Advancing Player Modelling in Rugby Union: An Evaluation of Path Analysis Techniques

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Data Analytics

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Advancing Player Modelling in Rugby Union: An Evaluation of Path Analysis Techniques

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Abstract

Rugby union outcomes have traditionally been predicted using team-level metrics like past results and rankings, overlooking within-match dynamics. This research aimed to quantify the impact of player selection and cohesion on match outcomes using advanced player modelling. However, significant limitations emerged applying path analysis techniques to available rugby event data, stalling progress. The focus shifted to evaluating path analysis efficacy for rugby modelling. Results showed issues with indicator reliability, estimate reproducibility, and model complexity. Small sample diversity and theoretical validity constraints contributed to instability. While the cohesion research goals proved unattainable presently, illuminating path analysis limitations remains informative. This methodological investigation highlights considerations for future player-level modelling like ensuring indicator dependability, addressing multicollinearity, and exploring nonlinear modelling. Though falling short of its aims, by critiquing the path analysis approach applied to rugby, this work provides practical guidance to enable enhanced dynamic modelling and quantification of player factors influencing match outcomes.

1 Introduction

Rugby Union is regarded worldwide as an energetic collision sport that heavily relies on quick and inch-perfect coordination between players. The current standard methods used to predict match outcomes tend to use past results and overall team performance metrics. They often overlook more advanced analyses that can isolate and measure the impact an individual player's actions can make during a match. There are techniques available that can potentially derive predictive statistics at the player level by valuing small-scale actions such as passes, carries and tackles. If this potential could be properly utilised it would allow for further research on some of the intangible factors which contribute to team effectiveness.

This project was initially aimed at implementing such a technique to investigate one of these elusive team factors, 'cohesion'. At that point, the thought was to use path analysis methods to estimate the average value of individual player contributions towards scoring and then to measure how each player's performance average changed when playing with different teammates in the same unit. Applying the methodology to the rugby data which was available presented significant limitations that halted any progress towards analysing cohesion.

The research became an examination of the path analysis methodology which was being employed instead. The research question became; What are the limitations in using this analytical approach and available data for quantifying predictive player-level statistics in rugby union? This research now aims to uncover why this technique struggled with the specific context of detailed player action modelling through an examination of the characteristics of the underlying data and the validity of the path model specifications.

While the original goals related to cohesion proved unattainable via this methodology in this research, exploring the limitations of the technique could still prove valuable. These insights can offer valuable guidance for future sports research, shedding light on factors to consider when exploring more advanced player-level path analysis. Although the focus has shifted, this methodological investigation still holds theoretical significance that can be practically applied.

The report structure is as follows. First, the relevant literature on player modelling and team factors is reviewed. Next, the original technique and data foundations are outlined. Then the methodological processes are described, and an evaluation of the results. The last section discusses the implications of the findings, possible future improvements, and some closing remarks.

2 Related Work

Sports prediction is widely researched using a wide variety of methods. However, most focus on aggregated team metrics, overlooking player-level modelling and team cohesion - quantifying individual contributions and chemistry between players. This research aims to at least partially explore the potential of modelling player-level performance and cohesion rather than just overall team metrics.

2.1 Existing Outcome Prediction Models

A variety of techniques have been applied to predict team sports outcomes. Traditional regression approaches, such as those used by Boshnakov, Kharrat and McHale (2017) and O'Donoghue et al. (2016), commonly rely on past results, rankings, and other variables to train predictive models. While these approaches have been effective to some extent, they heavily rely on retrospective team performance statistics and often overlook the within-match dynamics that are crucial in rugby.

In an effort to improve the accuracy of match outcome predictions, some studies have incorporated additional situational variables related to match conditions and team strengths. Robertson, Back and J. D. Bartlett (2015) and Baker and McHale (2015) have explored the use of pre-match odds, home advantage factors, weather data, and other potential indicators alongside past results. These models have achieved moderate accuracy in predicting match outcomes. However, they fail to fully account for the sequential, interconnected nature of rugby as an invasion sport.

One key aspect that has been overlooked in current rugby prediction models is the chains of possession events that ultimately lead to scoring outcomes. Rugby matches unfold through sequences of phases involving coordinated player actions such as rucks, mauls, scrums, lineouts, tackles, carries, kicks, and passes Hendricks et al. (2015). The progression up the field emerges from these interconnected events. However, existing forecasting models do not explicitly model or quantify these sequences and relationships.

To address this gap, some initial research has explored mining sequential patterns in rugby data using techniques like Markov chains and network analysis. Cintia et al.

(2015) and Novak, Palmer et al. (2021) have applied these approaches to identify common chains and connections between match events and situations. However, these studies stop short of mapping entire sequences or estimating predictive values. There is considerable scope to develop enhanced models that can effectively represent and capture the multidimensional action dynamics of rugby.

Advanced methods like recurrent neural networks (RNNs) have shown potential in modelling longitudinal dependencies in sports data. Watson et al. (2020) and Horvat and Job (2020) have demonstrated the effectiveness of RNNs in capturing complex patterns and dependencies. Successfully adapting neural networks to model rugby's complexities could provide significant improvements in model accuracy.

While various statistical and machine learning techniques have been used to predict rugby match outcomes, there is a need to incorporate additional situational variables and account for the sequential, interconnected nature of rugby as an invasion sport. Future research should focus on developing models that can effectively capture the chains of possession events and dynamics in rugby matches, potentially leveraging advanced methods like recurrent neural networks to improve forecasting accuracy.

2.2 Player and Action Modelling Approaches

A multitude of techniques have emerged for advanced player and action modelling in team sports, aiming to better comprehend the intricate dynamics influencing performance. Different methodologies provide unique perspectives but also suffer limitations in capturing the full complexity. Integration of complementary approaches appears necessary for comprehensive understanding.

Passing network analysis has proven valuable for quantifying cooperative connectivity between players and its association with team success (Fransen et al. 2021). By representing teams as networks of passing interactions, key metrics can be derived regarding connectivity, density, and centrality. More connected passing networks exhibit greater coordination and are more prevalent in winning teams. However, passing sequences alone insufficiently encapsulate the myriad situational variables that shape gameplay. Contextual factors like field position, phases of play, defensive pressure, and match status are overlooked. Hence passing networks offer partial but limited insights.

Hypernetwork models provide a robust conceptual framework capable of encapsulating the diverse relationships and interactions between multiple elements like players, teammate dyads, units, coaches, and environmental contexts (Ribeiro et al. 2019). This multidimensional approach moves beyond traditional binary analysis to enable representing complex dynamics. However, the conceptual nature of hypernetworks limits direct analytical quantification of probabilistic winning factors. The framework remains theoretical without statistical estimation of predictive weights and effects.

Path analysis techniques enable statistically modelling and estimating the magnitude of causal relationships between key performance indicators and team outcomes (Novak, Impellizzeri et al. 2021). The direct and indirect effects of factors like player actions, field position, and situational contexts on scoring can be quantified. However, specification of path models risks overlooking nonlinear dynamics or interacting effects between variables. Constraints like linearity assumptions limit complexity representation.

Data-driven player action indicators derived from event data can reveal superior tactics and actions differentiate winning teams (Cintia et al. 2015). But in isolation, these indicators insufficiently account for scoring contributions or contextual dependencies.

Traditional aggregated player metrics remain limited in representing multifaceted performance. Comprehensive skill assessment incorporating technical, physical, psychological and contextual factors is imperative (Hendricks et al. 2015).

In summary, current player and action modelling approaches provide useful but fragmented insights into team sports dynamics. Each methodology has advantages and limitations. To truly achieve comprehensive performance quantification likely requires integrated frameworks synergistically leveraging complementary techniques. This necessitates continued research on unified hybrid approaches capable of capturing cooperative dynamics, situational contexts, action sequencing, and multidimensional causal pathways within adaptable statistical structures.

2.3 Alternative Data Sources

The analysis of rugby matches has traditionally relied heavily on manual techniques like video coding and subjective evaluations by coaches and analysts (Hughes and R. M. Bartlett 2002). However, this approach is prone to human inconsistency and bias. The emergence of wearable sensors and computer vision facilitates collecting rich objective spatiotemporal data that could augment and enhance rugby analysis. However, these technologies have both strengths and weaknesses that must be considered.

Wearable sensors like GPS and inertial measurement units provide multivariate datasets capturing metrics on physical demands with high accuracy and reliability (Vickery et al. 2014). This enables robust quantification of match activities and workloads (Gabbett and Mulvey 2008). However, simply incorporating sensor variables into standard models has shown limited benefit.

Automated analysis of match footage via computer vision demonstrates the potential for extracting novel event statistics like ruck involvements and tackling metrics (Hopkinson et al. 2021). But robustly tracking occluded players in the dynamic rugby environment remains challenging (Yue et al. 2014). Manual verification is still required, limiting current practicality at scale.

Over multi-year periods, inertial sensors facilitate precisely quantifying longitudinal changes in match activities and player characteristics (Quarrie and Hopkins 2007). However, variations in methods and technologies make cross-study comparisons difficult currently. Integrating wearables and computer vision could provide more holistic data for informed game analysis (Lehra et al. 2022). However considerable research is still needed to translate these capabilities into real-world adoption.

There is certainly potential in wearable sensors and computer vision, but also challenges in implementing them effectively. They may become valuable tools for enhancing evidence-based analysis in rugby through further research. But pragmatic adoption remains on the horizon pending continued systematic evaluation.

2.4 Cohesion Factors in Sports Teams

Meta-analyses by Carron, Colman et al. (2002) and Carron, Bray and Eys (2002) found a significant positive quantitative association between cohesion and team success. Their research suggests that cohesive teams are significantly more likely to achieve better win-loss records and overall performance outcomes. While providing evidence for the importance of cohesion, they did not provide specific factors that may enhance team cohesion.

Other studies have examined how certain group dynamics might increase cohesion. For instance, Murrell and Gaertner (1992) found that players on more successful teams emphasised unity, shared experience, and common identity significantly more than less successful teams. Their findings imply that building shared goals through team-building exercises could measurably improve cohesion.

In contrast, Vincer and Loughead (2010) quantified the relationship between player leadership behaviours, team cohesion, and team success. Their findings suggest player leadership behaviours could significantly strengthen team cohesion, which in turn enhances team performance outcomes. While limited, this study provides a template for estimating the impact of incorporating definable factors like leadership into cohesion analyses.

The available research clearly highlights the importance of cohesion as a factor in team performance. Most studies have not quantified the potential improvements in analysis and prediction from proactively considering various additional facets impacting team cohesion. Those that do provide a model for future research to measurably improve team performance predictions.

2.5 Summary & Conclusions

The pursuit of predicting sports outcomes has been rigorously explored academically. Existing methodologies, from conventional statistical analyses to more machine learning approaches, have based their predictions on factors such as historical results, and team rankings. However, these models, despite their contributions, frequently neglect the nuanced interplay observed during a rugby match, particularly the significance of player selection and team synergy.

The predominant focus has been on retrospective team performance statistics, which, although essential, might not capture the full picture. For instance, the within-match dynamics, player interactions, and the synergy among team members are often neglected, despite their potential significance in determining match outcomes.

There's a gap in the existing body of knowledge, and a need for research that not only considers traditional metrics but also into the effects of player selection and team cohesion. Such an approach could lead to more holistic and potentially more accurate predictions of rugby match outcomes.

3 Methodology

This section provides a comprehensive overview of the end-to-end analytical methodology followed for this rugby analytics research project. As illustrated in Figure 1, the overall process closely aligns with the established KDD process framework (Knowledge Discovery in Databases; see Fayyad, Piatetsky-Shapiro and Smyth (1996)). This structured data mining approach guided the systematic analysis from raw data collection through to predictive modelling and evaluation.

The first phase focused on securing a dataset capturing key events and metrics from professional rugby matches. Exploratory Data Analysis was performed in Python using Pandas, NumPy, Matplotlib and Seaborn to better understand the dataset. Summary statistics, correlations, visualisations and aggregations revealed critical data properties and imbalances.

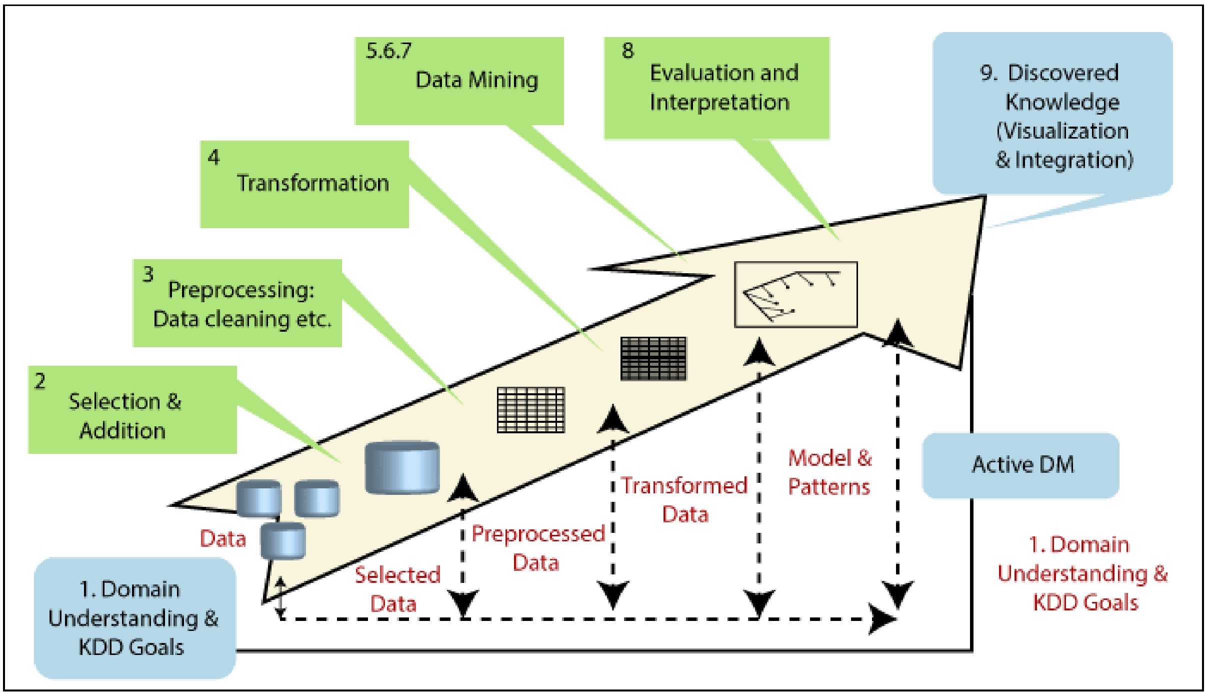

Figure 1: Knowledge Discovery in Databases process

This raw event data then underwent substantial cleaning and preprocessing using the Pandas library in Python to transform it into a consistent, structured format amenable to analysis. New features were engineered to encode critical rugby situational contexts and derived metrics. This feature set powers the subsequent modelling process

3.1 Data Collection

The dataset that forms the basis for this rugby analytics research is provided by Oval Insights, a sports analytics company focused on generating insights from rugby match event data.

Specifically, this dataset encompasses every match played during the 2020/2021 season of a premier northern hemisphere rugby union competition. It includes 16 teams representing 5 countries across 301 matches played in venues in those countries.

The data itself is first collected using a specialised live analysis tool on the stadium camera feeds with access to multiple simultaneous angles. This tracking data provides the foundation, but a crucial extra layer of detail and context is added by trained human reviewers. A specialised team of analysts watch every match live, annotating and categorising each significant on-ball event, such as passes, tackles and scrums. Over 70 distinct event types are encoded in the data dictionary.

For each event, the analysts record additional descriptive information covering attributes like player actions, pitch locations, possession context, as well as qualifying details about the nature of the event. Common descriptors include codes specifying whether a pass was flat, forward or popped, or if a tackle was dominant, assist or missed.

The end result of this extensive data collection process is an immensely detailed dataset, with over 300 columns providing granular information about each on-ball event. Each row in the raw dataset represents a single event, capturing attributes such as:

- The type of event (e.g. pass, kick, tackle, scrum)

- Descriptors qualifying the event (e.g. pop pass, box kick, dominant tackle)
- Identifier codes for the players involved
- Normalised x-y coordinate locations on the pitch of where the event occurred
- Sequence number and context of the event within a team's possession
- Match details like date, venue, weather conditions

In total this dataset consists of 246,554 distinct events across a full season, which should provide a solid foundation for analysis.

3.2 Exploratory Data Analysis

Extensive Exploratory Data Analysis (EDA) was undertaken using Python libraries such as Pandas, NumPy, Matplotlib and Seaborn to derive insights from the preprocessed rugby event dataset.

Summary statistics were generated to understand the distribution of the over 70 encoded event types. As seen in Figure 2, the 'ruck' event was found to be the most common, accounting for over 42% of the total events. In contrast, 'lineout' and 'tackle' events were much less frequent, each comprising around 11% of events.

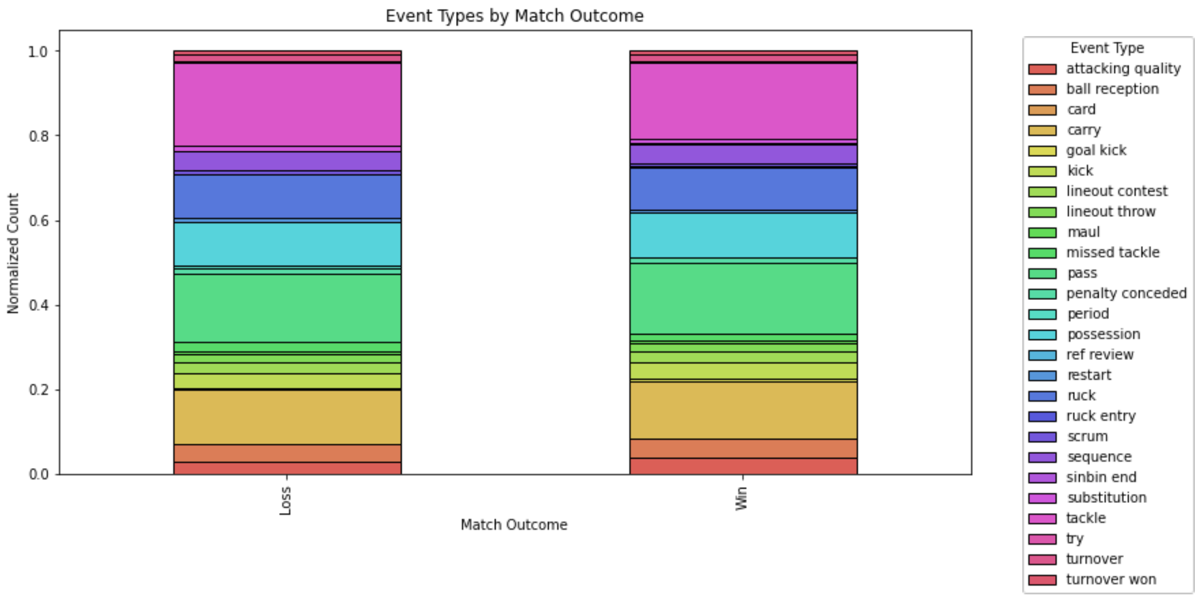

Figure 2: Frequency distribution of event types

A very strong positive correlation of 0.9 was observed between the x and y coordinate columns using Pearson's correlation coefficient. This indicates a high degree of linear relationship between the length and width location values, implying that events tend to occur in concentrated pitch areas.

The distribution of event types was analysed across match outcomes (wins/losses) as shown in Figure 3. Losing teams were found to have noticeably more tackle events compared to winning teams. This was noted in regards to path model structures further in the implementation phase.

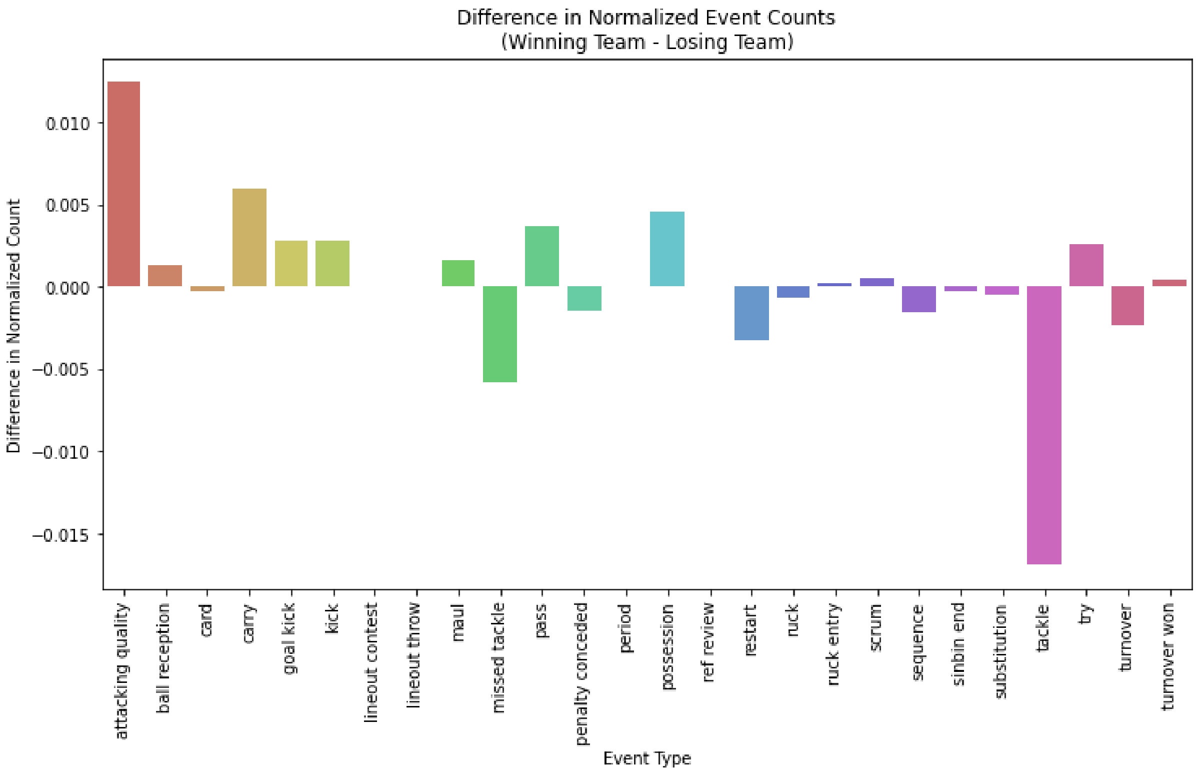

Figure 3: Event type frequencies segmented by match outcome

Hexagonal bin heatmap visualisations were generated to understand the concentration of on-pitch events in different field zones. As illustrated in Figure 4, a high density of events occurred in attacking third sections closest to the try line. Again this informed path structure decisions later in the implementation.

The extensive EDA phase provided critical insights into properties, imbalances, relationships and trends within the rugby event data. These findings guided the subsequent feature engineering process by revealing opportunities for new engineered features aimed at encoding tactical situations.

3.3 Data Cleaning and Preprocessing

Due to the scale and complexity of the raw data, the raw event dataset underwent substantial cleaning and preprocessing in Python using libraries like Pandas, NumPy and SciPy.

3.3.1 Transforming Data Types

The first phase focused on converting column data types into appropriate formats. Timestamp strings were cast to Pandas date-time objects to enable time-based filtering and grouping. Categorical columns encoded as numbers were converted to native string types to match their semantic meaning.

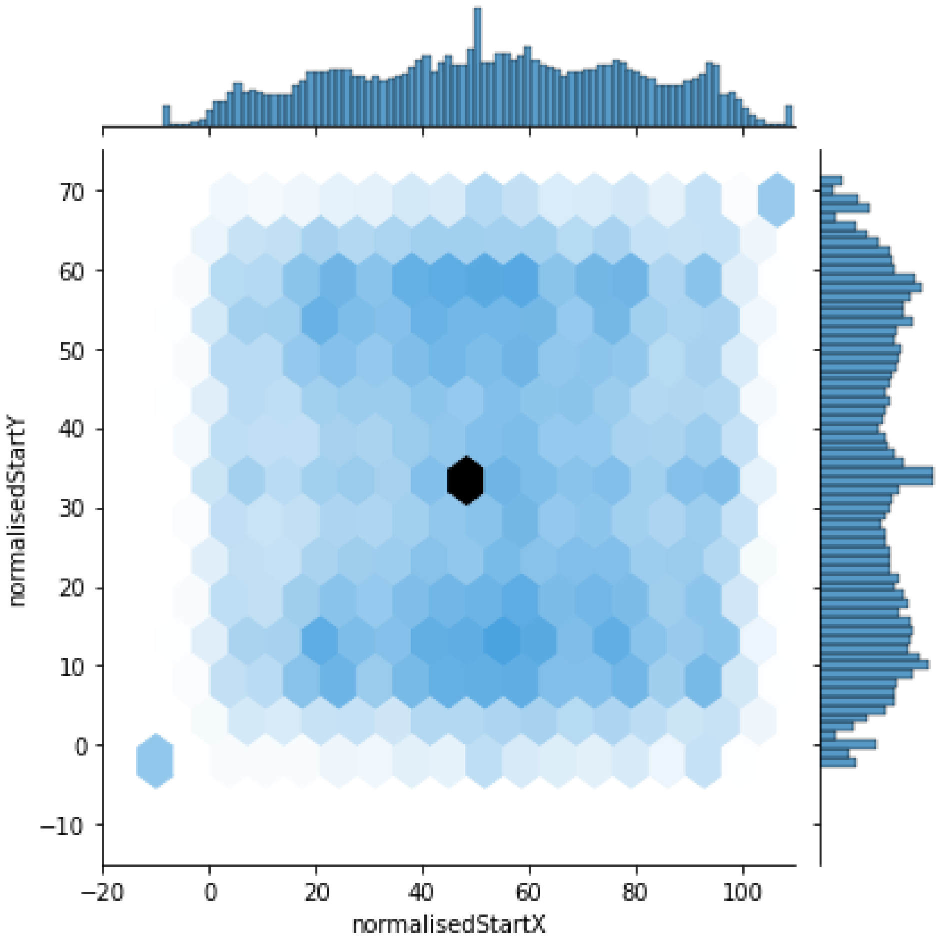

Figure 4: Hexagonal bin heatmap of event distributions

3.3.2 Cleansing String Columns

With logical data types established, string columns were cleansed by removing inconsistent white space, special characters and abbreviations. Values were standardised to a common case format to enable matching of related records. Units were also standardised across relevant measurement columns.

3.3.3 Normalisation of Continuous Features

For certain continuous variables like metres gained, min-max scaling was applied to normalise the data to a 0-1 range. This enabled normalised comparisons across matches and teams.

3.3.4 Enriching the Dataset

In addition, a number of transformations were applied to enrich the data and extract more information:

- Aggregated value columns were generated by combining related string pairs (e.g. a new column totalling the overall maul metres covered)

- The primary 'type_name' column containing the event type was one-hot encoded into 26 binary indicator columns to enable modelling
- Location zone columns were added by binning the x/y coordinates into pitch quadrants to capture event distributions
- Unique 'possession chain' identifiers were constructed by combining sequential possession numbers with the match IDs

3.4 Feature Engineering

Equipped with domain expertise and insights from analysis, extensive feature engineering is undertaken to derive new informative attributes.

The primary 'type_name' column containing the event type is one-hot encoded into 26 binary indicator columns using scikit-learn to enable modelling.

Location coordinates are utilised to construct spatial context features. Pitch zones are defined lengthwise from the try line at 5-metre intervals. Events are allocated to zones based on their x-coordinate to encode field position situations.

Possession events are linked together into sequences using engineered unique identifiers constructed by combining match IDs and possession numbers. This captures team dynamics across possessions.

Column names are cleaned by removing special characters, white space, and abbreviations to create a standardised scheme. A mapping dictionary renames columns into descriptive identifiers based on rugby semantics.

For player-level analysis, the dataset is grouped by the engineered possession identifiers to aggregate events at the possession level using Pandas. Similarly, grouping by match IDs aggregates events into full sequences.

This structured dataset enables the application of statistical and machine learning models to gain insights into professional rugby events, trends and dynamics

4 Design Specification

A 3-tier architecture is developed to implement the end-to-end rugby analytics pipeline, as depicted in Figure 5.

4.1 Data Layer

The foundational dataset contains highly detailed event-level statistics for every match in a premier professional rugby union competition. This raw data is provided by Oval Insights, a sports analytics company specialising in optical tracking data and human annotations.

The dataset captures over 70 distinct event types including passes, tackles, scrums and kicks. Each event has granular metadata such as location coordinates, player and team identifiers, descriptors, sequences and match context. In total, the dataset encompasses over 240,000 events across 301 matches involving 16 teams.

This multivariate time-series dataset is loaded into Pandas DataFrames in Python allowing the use of libraries such as NumPy and SciPy. The cleaned and preprocessed data layer provides the inputs for the application layer to analyse.

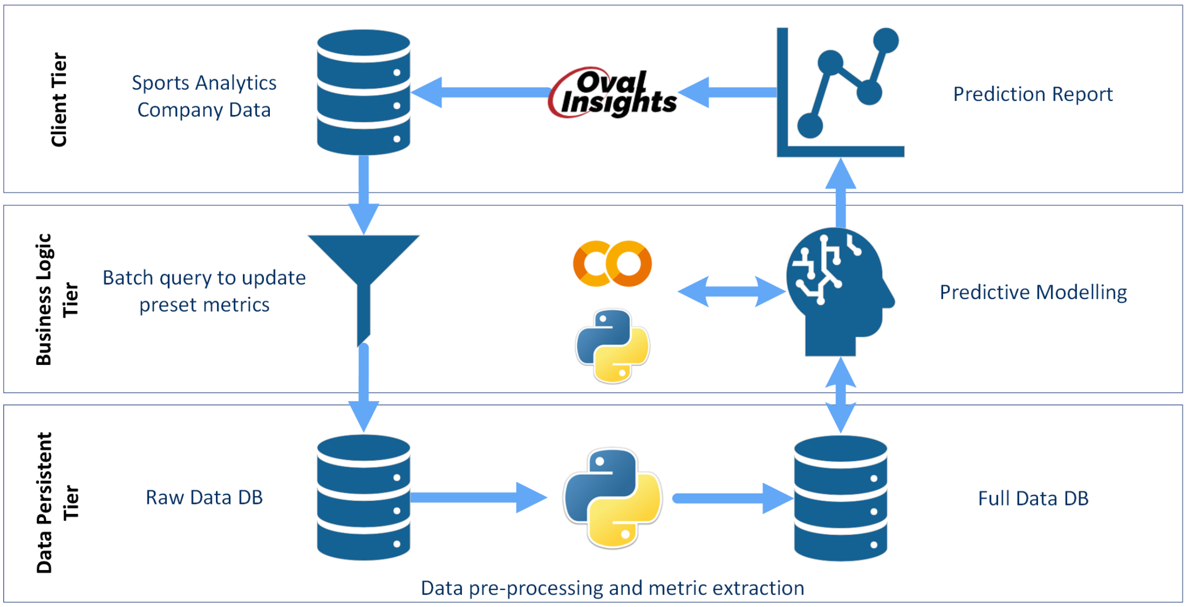

Figure 5: The original system architecture, prior to the shift in research focus

4.2 Application Layer

The Pandas DataFrames undergo substantial transformation to prepare the data for analysis. Data types are converted and columns are cleaned to have consistent formats. Relevant features are normalised to a standard scale using min-max scaling. Aggregated value columns are generated from string pair combinations. Categorical variables are one-hot encoded into binary indicators. Using rugby domain expertise along with exploratory analysis, additional features are engineered to encode critical match situational contexts.

For modelling, Covariance Based Structural Equation Modelling (CB-SEM) and Partial Least Squares Path Modelling (PLS-PM) are implemented using IBM AMOS and SmartPLS respectively. CB-SEM (Jöreskog 1978) is a covariance-based technique that attempts to reproduce the theoretical covariance matrix as closely as possible. It uses maximum likelihood estimation to optimise global model parameters. CB-SEM excels at confirming theories and causal relationships between constructs. It generally requires larger samples, multivariate normality, and parsimonious models.

In contrast, PLS-PM (Lohmöller 1989) is a variance-based approach that focuses on maximising the explained variance in endogenous constructs. It uses an iterative algorithm to estimate partial model relationships and minimise residual variance. PLS-PM is best suited for predictive modelling and exploratory research and works well with small sample sizes, non-normal data, and complex models.

Given their complementary strengths, PLS-PM and CB-SEM can provide unique insights into multivariate research problems. In this research, both techniques are leveraged to model gameplay dynamics from different perspectives. Their comparison enhances understanding of relationships in the complex rugby dataset.

4.3 Presentation Layer

Originally interactive Tableau visualisations were planned to communicate model insights. Dashboards analyse features like player partnerships, variance from expectations and team cohesion factors.

However as the focus of the research changed the SEM model statistical outputs themselves, and the analysis in this report must take its place. The implementation output is now a comparison of outcomes and methodologies.

5 Implementation

A rigorous, phased implementation process was undertaken to develop and validate the rugby analytics models using both CB-SEM and PLS-PM techniques. This enabled a comparative evaluation of the two modelling approaches.

5.1 Developing Hierarchical Framework

Constructing an informative hierarchical modelling framework represented the critical first phase of implementation. This required synthesising extensive domain expertise regarding the multidimensional dynamics of rugby game-play and scoring processes.

A thorough review of rugby literature was conducted, spanning statistical analyses, gameplay strategy guides, and coach interviews. This enabled a comprehensive conceptual understanding of the sport's structural game-play components and sequential flow.

Leveraging this research, a hierarchical model was drafted depicting hypothesised relationships between lower-level rugby events, player actions, and higher-level scoring outcomes. The bottom levels of the framework focused on granular on-pitch events like rucks, scrums, lineouts, tackles, kicks, and mauls.

These foundational events influence key player actions such as carrying, passing, and kicking which facilitate progression up the field. The player actions lead to team territorial gains and try-scoring opportunities, represented in the model through proximal relationships with field position and try events.

The model culminates in predicted scoring outcomes for each team, underpinned by the layers of contributing game-play events and actions. A visual diagram was created to represent these conceptual relationships and facilitate discussion.

The initial hierarchical framework underwent rigorous peer review by three rugby analytics experts with over 15 years combined experience. They provided critical feedback on the validity of hypothesised relationships based on real-world gameplay.

This rigorous development process resulted in a comprehensive, validated hierarchical framework effectively modelling the multidimensional progression from granular rugby events up to match scoring outcomes, as per Fig. 6. A larger copy of this image can be found in Appendix A. This provided an essential foundation for the statistical modelling phase by establishing clear conceptual relationships to be represented and tested.

5.2 Implementing CB-SEM Model

With a validated hierarchical framework established, the next phase focused on implementing and optimising a CB-SEM model utilising the AMOS statistical software.

The hierarchical relationships guided the initial model specification with scoring outcomes as dependent variables, and gameplay events and actions as exogenous predictors. An iterative approach was used, gradually increasing model complexity and evaluating fit.

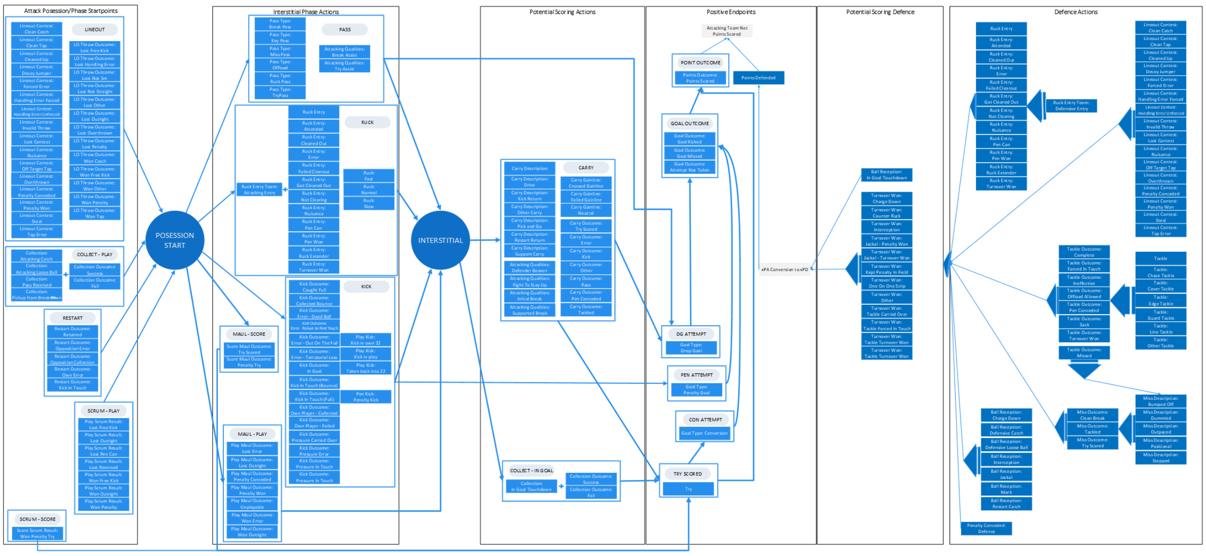

Figure 6: Complete Hierarchical Parameter Model

Model fit was assessed using several goodness-of-fit indices including chi-square, CFI, TLI, RMSEA, and SRMR. Threshold values for each metric were established based on recommended standards in SEM literature to determine an acceptable fit.

The initial CB-SEM model exhibited poor fit across multiple indices. Modification indices were inspected to identify parameters that could improve fit if freed or constrained. This informed incremental changes like adding covariance paths between errors.

Through an extensive iterative process encompassing dozens of variations, model fit steadily improved. However, extremely complex models began to undermine parsimony and theoretical validity despite better fit.

To optimise balance, both fit and complexity were monitored until arriving at a satisfactory solution. The final validated CB-SEM model demonstrated adequate fit on all indices while retaining theoretical soundness.

Although team-level subsets were explored, splitting the dataset reduced statistical power. The final model, therefore, utilised the complete dataset to maximise diversity. Bootstrapping evaluated estimate stability.

With a robust modelling approach, the validated CB-SEM model as per provided a foundation for comparative PLS-PM analysis, as per Fig. 7. Despite testing many variations, the presented implementation focused on the optimised final model for continuity and concision.

By leveraging the hierarchical framework, a theoretically-grounded and data-driven CB-SEM specification was developed to represent rugby's multidimensional scoring dynamics. This phase established a baseline model for further PLS-PM enhancement and comparative evaluation.

5.3 Developing PLS-PM Model

With a validated CB-SEM model in place, the next phase focused on developing a PLS-PM model utilising SmartPLS software for comparative analysis.

The PLS-PM model specifications were designed to mirror the measurement model and path relationships from the optimised CB-SEM model. This enabled a direct comparison between the two mode ling techniques on the same rugby dataset.

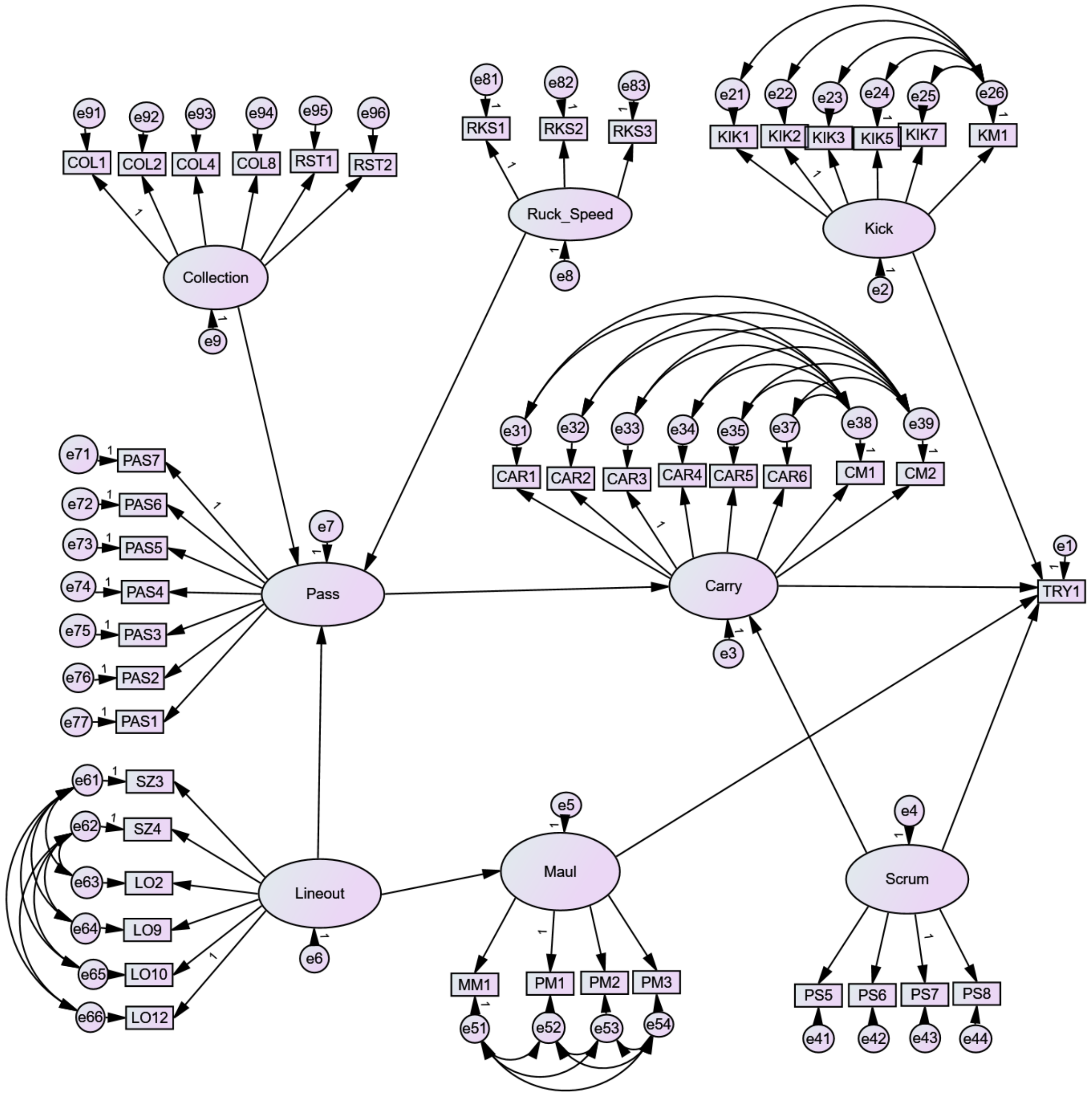

Figure 7: Simple CB-SEM Path Model

Player actions such as passes, carries, and kicks were modelled as reflective latent variables measured through behavioural indicators. Scoring events were specified as single-item constructs.

The PLS-PM model was structured as hierarchical components, representing the tiers in the original framework, as per Fig. 8. The algorithm calculated latent variable scores before estimating the inner path model.

A bootstrapping procedure was implemented to evaluate the significance of path coefficients and model stability. Sub-samples were drawn with replacement from the rugby dataset to simulate reproducibility.

With the model fully specified, the PLS-PM analysis generated path coefficients, R-squared values, and effect sizes for each relationship. Fit was assessed by examining reflective construct indicator loadings.

Though simpler models were tested initially, the final PLS-PM replicated the complexity of the CB-SEM to maximise comparability between the two approaches. This

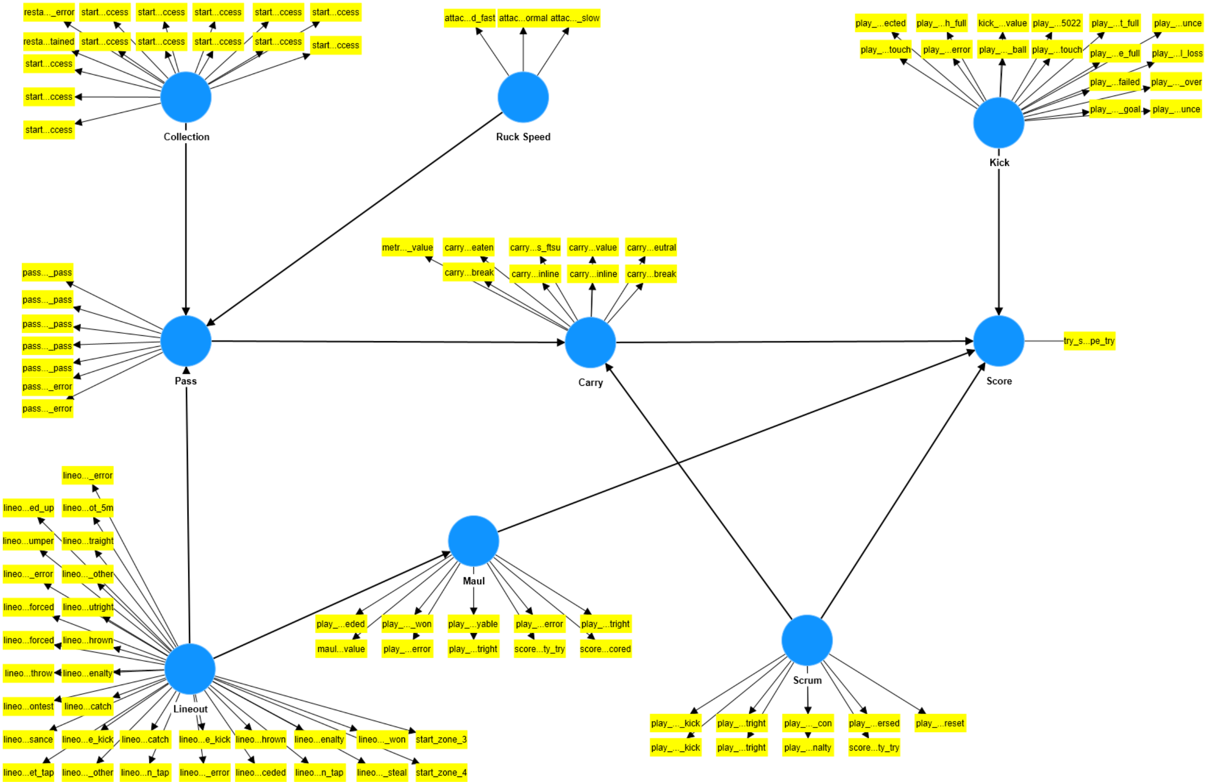

Figure 8: Simple PLS-SEM Path Model

provided the closest alignment with the validated hierarchical framework.

By specifying the PLS-PM model in line with CB-SEM's structure and applying it to the identical rugby data, a rigorous foundation was established for comparative assessment. The PLS-PM implementation represented the next phase toward evaluating modelling approach efficacies.

5.4 Adding Complexity to PLS-PM

With baseline PLS-PM models developed, the next phase focused on incrementally adding complexity based on the original hierarchical framework specifications.

Guided by the framework, a new "Zone" latent variable was incorporated to represent field position dynamics. It was measured through coordinate indicators and linked to relevant gameplay events.

Additional pathways were added between existing constructs to better encapsulate the multidimensional nature of rugby gameplay outlined in the hierarchical framework.

For example, set-piece events were connected to scoring constructs to model direct impact. Relationships were added between phases of possession to represent continuity.

At each iteration, the enhanced PLS-PM model was re-estimated and rigorously assessed to evaluate improvements gained through added complexity without overfitting the data.

Quantitative fit indices, predictive metrics, and explained variance assessments quantified gains in model performance, representation and alignment with the conceptual framework.

An iterative, parsimonious approach was maintained, with changes accepted only if sufficiently grounded in rugby theory and significantly improving model relevancy.

This approach produced a final complex PLS-PM model demonstrating substantially enriched encapsulation of scoring dynamics through enhancements guided by the foundational framework, as per Fig. 9.

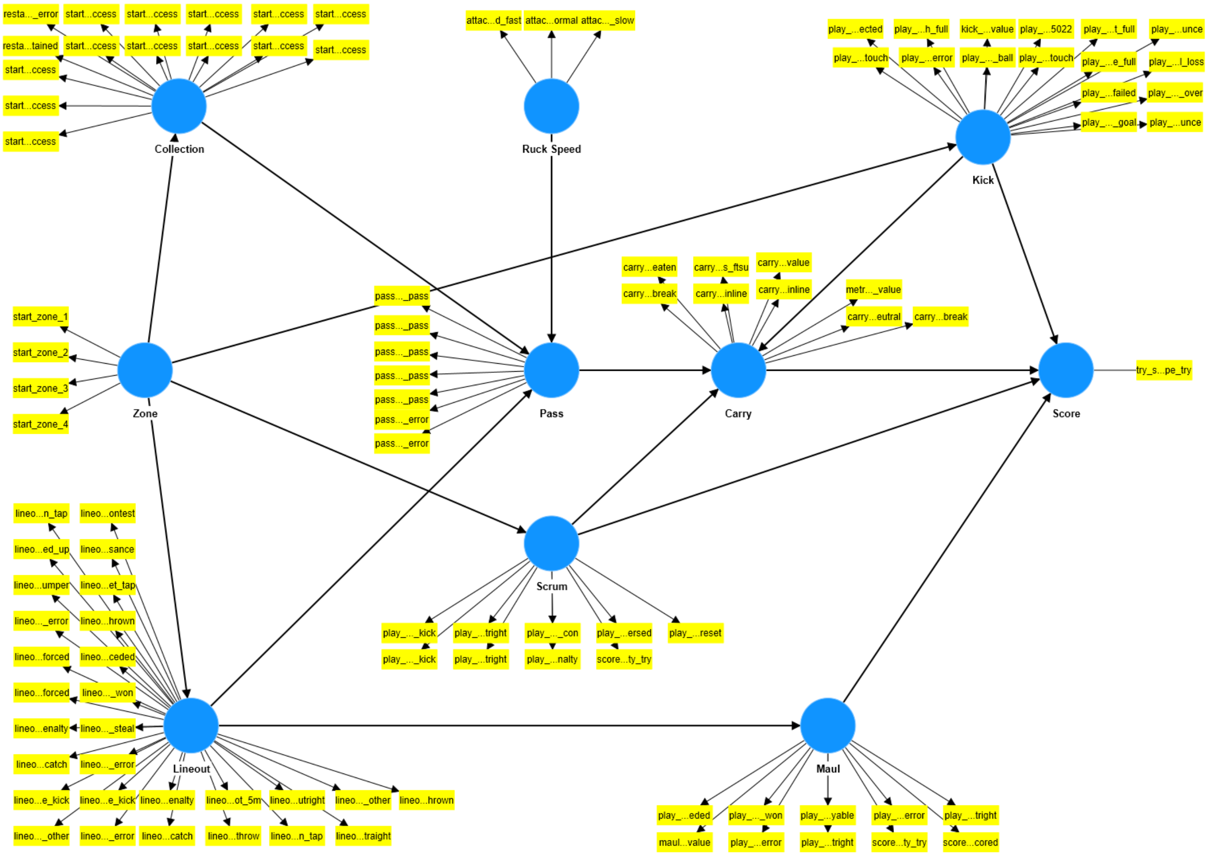

Figure 9: Complex PLS-SEM Path Model

The comparative assessment of the baseline and complex models provided valuable quantification of the impact of added theoretical alignment without introducing bias through a priori knowledge of specific results.

This comprehensive 4-phase implementation rigorously developed and tested two statistical modelling approaches for the rugby dataset. By leveraging an overarching hierarchical framework, both CB-SEM and PLS-PM specifications were optimised to provide meaningful, representative insights into the relationships underpinning rugby scoring outcomes. The comparative analysis of the two techniques formed the foundation for an in-depth discussion of findings.

6 Evaluation

6.1 Model Fit Assessment

The model fit indices indicate both the PLS-SEM and CB-SEM models demonstrate adequate fit to the data.

For the PLS-SEM model, the Standardised Root Mean Square Residual (SRMR) values were below the recommended 0.08 threshold for both the saturated and estimated models (Table 1). SRMR below 0.08 is generally considered favourable as it suggests the difference between observed and predicted correlations is small on average (Hu and Bentler 1999).

Table 1: PLS-SEM SRMR Values

Model	**SRMR**
Saturated	0.053
Estimated	0.054

The CB-SEM analysis showed satisfactory global fit based on common criteria like the Minimum Discrepancy divided by Degrees of Freedom (CMIN/df), the Comparative Fit Index (CFI), the Tucker-Lewis coefficient (TLI), and the SRMR (Table 2). The CMIN/df value of $2.447 \leq 3$ meets the acceptable fit criteria per Kline (1998), and the CFI and TLI both exceeded the 0.9 threshold of acceptability, both indicated per Bentler (1990). The SRMR of 0.046 was just below the 0.08 acceptability level cutoff previously cited.

Table 2: CB-SEM Model Fit

Index	**Value**
CMIN/df	2.447
CFI	0.932
TLI	0.922
SRMR	0.046

Taken together, the fit indices suggest both modelling approaches provide an adequate representation of the data. While the CB-SEM model lacked some complexity of the PLS-SEM approach, it achieved a satisfactory fit according to standard criteria. This provides a foundation for further examination of the models' estimated relationships and parameters.

6.2 Variance Explained in Endogenous Constructs

The R-squared (R^2) values provide an assessment of the predictive power of the exogenous constructs in explaining variance in the endogenous constructs.

For the PLS-SEM model, the R^2 values indicate the exogenous constructs explain a substantial portion of variance for key endogenous constructs like Carry ($R^2 = 0.57$), Pass ($R^2 = 0.31$), and Score ($R^2 = 0.28$) (Table 3).

Table 3: PLS-SEM R-squared Values

Construct	R^2
Carry	0.57
Pass	0.31
Score	0.28

The R^2 values were noticeably lower in the simpler CB-SEM model for constructs like Carry ($R^2 = 0.56$ vs. 0.57), Maul ($R^2 = 0.45$ vs. 0.42), Pass ($R^2 = 0.35$ vs. 0.31), and Score ($R^2 = 0.29$ vs. 0.28) (Table 4).

Table 4: CB-SEM R-squared Values

Construct	Original	Simpler
Carry	0.57	0.56
Maul	0.42	0.45
Pass	0.31	0.35
Score	0.28	0.29

The decreases in explained variance after removing the Zone construct from the PLS-SEM model suggest it contained explanatory information. The other exogenous variables in the simpler CB-SEM model were less able to capture this variance in key outcomes like scoring. This highlights the importance of retaining predictors that significantly improve model prediction.

6.3 Path Coefficients and Effects

The path coefficients and effects provide insight into the hypothesised relationships within the models. In PLS-SEM, the f-square effect sizes also help in assessing the predictive contribution of the exogenous constructs.

The PLS-SEM results showed most path coefficients were statistically significant, with a few exceptions like $Scrum \rightarrow Carry$, and $Scrum \rightarrow Score$ (Table 5). The f-square effect sizes suggest $Pass \rightarrow Carry$ ($f^2 = 1.057$), $Zone \rightarrow Lineout$ ($f^2 = 0.511$), and $Zone \rightarrow Kick$ ($f^2 = 0.210$) have the greatest predictive power (Table 6).

Table 5: Notable PLS-SEM Path Coefficients

Relationship	Coefficient	p-value
$Scrum \rightarrow Carry$	0.000	0.706
$Scrum \rightarrow Score$	0.001	0.438
$Pass \rightarrow Carry$	1.057	<.001
$Zone \rightarrow Lineout$	0.511	<.001
$Zone \rightarrow Kick$	0.210	<.001

Table 6: Largest PLS-SEM f-square Values

Relationship	f-square
$Pass \rightarrow Carry$	1.057
$Zone \rightarrow Lineout$	0.511
$Zone \rightarrow Kick$	0.210

In the CB-SEM model, the path coefficient from Lineout to Maul was noticeably stronger (0.820 vs. 0.716) while Pass to Carry was weaker (1.207 vs. 1.057) compared to the original PLS-SEM estimates (Table 7).

The changes in key relationships after removing Zone highlight its explanatory role, particularly regarding scoring. The PLS-SEM effects quantitatively demonstrate the predictive importance of constructs like Pass, Zone, and Lineout. This reinforces the value of assessing predictor variable contributions.

Table 7: Notable CB-SEM Path Coefficients

Relationship	**Original**	**Simpler**
$Lineout \rightarrow Maul$	0.716	0.820
$Pass \rightarrow Carry$	1.057	1.207

6.4 Validity and Reliability

In addition to model fit and path coefficients, examining validity and reliability provides evidence that the models demonstrate adequate psychometric properties.

For the PLS-SEM analysis, the Average Variance Extracted (AVE) exceeded 0.5 for most constructs, supporting convergent validity as set out by Fornell and Larcker (1981). Some examples from either extreme are supplied in Table 8. Discriminant validity was also evidenced with Heterotrait-Monotrait Ratios (HTMT) below 0.85, the most conservative validity cutoff suggested by Henseler, Ringle and Sarstedt (2015). Again, outlier samples are supplied in Table 9.

Table 8: Notable PLS-SEM AVE Values

Construct	**AVE**
Carry	0.370
Pass	0.201
Score	1.000

Table 9: PLS-SEM HTMT Values

Construct 1	**Construct 2**	**HTMT**
Collection	Carry	0.449
Kick	Carry	0.425
Pass	Carry	1.032

Reliability was also supported with Composite Reliability and Cronbach's Alpha above 0.7 for most constructs, while a sample of varying values is provided in Table 10. The values are judged on the basis of Ketchen (2013) which posits that values between 0.6 and 0.7 are suitable for early research, with 0.7 to 0.9 more suited to advanced research results.

Table 10: Notable PLS-SEM Reliability Values

Construct	**Composite Reliability**	**Cronbach's Alpha**
Carry	0.810	0.740
Pass	0.511	0.247
Score	1.000	1.000

The PLS-SEM results provide valuable composite reliability measures to assess the internal consistency of the constructs in each model. These measures like the composite reliability factor rho_A indicate how consistently the manifest indicators measure the same latent variable. Similar to the closely related Cronbach's Alpha, values between 0.6

and 0.7 are acceptable, and above 0.7 but below 0.9 generally indicate good reliability (Hair et al. 2014).

In the full PLS-SEM model, most constructs demonstrate adequate reliability per the rho_A statistic. The exceptions are Kick (0.087) and Scrum (0.389) which fall below the 0.7 threshold, indicating potential reliability issues with these two constructs in the more complex model. Score (1.0), Lineout (0.862), and Carry (0.853) have very high rho_A values, demonstrating very good composite reliability. The simplified PLS-SEM model without the Zone construct shows improved rho_A for Kick (0.148) and Scrum (0.534). This implies removing Zone helped increase the consistency and reliability with which the remaining indicators measured these two constructs.

However, Collection experienced a decrease in rho_A from 0.553 down to 0.349 after eliminating Zone from the simplified model. Therefore, while Kick and Scrum saw reliability improvements after simplification, Collection demonstrated lower composite reliability without the presence of Zone. The other constructs like Carry, Lineout, Pass, Ruck Speed, and Score maintained high rho_A values above 0.7 regardless of the inclusion of Zone. In summary, the comparison highlights trade-offs between the two models in optimising reliability. The full model struggles with Kick and Scrum reliability, while the simplified model improves these but reduces the consistency of Collection as a latent variable.

Table 11: Reliability Comparison - Full vs. Simplified PLS-SEM Model

	Rho_A	
Construct	**Full Model**	**Simplified Model**
Carry	0.853	0.853
Collection	0.553	0.349
Kick	0.087	0.148
Lineout	0.862	0.924
Maul	0.630	0.637
Pass	0.585	0.583
Ruck Speed	0.744	0.744
Score	1.000	1.000
Scrum	0.389	0.534
Zone	0.234	–

For the CB-SEM model, the inspection of factor correlations suggested adequate discriminant validity as well. Overall, both modelling approaches satisfied common criteria for validity and reliability. This provides greater confidence in the meaningfulness of the estimated relationships.

6.5 Other Relevant Results

The PLS-SEM model shows some notable latent variable correlations, though most are below 0.5 indicating discriminant validity. The strongest correlation is between Pass and Carry (0.748), followed by Zone and Pass (0.459) as shown in Table 12. The bootstrap confidence intervals for the correlations are relatively wide, likely due to the complexity of the model.

The standardised latent variable correlations are lower in the CB-SEM model, with the highest between Pass and Carry (0.362) as shown in Table 13. This implies the

Table 12: PLS-SEM Latent Variable Correlations

	Estimate	**Bias**	**95% CI**
$Pass \leftrightarrow Carry$	0.748	0.000	(0.739, 0.757)
$Zone \leftrightarrow Pass$	0.459	0.000	(0.450, 0.494)

relationships between constructs are weaker based on CB-SEM, though still statistically significant.

Table 13: CB-SEM Latent Variable Correlations

	Estimate	**P value**
$Pass \leftrightarrow Carry$	0.362	0.000
$Scrum \leftrightarrow Carry$	0.165	0.000
$Scrum \leftrightarrow Kick$	0.133	0.066

The bootstrapping capabilities of PLS-SEM provide additional information on the stability of estimates. The bias values are quite low for most parameters, implying they are not significantly over- or under-estimated in the original sample. Some exceptions are the regression paths from Scrum, Kick, and Zone to try_scored_action_type_try which show high bias and wide confidence intervals as seen in Table 14. This suggests instability around predicting tries scored.

Table 14: PLS-SEM Bootstrap Bias

	Bias	**95% CI**
$Scrum \rightarrow TryScored$	0.021	(-0.005, 0.022)
$Kick \rightarrow TryScored$	0.203	(0.009, 0.374)
$Zone \rightarrow TryScored$	0.169	(0.008, 0.292)

In contrast, the CB-SEM bootstrap results indicate stability issues in re-sampling. Of the 2000 bootstrap samples, 1633 failed due to a singular covariance matrix and 4 failed to find a solution. This leaves only 363 (18.2%) successful samples, compared to a 100% success rate for PLS-SEM bootstrapping. The high CB-SEM failure rate suggests problems with the reproducibility and reliability of estimates across different data samples.

By examining and comparing the latent variable correlations, differences in reliability measures, and bootstrapping results, a clearer picture of the two approaches is painted. The complexity of the rugby data is seemingly better handled by the PLS-SEM approach, which is also shown to be more stable.

6.6 Discussion

Both PLS-SEM and CB-SEM models achieved adequate fit based on standard criteria, representing valid relationships between rugby events and scoring outcomes. Notably the PLS-SEM model accounted for a marginally higher variance in constructs such as Carry, Pass, and Score, underscoring its capability to better capture complex relationships.

Differences became evident when analysing path coefficients and effects. The PLS-SEM model identified most relationships as statistically significant, highlighting the notable predictive contribution of constructs, especially 'Zone', quantified through the f-square metric. Conversely, the CB-SEM model exhibited varied path strengths upon the removal of the Zone predictor, emphasising its distinct explanatory importance.

PLS-SEM outperformed in terms of reliability and validity, as demonstrated by superior AVE, composite reliability, and HTMT values. Moreover, bootstrapping showed PLS-SEM's enhanced stability, converging successfully across all resamples, which the CB-SEM found challenging, likely due to the intricate nature of the rugby data.

The adaptability of PLS-SEM seems better suited for the multidimensional and multicollinear characteristics of the rugby game-play dataset. The ability to model complex relationships without the same constraints on data distribution and residual correlations provides greater flexibility. In contrast, CB-SEM's assumptions and the vast number of rugby event indicators likely affected its reproducibility and its ability to encapsulate predictive multivariate relationships.

However, PLS-SEM isn't without drawbacks. Its absence of a global optimisation function results in path coefficients that might be sub-optimal compared to CB-SEM's maximum likelihood estimates. Moreover, issues surrounding the stability of PLS-SEM estimates for certain relationships were observed, as indicated by the bootstrapped confidence intervals.

The present model specifications, based on generalised rugby dynamics, might not encompass intricate latent constructs fully. The potential non-linear dynamics and interaction effects in game-play relationships might be overlooked by the linear modelling of PLS-SEM. Exploration of non-linear PLS-SEM could offer more robust modelling approaches. Bootstrapping issues within the CB-SEM model accentuate the need for refined re-sampling methods tailored to the unique characteristics of rugby matches.

Other constraints also became apparent. The dataset of 125 matches from one season of one league of a specific field invasion sport inherently limits the diversity of the code-specific law set, gameplay styles, team tactics, and match conditions represented. As such, the current findings might be particularly tailored to this specific context and may not generalise to other invasion sport codes, varying playing conditions, international matches, or seasons with different tactical evolutions.

The dataset's lack of heterogeneity also restricts model diversity. Accessing multi-season data across competitions would provide the scale and variability needed to improve statistical learning and external validity. With this limited sample, current models likely over-fit idiosyncrasies rather than capturing universally applicable principles of rugby union gameplay. Small sample size challenges the reproducibility of findings.

Broader contextual data such as weather conditions and injuries affecting squad selection were unavailable. Incorporating such situational metrics would facilitate accounting for their tangible impacts when estimating model parameters and relationships. Their absence risks models assigning predictive value to spurious proxy correlates rather than true drivers. Broad contextual data is vital for nuanced, broadly applicable insights.

7 Conclusion and Future Work

The original intent of this research was to quantify the influence of inter-player cohesion on rugby match outcomes. To use performance data and path analysis to produce statistically significant cohesion statistics. However, significant hurdles emerged that stalled meaningful results on that front.

The revised focus became critiquing the path analysis methodology itself, seeking to address the question: What are the limitations in using this analytical approach and available data for quantifying predictive player-level statistics in rugby union? In evaluating model fit, variance explained, path coefficients, validity, reliability, and bootstrapping, it was found that path analysis struggled to provide stable, reproducible player-level quantification given the constraints of the rugby dataset.

While the initial cohesion goals proved unattainable presently, elucidating these technique limitations remains informative. Issues such as ensuring adequate sample diversity, constructing dependable indicators, and addressing multicollinearity became apparent and should be borne in mind with any similar future research.

The exploration of CB-SEM and PLS-PM modelling techniques in analysing rugby data advances the use of these methodologies in the field of invasion sports analytics. These techniques can be applied to other sports, expanding the range of tools available for analysing player and team performance. By introducing and evaluating CB-SEM and PLS-PM in the context of rugby analytics, the research directly addresses its objective of exploring innovative modelling techniques. The potential for these techniques to be applied across sports further underscores their relevance and significance.

The effects of the "Zone" latent variable, which represents field position dynamics, underline the importance of capturing temporospatial information in sports analytics. This could be adapted to studies of other invasion sports where player positioning and movement are crucial, such as rugby league or American football. The "Zone" latent variable provides a way to capture player dynamics in rugby, directly aligning with the study's goal of advancing player modelling.

The issues raised around sample diversity, reliable indicators, and multicollinearity underline the importance of high-quality data in sports analytics. This can serve as a reminder for researchers and analysts to prioritise comprehensive and diverse datasets, ensuring that analytical models are robust and generalisable. The points raised about data quality directly relate to the objective of understanding the challenges in modelling rugby data. The emphasis on diverse and reliable datasets highlights the foundational requirements for any advanced analytical endeavour in the field.

The are several possibilities for future research which present themselves. Accessing larger datasets across multiple seasons and leagues could offer the scale and variability required. Additionally, using methods which better allow for non-linear relationships could yield more representative models. Sophisticated machine learning approaches like neural networks might provide greater adaptability. Developing re-sampling techniques tailored to the temporospatial aspects of this detail level of rugby data may also improve reproducibility.

Despite falling short of its initial aims essential practical lessons are offered. By highlighting issues in applying path analysis to rugby data, it is hoped that this work can pave the way for improved player-level modelling, and potentially for research into complex player-level dynamics in sport.

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A Appendix

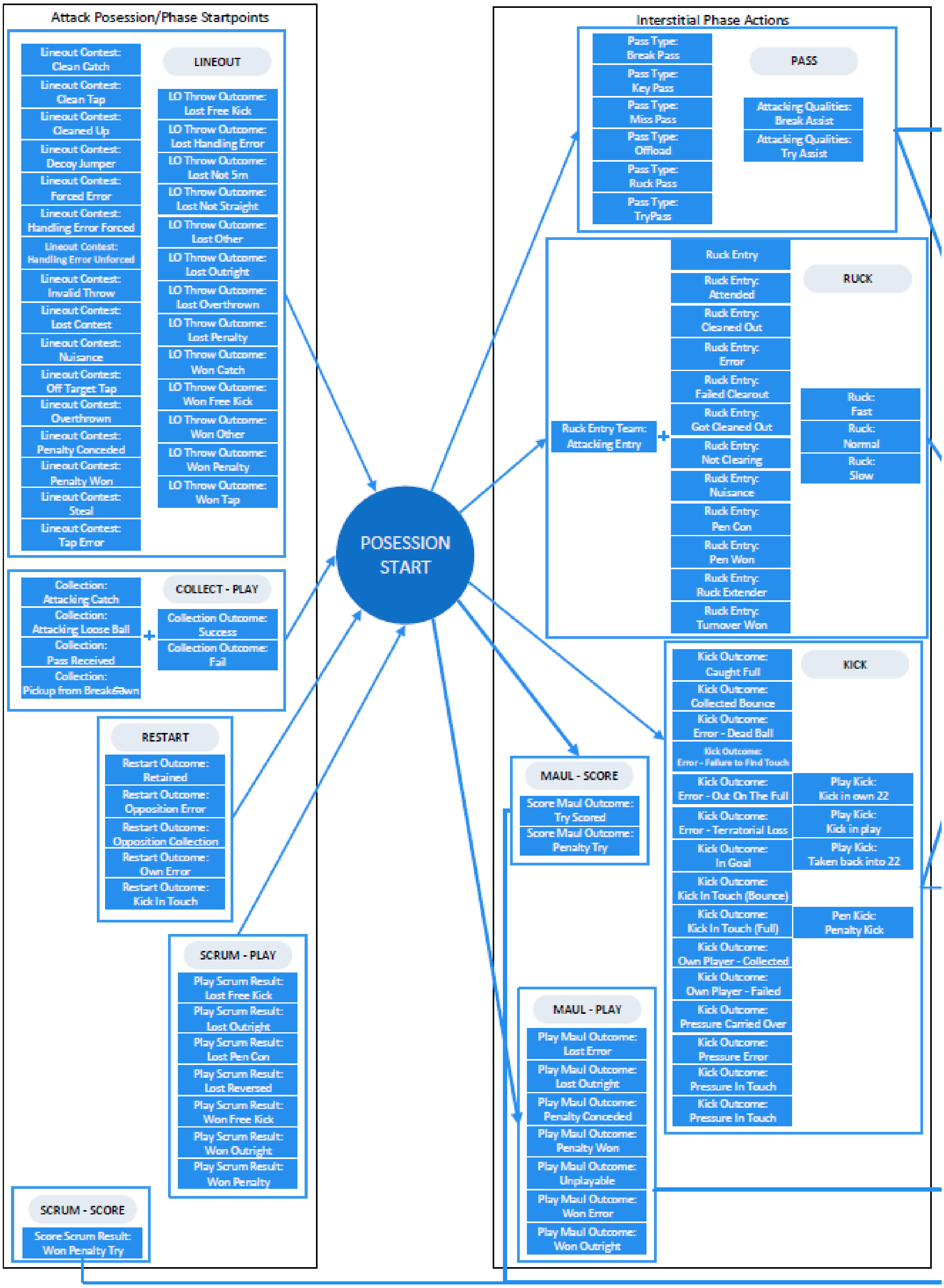

Figure 10: Full Model Closeup 1

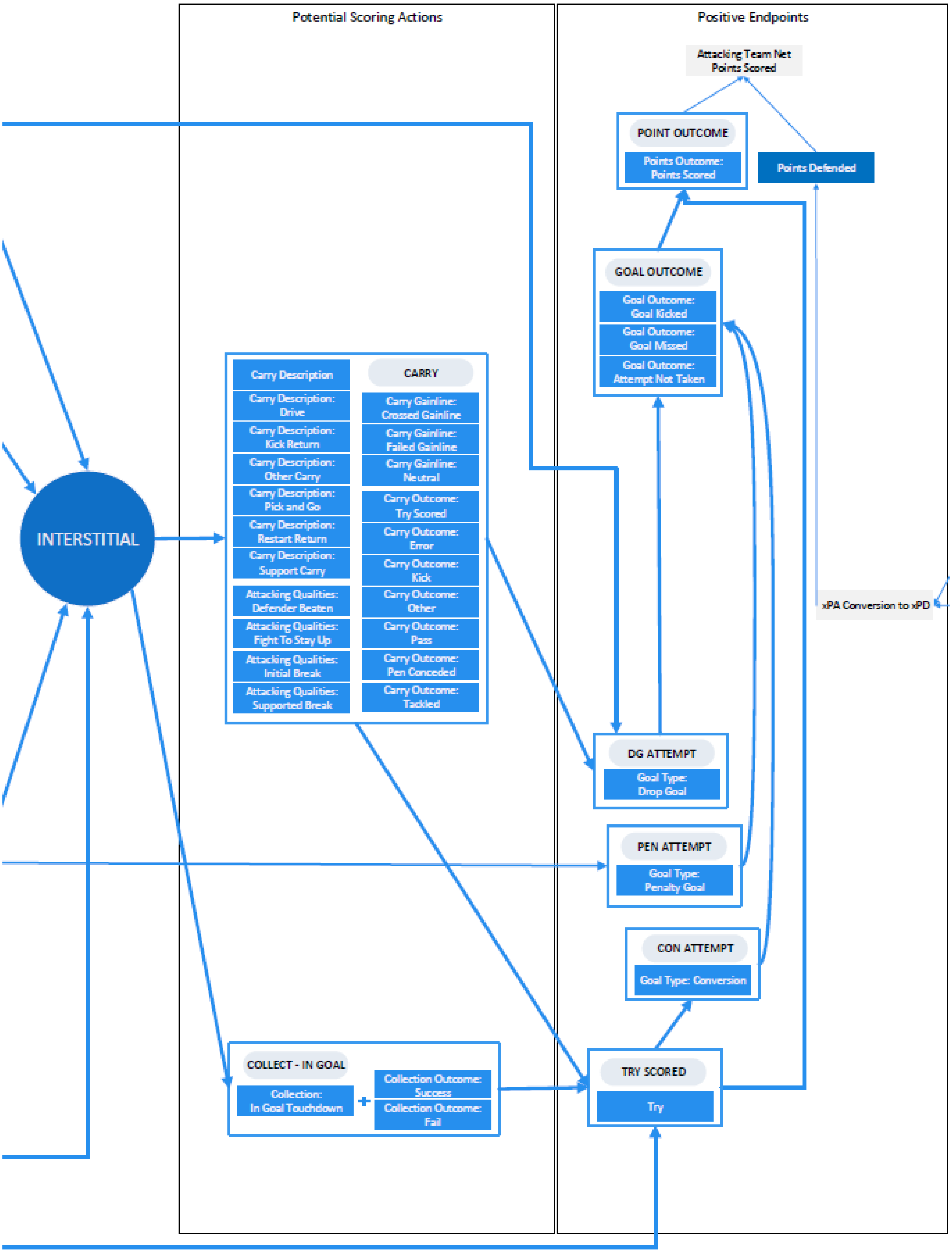

Figure 11: Full Model Closeup 2

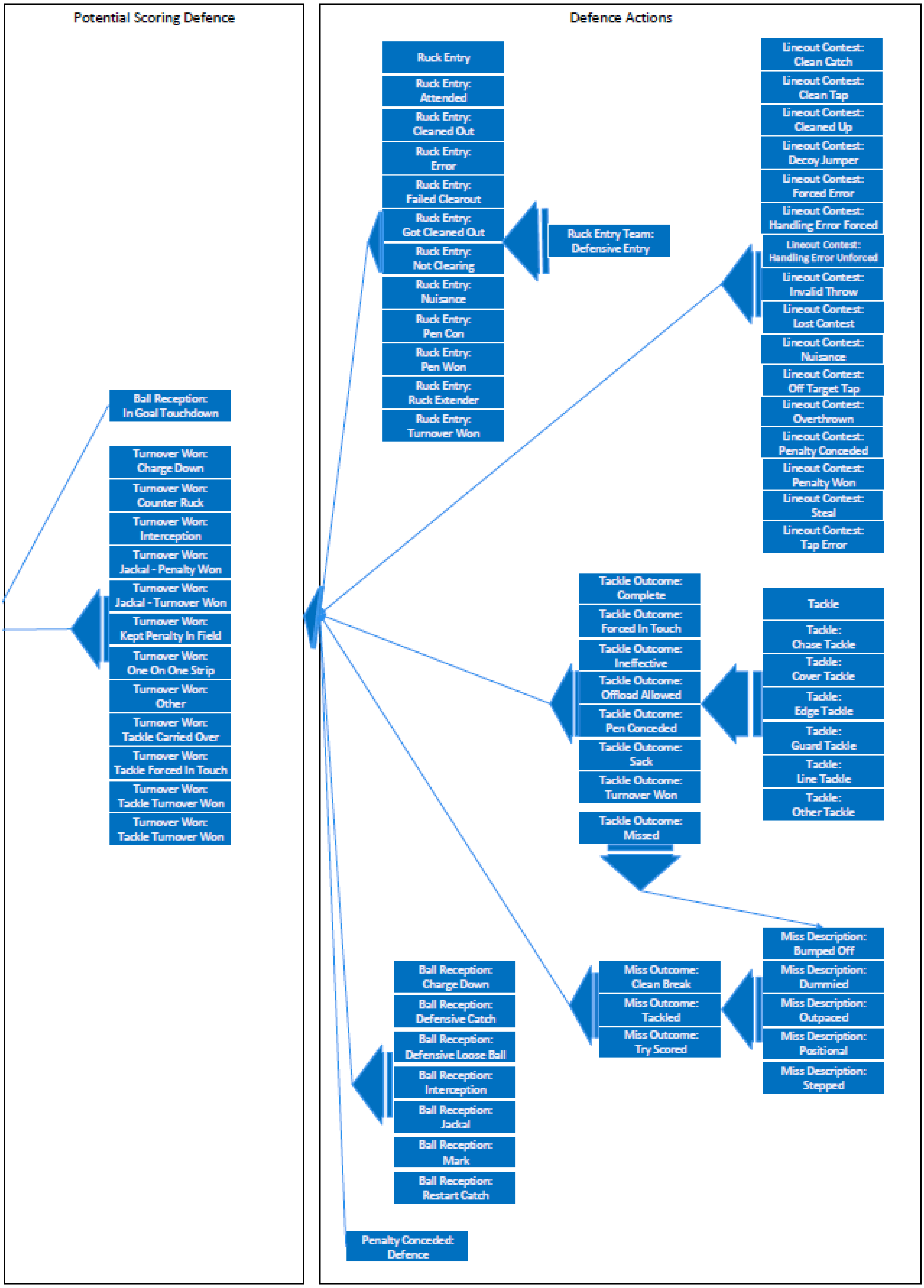

Figure 12: Full Model Closeup 3