning Performances in International Women's Rugby Union

Georgia A. Scott,[1] Ollie Edwards,[1] Neil E. Bezodis,[1,2] Mark Waldron,[1,2,3] Eifion Roberts,[4] David B. Pyne,[5] Jocelyn Mara,[5] Christian Cook,[6] Laura Mason,[1] M. Rowan Brown,[7] and Liam P. Kilduff[1,2]

[1]Applied Sports Technology Exercise and Medicine Research Centre (A-STEM), Faculty of Science and Engineering, Swansea University, Swansea, United Kingdom; [2]Welsh Institute of Performance Science (WIPS), Swansea University, Swansea, United Kingdom; [3]University of the Sunshine Coast, Sunshine Coast, QLD, Australia; [4]Welsh Rugby Union, Cardiff, United Kingdom; [5]Research Institute for Sport and Exercise (UC-RISE), University of Canberra, Canberra, ACT, Australia; [6]School of Science and Technology, University of New England, Armidale, Australia; [7]Biomedical Engineering, Faculty of Science and Engineering, Swansea University, Swansea, United Kingdom

Purpose: The efficacy of isolated and relative performance indicators (PIs) has been compared in rugby union; the latter more effective at discerning match outcomes. However, this methodology has not been applied in women's rugby. The aim of this study was to identify PIs that maximize prediction accuracy of match outcome, from isolated and relative data sets, in women's rugby union. ***Methods:*** Twenty-six PIs were selected from 110 women's international rugby matches between 2017 and 2022 to form an isolated data set, with relative data sets determined by subtracting corresponding opposition PIs. Random forest classification was completed on both data sets, and feature selection and importance were used to simplify models and interpret key PIs. Models were used in prediction on the 2021 World Cup to evaluate performance on unseen data. ***Results:*** The isolated full model correctly classified 75% of outcomes (CI, 65%–82%), whereas the relative full model correctly classified 78% (CI, 69%–86%). Reduced respective models correctly classified 74% (CI, 65%–82%) and 76% (CI, 67%–84%). Reduced models correctly predicted 100% and 96% of outcomes for isolated and relative test data sets, respectively. No significant difference in accuracy was found between data sets. In the relative reduced model, meters made, clean breaks, missed tackles, lineouts lost, carries, and kicks from hand were significant. ***Conclusions:*** Increased relative meters made, clean breaks, carries, and kicks from hand and decreased relative missed tackles and lineouts lost were associated with success. This information can be utilized to inform physical and tactical preparation and direct physiological studies in women's rugby.

Keywords: game statistics, decision modeling, multivariate analysis, team sports, women's sports

Team performance indicators (PIs) have been utilized within rugby union to provide insight into processes that lead to successful match outcomes.[1] Identifying PIs associated with winning outcomes allows practitioners to assess and develop match performances by improving technical, tactical, and physiological performance in training. PIs can be complicated by physiological states, but without robust PI data, the relationship between physiology and PIs cannot be easily addressed.[2] Data analysis techniques, such as supervised machine learning and hypothesis testing, have been used to identify key PIs in multiple men's competitions.[3–5] However, research investigating women's rugby union is limited, with very few studies involving women's teams. One study focused on performance within the Women's Rugby World Cup 2014 and reported that winning teams made more breaks and carries, won and stole more lineouts, and conceded less penalties than losing teams.[6] Sex differences were also highlighted, when compared with the Men's Rugby World Cup 2015, where women's teams adopted possession-based tactics, whereas men's teams embraced a territorial approach.[6] Understanding these patterns of physical and technical demands is needed to develop better training protocols specific to women's rugby, thus removing heavy reliance on men's training history.

A recent development in performance analysis research in rugby union is the use of relative PIs. This refers to the expression of PIs in context to the match played, with team values relativized to their opposition in each given match. Studies identified several relative variables that were significantly different between winning and losing teams, including kicks from hand, clean breaks, lineouts won, meters made, turnovers conceded, missed tackles, and average carry distance.[3–5,7] These variables are interpreted in context of the opposition; for example, winning teams need to increase their own meterage while concurrently decreasing opposition meters. There is debate as to whether relativized PIs improve prediction accuracy, with improvements seen in Premiership Rugby and the United Rugby Championship[4,5] but not in subelite Australian men's rugby.[7] Scott et al[5] used feature selection in combination with relative data to simplify the modeling approach, aiming to facilitate practitioner engagement with results. This approach allowed the simplification of models to a small number of PIs, without degrading prediction accuracy of modeling. Both the relative and feature selection approaches are yet to be investigated within the women's game.

The study by Barnes et al[6] into women's performance dates to 2014; however, the results may not relate to the current game because of factors including player pathway development, changes

Bezodis https://orcid.org/0000-0003-2229-3310
Waldron https://orcid.org/0000-0002-2720-4615
Pyne https://orcid.org/0000-0003-1555-5079
Mara https://orcid.org/0000-0003-2091-2608
Cook https://orcid.org/0000-0001-9677-0306
Mason https://orcid.org/0000-0002-9679-7063
Brown https://orcid.org/0000-0003-3628-2524
Kilduff https://orcid.org/0000-0001-9449-2293
Brown is now with the Welsh Institute of Performance Science (WIPS), Swansea University, Swansea, United Kingdom.
Scott (g.a.scott@swansea.ac.uk) is corresponding author, https://orcid.org/0000-0002-6599-5657

in body mass,[8] and professional status of female rugby players in several rugby nations.[9–11] This may lead to changes in what drives success over time, such as those reported across the professional era of men's rugby.[12,13] Investigators have also determined that few PIs differentiate between winning and losing across all competitions.[14] Furthermore, because sex-related differences in performance and physiological profiles likely exist, the application of current research from the men's game may not be appropriate.[6]

Studies within performance analysis in rugby union have been previously divided into 2 groups: the "what" covering key events and the "how" focusing on describing said events. This study aims to understand the "what," paving the way for future research into the "how."[15] Identifying key PIs is important to help drive tactical and coaching decisions, as well as prepare physically for match day. With these PIs, teams can build training drills that emulate match demands of the game, allowing players to develop new strategies in different areas of the game. Physical testing markers have also been linked to PIs, suggesting there is opportunity to improve performance with adapted strength and conditioning programs, and to allow more focused physiological studies in this area in the future. These studies have identified links between physical metrics such as sprint test performance, drop jumps, the yo-yo test, and sled drive test and PIs line breaks, dominant collisions, tackle success, and turnovers made.[16,17]

The primary aim of the current study was to identify PIs that maximize prediction accuracy of match outcome, from isolated and relative data sets, in women's rugby union. We also sought to determine whether relative data lead to an improvement in prediction accuracy and if feature selection can minimize models while upholding high prediction accuracy.

Methods

Design and Participants

The study design was a retrospective data analysis of key PIs in women's rugby, with data collected from major competitions across 15 international teams. Data sets containing PIs from women's matches were provided by OPTA (https://www.statsperform.com/opta/). There were 110 matches selected for training the model from all competitions available across the women's game (Table 1). This data set excluded any matches that ended with a draw. For each match, only either the winning or the losing team's PIs were selected to maintain independence of observations. These were selected randomly while maintaining a balance between winning and losing match performances.

OPTA data have been reported to have high interobserver reliability within football, with kappa values of .92 to .94.[18] Similar research is yet to take place in rugby union, but data are used by major clubs and broadcasters worldwide as well as in many studies in rugby.[3–5,7] The following 26 PIs were downloaded from each match: carries, meters made, defenders beaten, offloads, passes, tackles, missed tackles, turnovers conceded, kicks from hand, clean breaks, turnovers won, lineouts won, lineouts lost, scrums won, scrums lost, rucks won, rucks lost, penalties conceded, free kicks, scrum penalties, lineout penalties, tackle/ruck/maul penalties, general play penalties, control penalties, yellow cards, and red cards. Home and away status has been previously linked to team performance;[19] however, as this data set included World Cup matches, this was omitted to ensure consistency between competitions. PIs were selected in accordance with previous research in this area and to span across all areas of the game including attack, defense, set piece, and discipline.[5]

Table 1 Competition Matches: A Summary of What Competitions Formed the Training Data Set

Competition	Number of matches
Women's World Cup 2017	30
Women's Six Nations 2020–2022	38
Women's Super Series 2019	10
Women's International Tests 2017–2022	32

The 26 PIs formed the isolated data, whereas the relative data were calculated by deducing the difference in each PI between teams within each match. For example, if one team made 200 m and their opposition made 400 m, the relative meters made for each team would be −200 and 200, respectively. Nomenclature was used to identify which data set the feature represents as follows: PI_I indicated a PI in its isolated form and PI_R indicated a PI in its relative form. For example, $Tackles_I$ relates to isolated tackles, and $Tackles_R$ relates to relative tackles.

Statistical Analysis

Random forest classification was completed on the full data set for both isolated and relative data to categorize matches as either wins or losses. Each of the selected PIs represented a feature, with the total combination forming the feature space of the algorithm. This feature space was utilized to generate decisions on the classification of the match to either a win or a loss, across an ensemble of classification trees.

The ensemble of classification trees was created by constructing a new training set each time, with replacement, from the original sample.[20] This training set was drawn randomly using two-thirds of the full data set, with the remaining section of the data set forming the out-of-bag (OOB) test set. The tree was then tested using the OOB set.[20] From this set, the error rate (number of incorrect predictions divided by the total number of predictions) was computed. This value was averaged for each tree built to give an OOB error for the random forest model.[20]

The Mean Decrease Accuracy (MDA) was used to interpret the importance of each PI included in the models. MDA was calculated by permuting through each PI in a model and recording the difference in prediction error on OOB data with and without each PI. This difference was averaged over all trees and normalized, with z scores calculated to determine significance.[21] Partial dependency plots were also used to monitor relationships between match outcome and features used within modeling, by illustrating what values of the feature are associated within increased likelihood of winning or losing.

Maximum relevance minimum redundancy was used within an optimization loop to maximize the model accuracy in predicting matches, while minimizing the features used in modeling as used previously by Scott et al.[5] A similar process was used to optimize random forest classification parameters, including the number of trees and features considered at each split. Trees were tested between 50 and 2500 in 50 tree increments, whereas features were tested between 1 and the maximum number of features in 1-step increments. After all parameters were optimized, reduced models were finalized for both isolated and relative data sets.

After full and reduced models were established for each data set, data were sourced from the Women's Rugby World

Cup 2021 (played in 2022, due to COVID-19). This data set consisted of all 26 matches that took place within the competition (pools stages, quarter-finals, semifinals, and final). Only a winning or losing performance was chosen from each match as before, again randomly selected with a balance between the 2 classes.

The models were applied in prediction to the Rugby World Cup 2021 data, and McNemar tests were used to compare the isolated and relative results. The McNemar test statistic was calculated as follows:

$$\chi^2 = \frac{(B - C)^2}{B + C},$$

where B represented the number of outcomes correctly identified by the first model only, and C represented the number of outcomes correctly by the second model only.[22] A continuity correction was applied when $B + C < 25$ to main conservative estimates of significance in situations where cell counts were low.

A 5% significance level was utilized for P values and 95% confidence intervals (CIs) to indicate the precision of estimation. Analyses were performed in R and utilized the following packages: randomForest,[21] rfUtlities, mRMRe,[23] and rfPermute.

Results

The initial random forest classification for the training data set was completed on both isolated and relative data. The full isolated model correctly classified 82 match performances out of 110 within the training data, yielding an accuracy of 75%, with a 95% CI of 65% to 82%. Between the 2 outcomes, 71% of wins were correctly classified compared with 78% of losses.

The full relative model correctly classified 86 out of 110 match performances within the training data (78%; 95% CI, 69%–86%), including 76% of wins correctly classified and 80% of losses. This is a 3% improvement in accuracy compared with the isolated data; however, this difference was not statistically significant based on McNemar test ($\chi^2 = 0.4$, $P = .53$).

Feature selection was used on both data sets to create reduced models, and then random forest parameters were optimized. For the isolated data, the optimum number of features was identified to be 14. These features were *Red Cards*$_I$, *Scrums Lost*$_I$, *Lineouts Lost*$_I$, *Meters Made*$_I$, *Lineouts Penalties*$_I$, *Defenders Beaten*$_I$, *Missed Tackles*$_I$, *Yellow Cards*$_I$, *Clean Breaks*$_I$, *Free Kicks*$_I$, *Scrum Penalties*$_I$, *Carries*$_I$, *Tackles*$_I$, and *General Play Penalties*$_I$. In this reduced feature set, the optimum number of trees was 500, and features tested at each split were 2. The reduced isolated model, given the above parameters and features, accurately classified 82 out of 110 match performances within the training data (74%; 95% CI, 65%–82%), including 72% of wins and 76% of losses.

Optimization led to the selection of 12 features for the reduced relative model: *Red Cards*$_R$, *Meters Made*$_R$, *Lineouts Lost*$_R$, *Lineouts Penalties*$_R$, *Clean Breaks*$_R$, *Scrums Lost*$_R$, *Missed Tackles*$_R$, *Yellow Cards*$_R$, *Carries*$_R$, *Scrum Penalties*$_R$, *Kicks from Hand*$_R$, and *Rucks Lost*$_R$. The optimal number of features tried at each split was 6 for the reduced relative model. To ensure comparability of MDA between models, the number of trees was set to 500 to match the reduced isolated model. The reduced relative model correctly classified 84 out 110 match performances within the training data (76%; 95% CI, 67%–84%), of which it correctly identified 75% of wins and 78% of losses. McNemar test value was 0.11 ($P = .75$), illustrating that relative data did not significantly outperform the isolated data.

There was no significant difference between full and reduced model performance, with McNemar's values of 0 ($P = 1$) for the isolated models' comparison and 0.1 ($P = .75$) for the relative models' comparison.

Both full models were used in prediction on the Rugby World Cup 2021 data set. The full isolated model accurately predicted 25 out of 26 match performances (96%; 95% CI, 80%–100%), including 92% of wins and 100% of losses. With the full relative model, all 25 out of 26 match performances were correctly predicted (96%; 95% CI, 80%–100%), with 92% of wins and 100% of losses. In prediction, the full relative model performed identically to the full isolated model.

Both reduced models were also used in prediction on the Rugby World Cup 2021 data set. The reduced isolated model accurately predicted 26 out of 26 match performances (100%; 95% CI, 87%–100%). With the reduced relative model, 25 match performances out of 26 were correctly predicted (96%; 95% CI, 80%–100%), with 92% of wins and 100% of losses. In prediction, the difference between reduced relative model and reduced isolated model was negligible ($\chi^2 = 0$, $P = 1$). When the full and reduced models were compared in prediction, there was negligible difference between the full and reduced isolated models ($\chi^2 = 0$, $P = 1$) and no difference between the relative models.

The MDA z values for each feature in the model are summarized in Table 2 along with the corresponding P values. Within the reduced isolated model, only 6 features were identified at the 5% significance level. These features were *Meters Made*$_I$, *Lineouts Lost*$_I$, *Defenders Beaten*$_I$, *Clean Breaks*$_I$, *Missed Tackles*$_I$, and *Scrums Lost*$_I$. Within the reduced relative model, only 6 features were identified including *Meters Made*$_R$, *Clean Breaks*$_R$, *Missed Tackles*$_R$, *Lineouts Lost*$_R$, *Carries*$_R$, and *Kicks from Hand*$_R$.

Figure 1 illustrates partial dependence plots for the reduced isolated model. *Meters Made*$_I$, *Defenders Beaten*$_I$, and *Clean Breaks*$_I$ were positively associated with winning (Figure 1A, 1C, and 1D), whereas *Lineouts Lost*$_I$, *Missed Tackles*$_I$, and *Scrums Lost*$_I$ (Figure 1A, 1E, and 1F) were negatively associated with wins. Figure 1A shows no clear increase in winning probability after approximately 600 m made, and Figure 1C indicates no increase after 40 defenders beaten. Figure 1D also indicates no clear increase in winning probability after approximately 20 clean breaks. Equally, no clear increase in losing probability was seen after more than 6 lineouts lost (Figure 1B) and 50 missed tackles (Figure 1E).

Partial dependence plots for the reduced relative model are presented in Figure 2. Figure 2A, 2B, 2E, and 2F illustrate positive association with winning for *Meters Made*$_R$, *Clean Breaks*$_R$, *Carries*$_R$, and *Kicks from Hand*$_R$. Figure 2C and 2D show *Missed Tackles*$_R$ and *Lineouts Lost*$_R$, which were negatively associated with winning. There was no increase in probability of winning after approximately 400 relative meters made (Figure 2A). Relative clean breaks had little effect on the probability of winning after 10 more clean breaks than the opposition (Figure 2B). There was no increase in the likelihood of losing after a team had missed approximately 30 more tackles or lost 5 more lineouts than their opposition (Figure 2C and 2D). There was no increase in probability of winning after a team makes 100 more carries or 12 more kicks than their opponent (Figure 1E and 1F).

Discussion

Unlike previous research into contextualized PIs, the use of PIs relative to the opposition's performance did not significantly

Table 2 Mean Decrease Accuracy z Scores and Associated P Values Based on the Isolated and Relative Reduced Model Features

Isolated features	Mean decrease accuracy z score	P	Relative features	Mean decrease accuracy z score	P
Meters Made$_I$	15.4	.01	*Meters Made$_R$*	23.0	.01
Lineouts Lost$_I$	12.7	.01	*Clean Breaks$_R$*	14.2	.01
Defenders Beaten$_I$	12.4	.01	*Missed Tackles$_R$*	14.2	.01
Clean Breaks$_I$	10.9	.01	*Lineouts Lost$_R$*	12.4	.01
Missed Tackles$_I$	8.3	.01	*Carries$_R$*	10.2	.02
Scrums Lost$_I$	4.9	.04	*Kicks from Hand$_R$*	9.4	.02
Carries$_I$	4.8	.07	*Scrums Lost$_R$*	1.1	.27
Scrum Penalties$_I$	1.7	.21	*Rucks Lost$_R$*	1.1	.24
Tackles$_I$	0.7	.38	*Lineouts Penalties$_R$*	1.0	.26
Lineouts Penalties$_I$	0.4	.36	*Scrum Penalties$_R$*	–0.2	.49
Free Kicks$_I$	0.1	.43	*Red Cards$_R$*	–0.7	.48
Yellow Cards$_I$	–1.1	.64	*Yellow Cards$_R$*	–2.4	.78
Red Cards$_I$	–1.9	.69			
General Play Penalties$_I$	–3.8	.94			

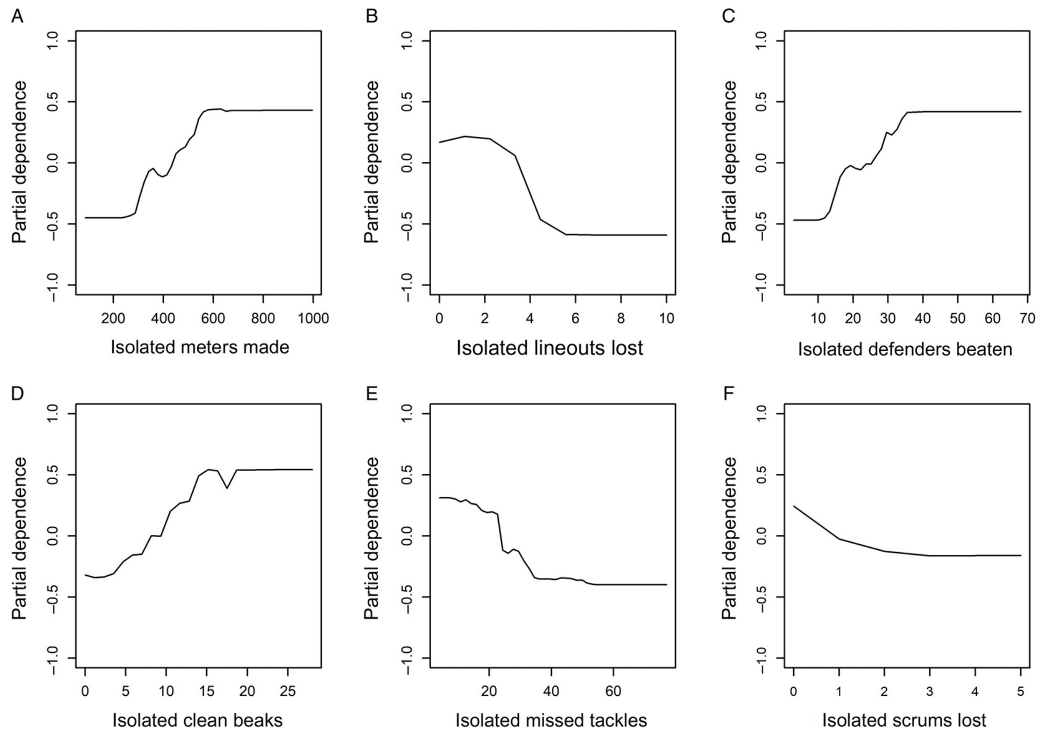

Figure 1 — Partial dependence plots for significant isolated features (based on mean decrease accuracy values). The plots show the marginal effect of isolated meters made (A), isolated lineouts lost (B), isolated defenders beaten (C), isolated clean breaks (D), isolated missed tackles (E), and isolated scrums lost (F) on classification of match outcome. The *x*-axis contains the range of values for each of the previously named performance indicators, and the *y*-axis contains the partial dependence. Negative values of partial dependence indicate an increased likelihood of a match performance being classified as a loss, and positive values indicate an increased likelihood of a performance being classified as a win.

improve match outcome prediction in this data set. Conversely, this study corroborated previous research into feature selection use in modeling within rugby union. That is, reducing models using feature selection did not negatively impact model efficacy. This study demonstrated that relative meters made, clean breaks, kicks, lineouts lost, missed tackles, and carries were significant differentiators between winning and losing performances in women's international rugby union. This information is useful for a variety of applications, including coaching and tactical strategies, player selection, and both technical and physiological aspects of training.

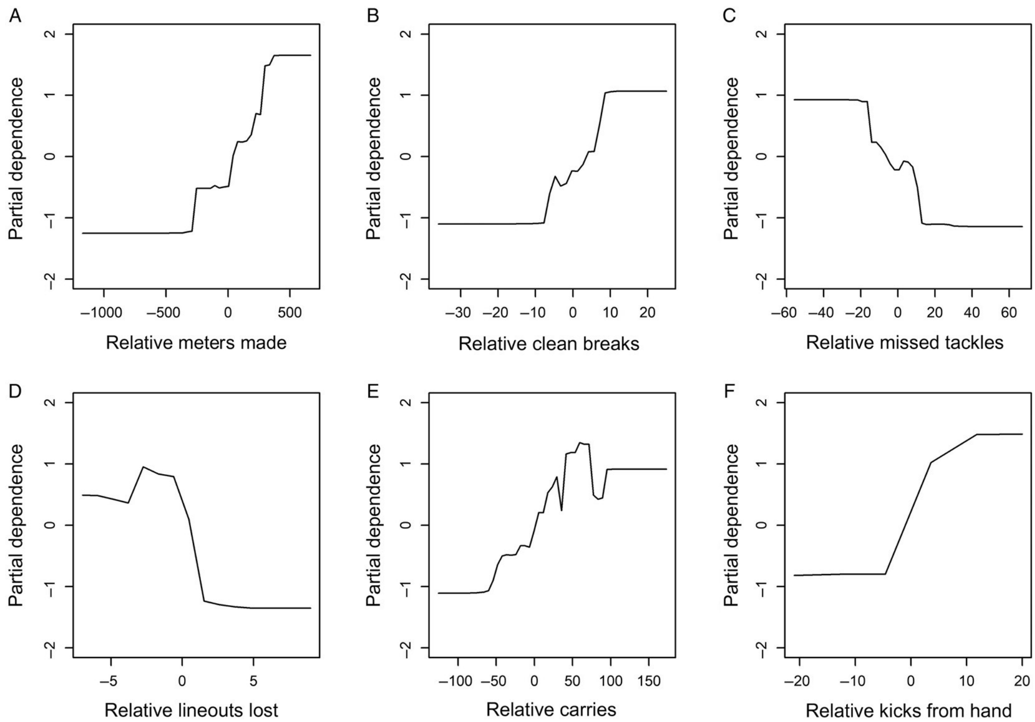

Figure 2 — Partial dependence plots for significant relative features (based on mean decrease accuracy values). The plots show the marginal effect of relative meters made (A), relative clean breaks (B), relative missed tackles (C), relative lineouts lost (D), relative lineouts lost (E), and relative kicks from hand (F) on classification of match outcome. The *x*-axis contains the range of values for each of the previously named performance indicators, and the *y*-axis contains the partial dependence. Negative values of partial dependence indicate an increased likelihood of a match performance being classified as a loss, and positive values indicate an increased likelihood of a performance being classified as a win.

Meters made and clean breaks were discriminating variables in both isolated and relative models, and defenders beaten was identified within the isolated modeling, demonstrating the importance of attacking metrics in successful performances. Inclusion of these PIs in both models highlights the need to outperform the opposition in these parts of the game, which could theoretically be achieved by limiting opposition meters and breaks. Research into the men's game has reported similar observations.[5,7] Meters made and clean breaks are reportedly associated with sprint speed in the men's game; therefore, further research is required to interpret the strength of this relationship in the women's game. Collision dominance, the act of driving additional meters once a tackle is initiated in attack or reducing meters made in the tackle when in defense, allows teams to increase relative meterage. Collision dominance in female players has been associated with increased acceleration momentum and lower skinfold measurement in forwards, and increased single-leg isometric squat relative force and decreased body mass in backs.[24] Training interventions to improve these metrics may increase meterage on match day. Such an approach can also enlighten similarities and differences in training response and accompanying physiology between males and females.[25]

Carries also featured in the relative model, demonstrating that increased carries compared with the opposition were associated with winning performances. This has been identified in women's rugby previously as an isolated PI within the Women's Rugby World Cup 2014.[6] A study comparing physical performance and PIs into the women's game has linked carries per minutes to certain physical aspects. This study suggests that body mass, skinfolds, and 0- to 10-m acceleration momentum were all positively associated with carries per minute, while aerobic speed and relative single-leg squat force were negatively associated in forwards.[24] This suggests that physical performance may have influence on carrying ability. Furthermore, as discussed previously with the meters made PI, there may be a link between the success of the carry PI and collision dominance. This is an area of future research interest within the women's game.

The current data demonstrate that "set piece" was important within the women's game. Isolated and relative lineouts lost were both discriminating indicators of successful performances, with winning teams losing fewer lineouts than their opposition. Lineout success was identified as a key PI discriminating between winning and losing at the Women's Rugby World Cup 2014.[6] Lineouts form a large part of set piece preparation within teams and can be used in conjunction with kicking strategies to gain territory and create scoring opportunities. Therefore, it is important for teams to develop a strong lineout strategy in both attack and defense. This work will involve technical elements of the lineout and physical preparation of players to enhance jumping performance. Scrums lost were also identified within the isolated modeling, showing the importance of this part of set piece. This suggests that interventions focused on scrum preparation and strength may benefit women's teams.

Kicks from hand featured in the relative model, highlighting that kicking more than the opposition was an indicator of successful match performances. A previous study of women's PIs identified that winning teams kicked more than losing teams within their own 22- to 50-m area but less in the opposition 22- to 50-m area.[6] Without field context in our data set, it is difficult to decipher whether this relationship is evident in our study. This is a limitation and future research should further examine relationships between kicking and success.

Missed tackles also featured within modeling, implying that a high missed tackles count is linked to unsuccessful match outcomes, as well as more missed tackles than the opposition. Missed tackles allow the opposition to continue to make meters and may create try scoring opportunities; hence, it is intuitive that high values lead to losing. Tackle completion has also been reported as discerning between winning and losing within women's rugby,[6] which suggests that overall tackle strategy may be a key area of intervention for losing teams. Men's research has identified increased leg drive from the tackler as linked to increased tackle success and conversely found fatigue to be a driver of tackle impairment.[26,27] Further research is required to understand whether these physical changes can have similar impact within the women's game. Fatigue remains an area of contemporary physiological interest in females.[28]

The current study aligns with research in multiple men's competitions including Premiership Rugby,[4] United Rugby Championship,[5] subelite men's rugby,[7] and international men's rugby.[3,29] The similarities suggest that there is substantial overlap in the PIs associated with success between different sexes and competitions. Research within rugby sevens identified PIs in common between sexes as well as sex-specific PIs.[30] Both studies into women's PIs have been analyzed alongside men's, while no research has analyzed women's rugby in isolation. A study of women's collision sports has highlighted gaps in research into technical, physical demands, and preparation strategies in women's rugby union.[31] Dedicated research is required in women's rugby to understand how tactical, technical, and physiological performance can enhance match day success.

Random forest modeling is a recognized and popular method within rugby union performance analysis research[3–5,32] and copes well with multicollinearity, unlike methods such as logistic regression. Random forest benefits from a wrapper method for feature selection that is not seen in logistic regression and avoids overfitting to the same extent at which it can occur in methods such as gradient boosted trees. Furthermore, the use of partial dependence plots within this study has allowed the understanding of certain cutoff(s) in the performance of the key PIs, where executing more of the action does not necessarily lead to further improvement or diminished success. Feature selection, namely maximum relevance minimum redundancy, has been used previously in rugby union with similar results reported to this study.[5] Principal component analysis has also been used within rugby league to achieve similar results;[33] however, this method will yield results in the form of components based on a combination of different variables. This, in turn, can complicate results and their use in practical settings. Utilizing maximum relevance minimum redundancy allows the user to maintain simple PIs and promote the interpretability of analysis for easier implementation by applied practitioners.

Relative PIs did not improve model accuracy within this data set, in contrast to analyses in the Men's World Cup, Premiership Rugby, and the United Rugby Championship.[3–5] This study emulated results seen in subelite men's Australian rugby, where relative data also did not significantly improve prediction accuracy.[7] Points difference drives match outcome; hence, the relationship PIs have with points difference is important in the machine learning process. In practice, large point differences, as seen in many matches in this data set, may suggest that maximizing individual efforts is more important than preventing opponents' actions. Future research is required to understand this relationship, and why relative data are beneficial in some cohorts but not others.

As previously discussed, results presented in this study form an understanding into "what" key events are important, and the next stage would be to understand the "how."[15] Given the simplified PIs produced by this research, a clear next step of analysis would be to explore these PIs further and begin to understand the contextual factors that promote successful strategies, for example, a successful lineout strategy or clean break opportunity similar to what has been previously researched in the men's game.[34] PIs also offer the possibility to better target physiological and training-based experimental work to further prepare and develop the woman rugby player.

Practical Implications

- Attacking qualities, such as clean breaks, carries, and meters made, are essential to winning performances; therefore, interventions around players' lower body power, acceleration, and speed may support improvements in these areas.
- Set piece performances are also key to winning outcomes, and particular attention should be paid to both team strategies as well as understanding opposition lineout tactics.
- Relative data are not essential to interpret performance postmatch within women's rugby but may assist the development of opposition analysis.

Conclusions

Increased relative meters made, clean breaks, kicks from hand, and carries and decreased lineouts lost and missed tackles, were associated with match success in women's rugby union. It appears that a combination of territorial and possession tactics is required for winning performances, as are adequate resources given to set piece preparation, particularly lineouts. Use of relative data did not yield a significant improvement in prediction accuracy, despite this effect being observed in many men's competitions.

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