Multivariate Performance Metrics and Positional Analysis in Elite Soccer: Insights from New Zealand Player Data

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1. Abstract

Motivated by the need to enhance player performance analysis in sports, this research is aimed to analyse athlete performance data and derive insights from various performance metrices to make careful decisions for training strategies. Using the datasets of player metrices, quantification of various physical and technical aspects by 'player' and 'position' is done using SAS and Python by employing techniques like descriptive statistics, linear regression and ANOVA test. Finding revealed that 'Luca Bordignon' and 'Ned Thompson' performed exceptionally good while Player 10 was week performer. Moreover, Midfielder and defender position is highly demanding. Future steps might involve more injury risk analysis and extensive data collection to include various age groups, enabling more comprehensive performance comparisons by using advanced analysis techniques like machine learning.

2. Introduction

Soccer is physically demanding sport in which competitors cover 9.7-13.7 km every match and undertake high -intensity accelerations and decelerations every 45-90 seconds [2]. Aside from the physical challenges, soccer players perform a variety of technical and physical activities such as passing, crossing, running and shooting at goal. Repetition of these actions might result in overuse injuries, putting a burden on teams and society. Soccer has second highest number of ACC claims in New Zealand, with nearly 40,000 new sports injury claims in 2022 [3]. Previously, only basic player tracking metrices could be used to determine the physical actions of soccer training load. Recent advancement in wearable sports technology, on the other hand, have enabled sports teams to collect data associated with both physical and technical actions. Despite of these advances, little is known about quantification of these physical and technical performance metrices. As a result, being able to quantify the frequency and amplitude of running efforts along with passes, crosses and shots with each leg within a training environment may help to get critical information about the neuromuscular demands of these players at each level.

This research is important because it helps to understand soccer training better in terms of quantification of performance metrices. The findings of this research will help coaches in decision making regarding training loads. By enhancing coach's decision making around different actions, the tactical capabilities of the athletes in national and international matches may be increased. Descriptive analysis is particularly used for this study. In addition to it, some other techniques like ANOVA test and linear regression are used to make comparison among various performance metrices. The following sections of the report will provide a detailed exploration of methodology, results and implications arising from this study.

3. Literature

3.1 Existing Research

The study seeks to contribute to the growing field of soccer analytics by examining various aspects of performance metrices and positional analysis. This literature review critically examines existing research on soccer player performance analysis.

A study 'Quantifying and comparing training load' [4] aimed to quantify and compare the training load of professional players by using local positioning measurement systems to analyse some physical actions. This study concluded the reduction in training load as match approaches. The findings shed light on the importance of load management for different player categories and position-specific training. 'Monitoring technical actions' [5] is another study which checked the reliability of foot-mounted inertial measurement unit (IMUs) for monitoring technical actions in soccer players. The study identified differences in technical actions within Macrocycles, among playing positions, and across different drill categories. The findings highlight the suitability of IMUs for tracking technical aspects of performance and reveal that training sessions become more technical as matches approaches.

'Quantifying volume and high- speed technical actions of professional soccer players using IMU's' [6] explores the validity and reliability of IMU's to measure the volume and speed of technical actions in professional soccer players. The study highlights that fixture proximity and drill categories influence the frequency and intensity of technical actions. It emphasizes the importance of considering both volume and speed of technical actions when designing training program. One study under title 'training load in English premier league' [7] focused on quantifying the training load of professional soccer players in the English Premier League. Data was collected through GPS, heart rate, and rating perceived exertion measures. The findings provide insights into how training load varies across season.

Research titled as 'training load monitoring in high level football' [8] involved 41 professional players and revealed that key points of training load monitoring practices. It highlighted the widespread use of GPS and heart-rate monitors but also challenges in understanding the performance enhancement. These results highlight the importance of working better with coaches and overcoming obstacles to make training load monitoring more effective. Another important study which involved 26 footballers from French 5th division team who underwent a 9-week training intervention, is 'Acute responses to wearable resistance in soccer training' [9]. This study aimed to investigate the use of wearable resistance for soccer-specific training and it analysed locomotor, internal load, and neuromuscular responses in players using wearable resistance. The study found that when using wearable resistance during full training sessions, the group with resistance did more running, sprints, and physical work compared to the group without resistance. This suggests that wearable resistance can be a good way to improve how players move during soccer training without causing big changes in the muscle responses. But it is still needed to do more research to understand how this might affect performance in the long run.

'Drill distribution and technical characteristics in female soccer' [10] research had purpose to understand how different soccer training exercises for female players vary in terms of how they affect running and technical skills. It looked at data from 458 female soccer players over 28 weeks, using IMUs to collect technical and locomotor data. It discovered that most of the training time was spent on drills that focus on skills and small-sided games. Technical drills resulted in the highest number of touches, release, total distance, and high-speed activity which were lowest for position-specific drills. This study also found that some drills took longer and had more actions per minute compared to others. This study is useful for coaches and those planning training sessions for female soccer players because it helps them top design more efficient and effective training programs. One more study with title 'validity and Reliability of foot-mounted inertial measurement units (F-IMUs)' [11] concurrent validity and between-unit reliability of IMU's were investigated during running drills. Sixteen participants performed running drills while wearing F-IMU's sensors for comparison to a 3d motion capture system. The study found that the foot-mounted sensors worked well in measuring speed and very reliable when comparing different units. But, when things got superfast, the F-IMU's did not match the 3D capture system so closely. So, the study recommends that F-IMU's can be used to track speed and movements in team sports. However, it is important to be careful when looking at really fast movements because the F-IMU might not give exact speed.

3.2 Research methods and challenges

The above studies employ a mix of technological tools like GPS, IMU etc to collect the data which in line with this research which shows the increasing reliance on the technology to measure performance metrices accurately. The challenge of data integration and interpretation is common. While technology can provide extensive data, the ability to translate these metrices into actionable insights for coaches remains a challenge. Many of these studies use statistical analysis to derive meaningful conclusions which indicates the importance of quantitative approaches to understand performance metrices.

3.3 Relevant Gap

Although existing research provide deep knowledge about Soccer, but several areas need further research. Only few studies consider multivariate performance metrices, which can offer more insights about player performance. Moreover, there is need for research focussing on the practical application of data-driven insights for coaching and training. Many studies identify metrices, but do not explain deeply into how this information is used to enhance player performance. Also, previous studies took into account technical actions, but not the physical actions performed by soccer players in the match. This research is contributing to bridge gap in the existing research especially in the context of multivariate performance metrices because the dataset used for this research includes more than 150 features associated with performance. Also, it focuses on the physical actions in addition to the technical actions which is also helpful in covering the gap.

4. Research Objectives and Scope

The whole research is divided into three parts which are in the form of research objectives. The aim of this research is to

1.To quantify the physical and technical actions (Multivariate analysis) of youth New Zealand professional Soccer players by grouping them according to player name.

2. To quantify the physical and technical actions (Multivariate analysis) of youth New Zealand professional Soccer players by grouping them according to player position.

3. To run Linear Regression Model to check dependency of features on one another.

The aim of this research is to bridge gap in the previous studies on the Soccer sport which was linked with multivariate analysis and inclusion of physical actions along with the technical actions. The scope of this research is focused on enhancing player performance analysis in context of soccer by analysing the player performance data and develop deep understanding from various performance metrices. It aims to provide an understanding of physical and technical aspects of the player performance and it concentrates on the youth New Zealand professional Soccer players. It involves the quantification of physical and technical aspects using multivariate descriptive analysis. The study contributes to the field of soccer analytics by providing valuable insights into player performance metrices.

5. Methodology

In this section, methods used to do the whole research are explained which underpins the analysis and findings presented in this report. The methodology includes several crucial steps:

5.1 Data exploration

This is an important phase in the research process that serves as a foundational step for understanding, analysing and deriving results from the datasets. The primary objective of the data exploration is to gain an understanding of dataset's structure and content. It includes collection, cleaning and correlation analysis steps which are explained in the following sections.

5.1.1 Data collection

This research project used pre-existing data which was collected using foot-mounted inertial units [12] by Wellington Phoenix Football club's performance team during training. In order to prevent problems related to the consistency of data between units, all players wore same IMUs [Figure 1] for the entire duration of data collection. The datasets include the player metrices like total touches, receives, releases, turn count, top speed, work rate etc from various training sessions between April-July 2023, of under 19 years of age players. This data was in 60 different excel files which were embedded in 15 folders according to dates. Every folder contained 4 excel files, 3 for elite performance and 1 for possession. This data is used to quantify the magnitude and frequency of physical and technical actions occurred during the training sessions.

Figure 1: Foot mounted Inertial measurement unit for the left ankle

5.1.2 Data preprocessing

In data preprocessing phase, 60 separate excel files were combined and cleaned to make two datasets 'elite dataset' and 'possession dataset' which have the structure given in Table 1. To create two datasets for research, Python Pandas library was employed and whole process involved loading, cleaning, using 'iloc' to ensure data uniformity across matches, and concatenating the individual match datasets. It was also tried to merge above said two datasets, however, due to unequal number of rows (large difference), it gave a large number of missing values which could probably affect the result. So, all analysis was done with two datasets containing physical and technical actions. This phase was really important because it allowed to study and compare how players did in many different matches. In both datasets, 'Height', 'Weight of players had missing values which were imputed manually by using other rows containing the same information. Missing values in other columns were dealt using KNN technique with n-neighbours equal 5.

Dimensions	Elite dataset	Possession dataset
Rows	660	11865
Columns	185	21

Table 1:Datasets structure

5.1.3 Correlation Analysis

As there were total 185 features of the elite dataset, so feature selection using correlation matrix and heatmap was done to select important columns.

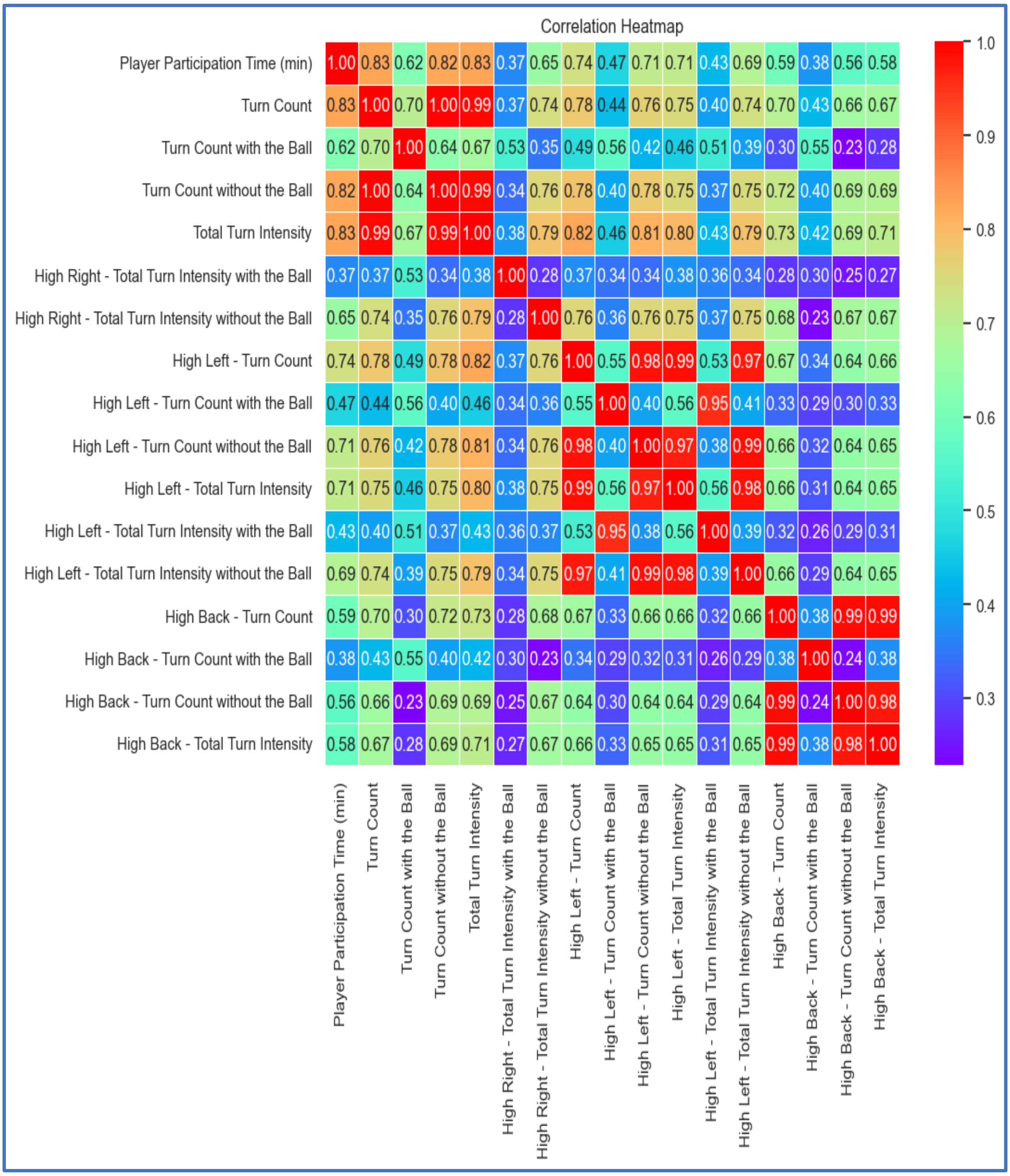

Table 2: Heatmap showing Correlation

Table 2 and Table 3 present heatmap produced. Due to strong relationship among some features, only 20 features of both the datasets are used for further analysis which are 'Possession Time ', 'Time to Release ', ,'Release Velocity', 'Overall Total Steps', 'Release Velocity Min', 'Total time on the ball', 'Sprint Count', 'Intense Speed Changes Acc/ Decl actions per min', 'Total Touches', 'One-Touch', 'Receives', 'Releases', 'Total Possessions', 'Total Touches', 'Turn Count', 'Total Turn Intensity', 'Top Speed', 'Work Rate'.

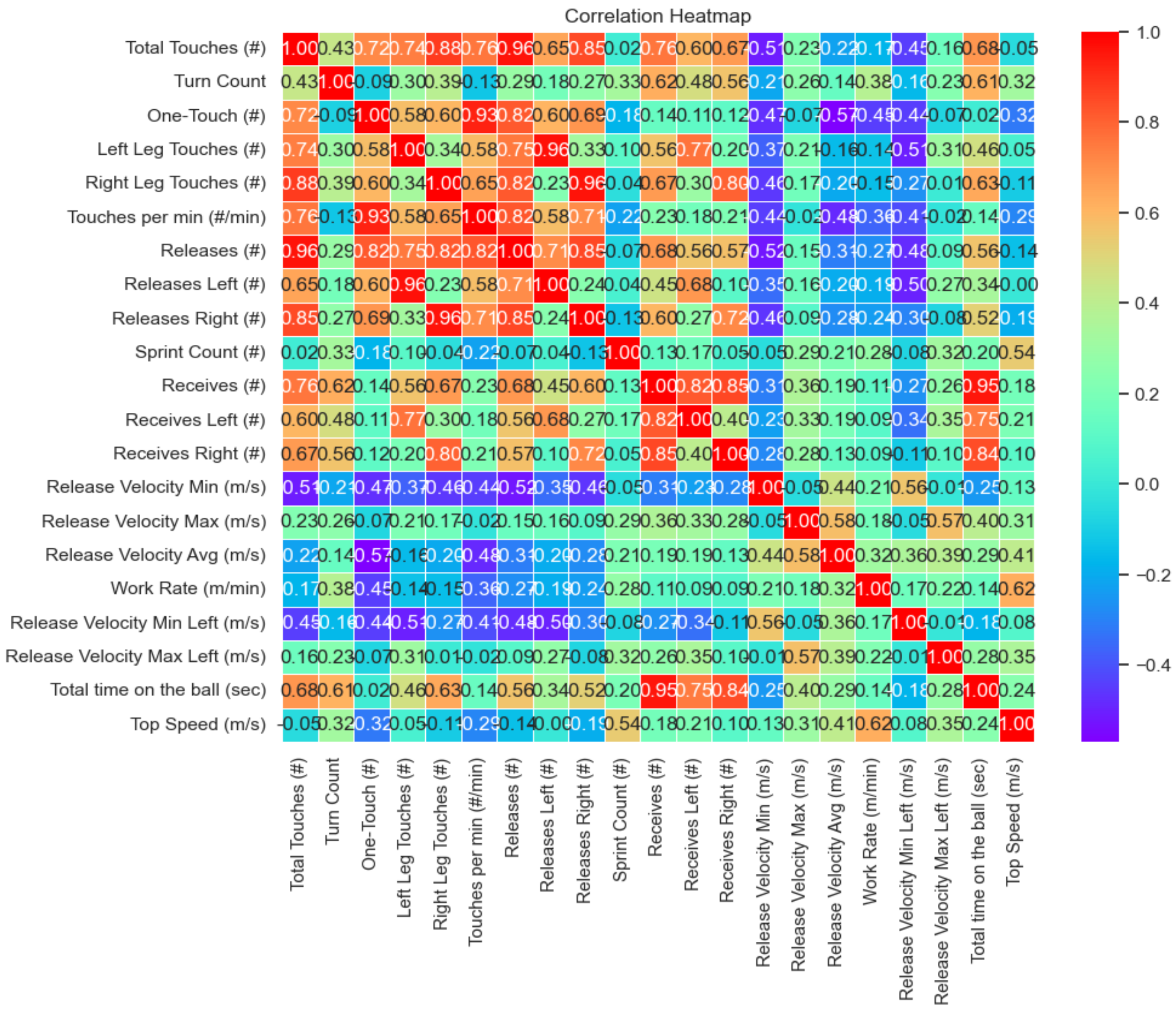

Table 3: Heatmap showing relationship among features

Due to strong relationship among some features, only 20 features of both the datasets are used for further analysis which are 'Possession Time ', 'Time to Release ', ,'Release Velocity', 'Overall Total Steps', 'Release Velocity Min', 'Total time on the ball', 'Sprint Count', 'Intense Speed Changes Acc/ Decl actions per min', 'Total Touches', 'One-Touch', 'Receives', 'Releases', 'Total Possessions', 'Total Touches', 'Turn Count', 'Total Turn Intensity', 'Top Speed', 'Work Rate'.

5.2 Data analysis

After data exploratory phase, the unified datasets were used to do further analysis. Quantitative approach is used to understand performance metrices. The whole research is based on descriptive statistics, content analysis and Regression analysis. Python and SAS are used for the study. Table 4 provides information about variables taken for analysis and Table 5 is for methods used for three objectives.

VARIABLES USED	
1. 'Total Touches (#)', 2. 'Turn Count', 3. 'One-Touch (#)', 4. 'Left Leg Touches (#)', 5. 'Right Leg Touches (#)', 6. 'Touches per min (#/min)', 7. 'Releases (#)', 8. 'Sprint Count (#)', 9. 'Receives (#)', 10. 'Sprint Count (#)',	11. 'Receives (#)', 12. 'Turn Count', 13. Participation Time (min)', 14. 'Turn Count with the Ball', 15. 'Turn Count without the Ball', 16. 'Total Turn Intensity', 17. 'Total time on the ball (sec)', 18. 'Top Speed (m/s)''Player 19. 'Release Velocity Avg (m/s)', 20. 'Work Rate (m/min)',

Table 4:Variables used for Research

Relationship examination which is done using linear regression. A multiple linear regression model is constructed. This selection assumes that 'Total Possession' is an essential indicator of team or player performance in Soccer. It represents how much time a team or player has control of ball during a game, which can be critical in determining the outcome of match.

objective	Approach	Software	method	Group by	Library used	Variable used
1	Quantitative	SAS	Descriptive statistics: Proc means	Player Name	None: BASE SAS	Table 4
2	Quantitative	SAS	Descriptive statistics: Proc means	Player Position	None: BASE SAS	Table 4
3	Quantitative	Python	Linear Regression	No grouping	Stats models	**Response**: 'Total Possessions' **Predictors**: 'Turn Count', 'Total Touches (#)', 'Top Speed (m/s)', 'Sprint Count (#)', 'Release Velocity Average (m/s)', and 'Work Rate (m/min)'as predictors

Table 5: Methods used for Analysis

The Ordinary least regression (OLS) is fitted, providing insights into the significance of the relationships between predictors and response. This analysis provided the factors influencing the 'Total possession'.
Model assumptions are
1.The model assumes a linear relationship between the predictors and the response variable.
2.The model assumes that the errors are normally distributed.
3.The model assumes that the predictors are not highly correlated with each other which means no multicollinearity.

6. Results

6.1 Objective 1

This objective is examined using proc means statement taking grouping by player Name and output is given in Table 6 and Table 7 depicts the significant variation in player performance across different metrices. For most players, total touches ranges from around 24 to 140 touches with mean of 75 touches, turn count is between 50-260 with average 143 and Possession time is from 11 to 44 min (during full match) with mean 19 minutes which are highest for 'Luca Bordignon' and 'Ned Thompson', indicating their involvement in the game. Releases and 'Receives' are also exceptionally high for these two players with 43 receives and 56 releases on average whereas Louis Wicks has lowest count with 5 receives and 7 releases which shows his limited involvement in the game.

Player Name	Total Touches (#)	Receives (#)	Releases (#)	Total Possessions (#)	Possession Time (min)	Turn Count	Top Speed (m/s)	Work Rate (m/min)	Sprint Count (#)
Agustin Coronel	47.73	7.73	17.62	19.1	18.75	114.6	7.2	103	2.15
Alex Braakhuis	51.78	11.6	22.89	23.1	21.98	111	7.2	112	1.33
Alfie Crookston	112.17	20.5	48.17	48.3	17.92	96.67	7.4	101	1.67
Anaru Cassidy	96.41	24.1	39.31	40.5	18.54	174.3	6.7	116	0.62
Athan Thompson	89.22	18.8	37.56	38.7	18.66	159.8	7.7	119	5.33
Carlos Ranui	108.5	35.2	46.66	46.7	19.48	180.9	6.8	101	0.88
Daniel Makowem	66.25	11.5	28.75	30.8	11.15	131.3	7	109	3.5
Declan Street	62.77	15.3	24.74	25.6	20.18	127	7.5	112	4.71
Eamonn McCarron	32.14	8.43	18.57	18.6	23.15	56	5.4	61.3	0
Fergus Gillion	109.42	28.8	45	45.7	19.87	265.1	7.3	129	2.67
Fletcher Pratt	85	12.6	26.44	30	13.98	120	6.4	100	0.89
Gab Sloane-Rodrigues	78.09	10.6	30.36	32.2	16.05	136.9	7.1	105	3.45
Harrison Kowalczyk	30	4	8	9.33	19.1	180.7	7.1	123	3.33
Hayden Thomas	88.79	26.1	36.46	37.3	21.98	196.4	7	111	1.07
Jack Perniskie	102	4.67	50.67	50.7	12.82	52.33	6.4	107	0
Jayden Smith	37.57	8.57	19.71	19.7	21.36	48.14	7.1	102	1.43
Jesper Edwards	105.14	37	47.33	47.7	21.71	170.9	7.9	111	2.38
Joseph Cornille	67.89	17.8	27.36	27.9	18.45	157.1	7.1	111	1.5
Joshua Deacon	96	31.7	40.57	40.6	19.02	131	7.2	97.8	2.86
Ned Thompson	140.22	37.2	55.56	56	140	140.9	7.3	105	2.44
Player 10	39.2	10.8	19.2	19.2	39.2	NaN	6	84.5	2.4

Player 6	45.33	10.7	15.33	16	45.3	NaN	6.6	119	0
Lewis Partridge	87.5	24	35.1	36.9	16.78	143.1	7.5	120	8.2
Louis Wicks	24	5	7	7	44.01	72	6.5	119	0
Luca Bordignon	124.67	42.7	51.33	51.3	19.96	231.3	6.8	104	0
Luke Flowerdew	42.48	6.3	12.39	13.6	15.98	133.3	7.6	106	4.68
Luke Supyk	62.7	12.9	18.96	21	21.53	189	7.6	107	5.33

Table 6: Player's performance metrices on average

On the other hand, Work rate (84 to 128m/min) and Sprint count (0 to 8) is high for 'Player 10 and 'Player 6' who are below average performers in other metrices which indicates that their playing style is more about energy and effort rather than taking ball control and playmaking. Fergus Gillion has highest turn count and total turn intensity depicting his activeness in field.

Player Name	Total Touches (#)	Receives (#)	Releases (#)	Total Possessions (#)	Total Touches (#)	Turn Count	Total Turn Intensity	Top Speed (m/s)	Work Rate (m/min)	Sprint Count (#)
Luqman Ibrahim	50	9	10	12	50	79	371	8	114	7
Matteo Lidstone	118	37.3	47.33	48.7	118	200.7	827	7.3	110	2
Mick Reid	78.43	12.4	28.57	29.9	78.4	113	514	7.3	102	2
Ned Thompson	140.22	37.2	55.56	56	140	140.9	540	7.3	105	2.44
Oli Grosso	72.33	6.17	31.67	32.3	72.3	114.8	453	7.2	104	2.67
Paris D'Lamini	67.95	15.7	25.48	26.6	68	152.5	579	6.6	108	0.29
Player 10	39.2	10.8	19.2	19.2	39.2			6	84.5	2.4
Player 6	45.33	10.7	15.33	16	45.3			6.6	119	0
Raphael Conway	89.73	21.3	33.07	35.1	89.7	214.2	843	6.8	119	0.8
Reuben Barr	117.33	35.7	55	55	117	143.5	554	6.8	106	1
Riley Allison	25	5	8	10	25	99	431	7	109	0
Ryan Hamilton	79.88	18.9	32.3	33.3	79.9	142.7	566	7.1	110	2
Ryan Watson	74.83	20	25.58	27.3	74.8	163.6	704	7.3	128	3.83
Sam Law	56.78	11.9	27.22	27.4	56.8	144.6	556	7	118	0.22
Sam Proctor	43.3	7.73	13.33	14.4	43.3	177.7	743	7.7	121	5.93
Seth Karunaratne	78.81	24.5	35.94	36.3	78.8	183.3	697	7.4	102	2.62
Thomas McKnight	61.27	11.5	23	23.7	61.3	155.3	647	7.5	124	3.45
Xuan Loke	84.88	25.2	34.96	35.7	84.9	147	593	8	104	7.15

Table 7: Average performance metrices for player

These insights provide a comprehensive view of each player's performance in term of ball handling, speed, work rate and passing abilities. This information can be used to make informed decisions about player selection and tactics in soccer game.

To visually explore the distribution, Boxplots are created, and comparison is made using ANOVA test which assess the group difference.

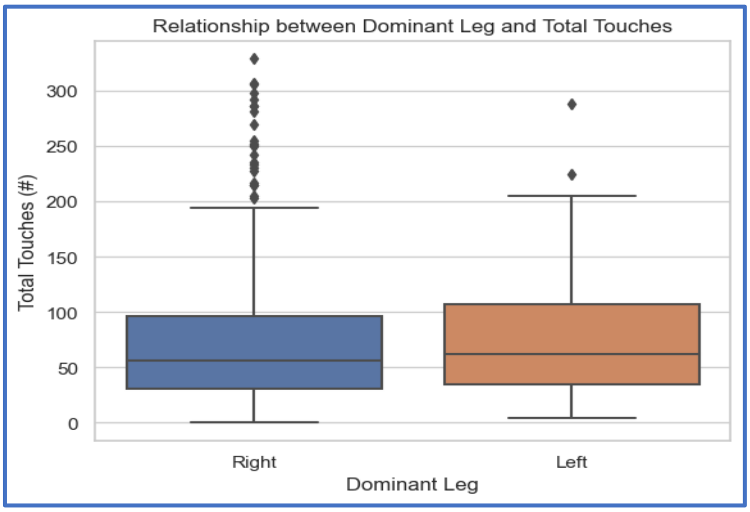

Figure 2:Boxplots to compare leg dominancy.

It is also important to understand whether leg dominancy make a difference in performance or not. As it can be seen from the figure 2 that the left leg is slightly more helpful in total ball touches than right.

6.2 Objective 2

This objective is done again using descriptive statistics and grouping is done by player Position in the field and output is shown in the Table 8 elucidates that Defenders (81) have the most ball touches while Goalkeepers (32) have fewest which are in line with real world as well. Releases, Receives and Total Possessions are highest again for Defenders which demonstrates their control of the game. Goalkeepers exhibit characteristics such as lowest work rate, longest time to release, highest minimum release velocity and participation time, highlighting their position focused on guarding the goal and they have consistent involvement.

Position Category	Total Touches (#)	Receives (#)	Releases (#)	Total Possessions (#)	Time to Release (sec)	One-Touch (#)	Turn Count	Work Rate (m/min)
Defenders	81.52	22.44	34.05	34.71	1.14	12.27	147.51	107.3
Forwards	54.57	9.33	18.67	19.99	0.81	10.65	149.26	110.2
Goalkeepers	32.14	8.43	18.57	18.57	0.95	10.14	56	61.31
Midfielders	78.47	18.72	29.38	30.84	1	12.12	167.58	114.63

Table 8:Player's performance metrices on average by position

Table 9 suggests that Midfielders on the other hand, undergoes a high number turns and intense speed changes per minute, suggesting their dynamic role in both attack and defence. Forwards have highest Sprint Count and top speed during the game which shows their need for speed and power in attacking.

Position Category	Release Velocity Min (m/s)	Total time on the ball (sec)	Sprint Count (#)	Player Participation Time (min)	Acc/Decl actions per min	Possession Time (min)	Release Velocity (m/sec)	Top Speed (m/s)
Defenders	6.45	44.82	2.94	47.74	1.26	19.22	12.36	7.28
Forwards	7.13	21.25	4.45	47.16	1.33	16.92	10.18	7.48
Goalkeepers	7.25	17.71	0	60.21	0.35	23.15	13.58	5.44
Midfielders	6.59	35.91	1.77	46.57	1.12	19.25	11.33	6.97

Table 9:Some more Player's performance metrices on average by position

Bar graph in Figure 3 compares the various performance metrices according to position of player. Goalkeepers perform less technical and physical actions whereas Midfielders are more into these actions.

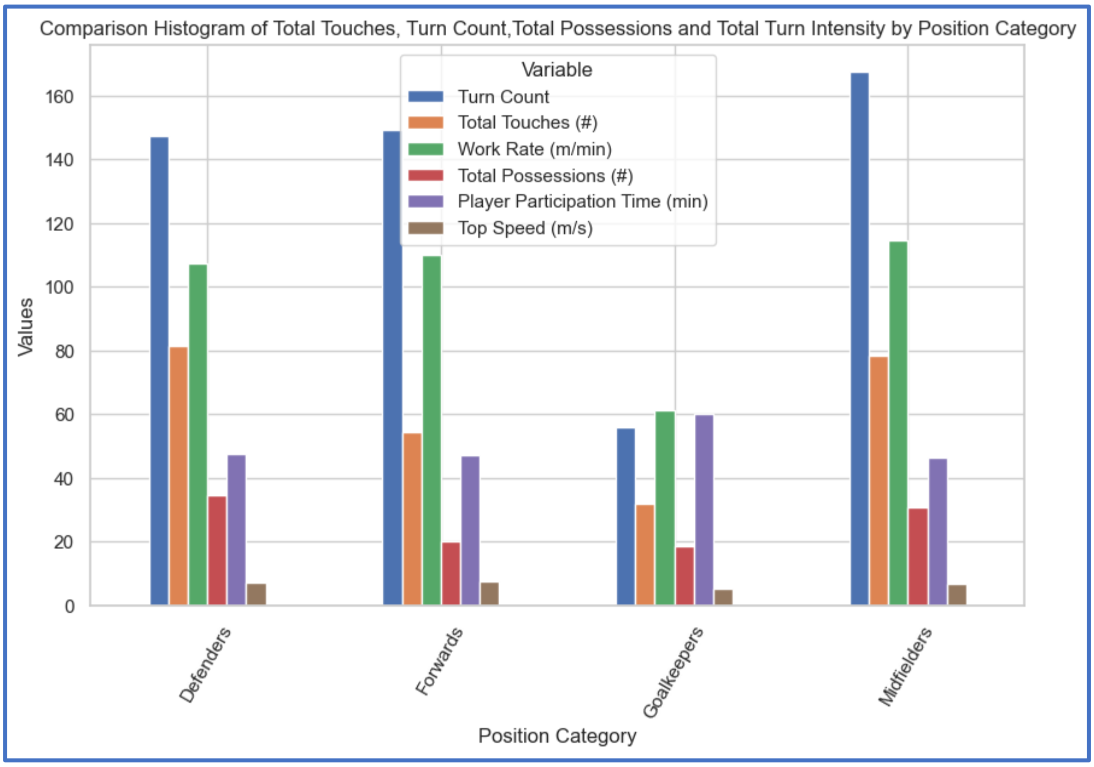

Figure 3:Comparison of various performance metrices by Position

6.3 Objective 3

The third objective is link with Model implementation and Linear regression model is done using 'Total Possessions' as Response variable. P- values from model summary are given in Table 10. Top Speed(m/s) is not statistically significant, as the P-value is relatively high (0.4). Changes in the top speed do not have a strong linear relationship with Total Possessions. All other predictors are significant (P- value < 0.05) which indicates that they have linear relationship with response. Turn count, Release velocity Avg (m/s), Sprint Count and Work Rate (m/min) have negative linear relationship with the Total Possessions, however, Total touches are positively associated.

S.No	VARIABLE	Coefficient	P>|t|
1	Turn Count	-0.02	0.000
2	Total Touches	0.47	0.000
3	Sprint Count	-0.113	0.001
4	Release velocity Avg (m/s)	-0.693	0.000
6	Top Speed (m/s)	1.073	0.400
7	Work Rate (m/min)	-0.032	0.000

Table 10: Output from linear Regression Model

6.3.1 Interpretation of estimated coefficients

As per model summary, Total Possessions are expected to decrease by 0.02, 0.113, 0.69 and 0.032 with a unit increase in Turn Count, Sprint Count, Release Velocity Average and Work Rate (m/min) respectively. It means that they have inverse relationship with Total possessions. On the other hand, Total possessions increase by 0.47 units by a unit increase in total touches.

7. Conclusion, Limitations & Future Work

Overall, these metrices can be used to analyse and compare the performance and playing styles of different positions. The analysis of player performance by 'Player Name' revealed important variations. Players Like 'Luca Bordignon' and 'Ned Thompson' showed exceptional performance. In case of Position analysis, Defenders may focus on maintaining possession and making fewer sprints, while forwards may prioritize quick releases and higher sprint count. These insights can help in decision making for strategies and player roles. Also, it is notable that Player's running speed does not have any influence on the Total possessions of ball by player or the team.

Every study has some limitations, and this study is not an exception. The study relies on existing data collected using foot-mounted inertial units which may have inherent limitations or errors. Other limitation is linked with lot of missing values in the datasets which were imputed by KNN technique. As analysis used imputed data, it is probable that results might got affected. Also, the dataset focussed on the youth New Zealand professional soccer players, which may not be representative of all player population.

Although this study has some limitations, but the findings of this research build several promising directions for the future research that can contribute to deeper understanding of player performance analysis in Soccer. Future research could include more advanced analytics techniques, such as machine learning, to predict player performance or injury risk. Given the high incidence of soccer-related injuries, future work could focus on how performance metrices relate to injury and prevention. In addition, expanding the dataset to encompass different age categories or groups will enable a deeper understanding of performance metrices across entire spectrum of player development.

8. Data confidentiality and privacy

This study involves data provide by Wellington Phoenix, which is subject to a confidentiality agreement. As per the terms of agreement, the dataset or its link can be shared due to the data privacy concerns. This study strictly follows the confidentiality and ethical guidelines set in the agreement, ensuring the protection and responsible use of the provided data.

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